Advances in Analytics for Learning and Teaching

Muhittin Sahin
Dirk Ifenthaler *Editors*

Visualizations and Dashboards for Learning Analytics

Springer

Advances in Analytics for Learning and Teaching

Series Editors
Dirk Ifenthaler, Learning, Design and Technology, University of Mannheim
Mannheim, Baden-Württemberg, Germany
David Gibson, Teaching and Learning, Curtin University, Bentley, WA, Australia

This book series highlights the latest developments of analytics for learning and teaching as well as providing an arena for the further development of this rapidly developing field.

It provides insight into the emerging paradigms, frameworks, methods, and processes of managing change to better facilitate organizational transformation toward implementation of educational data mining and learning analytics. The series accepts monographs and edited volumes focusing on the above-mentioned scope, and covers a number of subjects. Titles in the series *Advances in Analytics for Learning and Teaching* look at education from K-12 through higher education, as well as vocational, business, and health education. The series also is interested in teaching, learning, and instructional design and organization as well as data analytics and technology adoption.

More information about this series at http://www.springer.com/series/16338

Muhittin Sahin • Dirk Ifenthaler
Editors

Visualizations and Dashboards for Learning Analytics

Springer

Editors
Muhittin Sahin
University of Mannheim
Mannheim, Germany

Dirk Ifenthaler
University of Mannheim
Mannheim, Germany

Curtin University
Perth, WA, Australia

ISSN 2662-2122 ISSN 2662-2130 (electronic)
Advances in Analytics for Learning and Teaching
ISBN 978-3-030-81221-8 ISBN 978-3-030-81222-5 (eBook)
https://doi.org/10.1007/978-3-030-81222-5

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

Learning analytics involve collecting, analyzing, measuring, and reporting data in learning environments in order to support learning as well as improving learning environments. More precisely, learning analytics use static and dynamic data from learning environments and their contexts for enabling: (a) real-time modeling about learners and learning, (b) estimation and optimization of learning processes, (c) assessment, revision, and analysis of data for learning environments and educational decision-making. Hence, the aim of learning analytics is to increase the effectiveness and efficiency of education.

Learning analytics applications such as visualizations and dashboards are being developed that use learner-generated data and other relevant information to personalize and continuously adapt the learning environment. Visualizing is expected to create awareness and reflection among learners. Functions of visualizations include exploration, discovery, summarizing, presenting, and enjoying. The visualization is applied in digital learning environments via dashboards.

Current research on dashboards aims to identify which data are meaningful to different stakeholders in education and how the data can be presented to support learning processes. The objectives of dashboard studies include: (a) increasing the awareness about the learning process, (b) supporting cognitive processes, (c) identifying students at risk, (d) providing immediate feedback, (e) displaying achievement level, (f) providing procedural information, (g) supporting decision-making, (h) informing, (i) showing participant relationships, (j) comparing, and (k) reflecting. Most visualization techniques stem from statistics, including bar charts, line graphs, tables, pie charts, and network graphs.

The purpose of this edited volume "Visualizations and Dashboards for Learning Analytics" is to advance the scientific and practical knowledge on visualizations and dashboards for learning analytics applications. It features five major parts: Part I – *Theoretical and Technological Perspectives Linking Visualization and Dashboard Design*, Part II – *Practices and Evidence from the Learner's Perspective*, Part III – *Practices and Evidence from the Educator's Perspective*, Part IV – *Systems Design for Learning Analytics Applications*, and Part V – *Future Directions of Visualization and Dashboard*.

Without the assistance of experts in the field of learning analytics, the editors would have been unable to prepare this volume for publication. We wish to thank our board of reviewers for their tremendous help with both reviewing the chapters and linguistic editing. In addition, we would like to thank the Series Editors of "Advances in Analytics for Learning and Teaching" for guiding the publication process and including our work in the book series.

Izmir, Turkey
Mannheim, BW, Germany — Muhittin Sahin
Perth, WA, Australia — Dirk Ifenthaler

Contents

About the Editors

Muhittin Sahin (musahin@mail.uni-mannheim.de; muhittin.sahin@ege.edu.tr) is an academic staff at Ege University, Turkey, and postdoctoral researcher at the University of Mannheim, Germany. His research interests relate to instructional technology, learning analytics, educational data mining, multi-criteria decision-making, statistic, sequential analysis, e-assessment, and intelligent learning management systems. He also collaborates on a project about developing an adaptive intelligent tutoring system.

Dirk Ifenthaler (dirk@ifenthaler.info; www.ifenthaler.info) is Professor and Chair of Learning, Design, and Technology at the University of Mannheim, Germany, and UNESCO Deputy Chair of Data Science in Higher Education Learning and Teaching at Curtin University, Australia. His previous roles include Professor and Director, Centre for Research in Digital Learning at Deakin University, Australia; Manager of Applied Research and Learning Analytics at Open Universities, Australia; and Professor for Applied Teaching and Learning Research at the University of Potsdam, Germany. He was a 2012 Fulbright Scholar-in-Residence at the Jeannine Rainbolt College of Education, at the University of Oklahoma, USA. His research focuses on the intersection of cognitive psychology, educational technology, data analytics, and organizational learning. His research outcomes include numerous coauthored books, book series, book chapters, journal articles, and international conference papers, as well as successful grant funding in Australia, Germany, and USA. He is the Editor-in-Chief of the *Technology, Knowledge and Learning*, Senior Editor of *Journal of Applied Research in Higher Education*, and Deputy Editor-in-Chief of *International Journal of Learning Analytics* and *Artificial Intelligence for Education*.

About the Authors

June Ahn (junea@uci.edu) is an associate professor at the University of California-Irvine School of Education. He studies the design, implementation, and evaluation of learning technologies. His research spans a variety of topics including social media and games for learning, online learning, and blended learning. However, he has a particular interest in understanding the sociotechnical systems surrounding new learning technologies – or how social, cultural, and institutional factors intersect with the new possibilities afforded by technology. His prior experiences include work as a middle school math teacher, high school computer science teacher, technology director at a K-8 school, and faculty member and Director of the Human-Computer Interaction Lab (HCIL) at the University of Maryland, College Park.

Gökhan Akçapınar (gokhana@hacettepe.edu.tr) is an associate professor at the Department of Computer Education and Instructional Technology, Hacettepe University, Turkey. His research interests are in the areas of Educational Data Mining (EDM) and Learning Analytics (LA). For the last 10 years, he has been conducting research on developing educational early-warning systems for at-risk students, modeling students' learning behaviors, designing data-driven interventions, and developing learning analytics dashboards. As a postdoc researcher, he worked on an educational big data analysis project at the Academic Center for Computing and Media Studies, Kyoto University, Japan. He is also codirector of the Hacettepe University Distance Education Application and Research Center.

Gokce Akcayir (akcayir@ualberta.ca) is an SSHRC postdoctoral fellow at the University of Alberta. She joined the Educational Technology, Knowledge, Language, and Learning Analytics (EdTeKLA) research group in 2018. She received both of her master's and PhD degrees in Educational Technology. Her research interests include augmented reality in education, computer science education, and community-engaged research.

Aruna Awasthi (aruna.awasthi@rmit.edu.au) is a senior data analyst at RMIT University. Her research interests revolve around learning analytics, researching learning and teaching, tracking student performance, analyzing university data, and using evidence to improve teaching and learning. She considers herself a learning analyst to adopt effective learning strategies using computational analysis techniques from data science.

Furkan Aydin (furkanaydin@ksu.edu.tr) is an instructor at Computer Technologies at Kahramanmaraş Sütçü İmam University in Kahramanmaraş, Turkey. He holds an MSc in Computer Education and Instructional Technology from Sakarya University. He is currently a PhD student in Computer Education and Instructional Technology at Hacettepe University. His academic interest areas are e-learning, intelligent tutoring systems, educational data mining, learning analytics, and feedback.

Fatma Bayrak (fbayrak@hacettepe.edu.tr) is an assistant professor at Computer Education and Instructional Technologies at Hacettepe University in Ankara, Turkey. She holds an MSc and a PhD in Computer Education and Instructional Technology from Hacettepe University. Her academic interest areas are e-learning, formative e-assessment, technology-enhanced assessment, assessment analytics, feedback, and reflective thinking.

Liz Bennett (e.bennett@hud.ac.uk) is Director of Teaching and Learning within the School of Education and Professional Development at the University of Huddersfield. Her professional interests are in the adoption of technology particularly within higher education, and she is a coeditor of *Research in Learning Technology*, the journal of the Association for Learning Technology.

Florian Berens (florian.berens@uni-goettingen.de) is a research assistant and a PhD student at the Center of Methods in the Social Sciences at the University of Goettingen. The core of his research is the measurement of attitudes and beliefs in statistics education and, in particular, the investigation of their consequences for learning. For this purpose, he uses multiple methodological approaches, especially Learning Analytics. Technology-enhanced learning becomes both a teaching and research interest, in which he focuses on software design and students' usage behavior. He also uses the methodological plurality of his work for method development and reflection.

Ying Cai (yingcai@utexas.edu) is a doctoral student in the Learning Technologies program at The University of Texas at Austin. After receiving a Master's degree in Chinese Language and Literature from the University of Massachusetts Amherst, she had worked as an instructor of Chinese at a high school in Massachusetts. Her research focuses on integrating technology into education, and she is particularly interested in technology-enhanced language learning. She engages in research topics such as Game-Based learning, learning analytics, MOOCs as an online learning tool, and second language acquisition.

Fabio Campos (fabioc@nyu.edu) is a Brazilian researcher and doctoral candidate in the Education, Communication, and Technology program at New York University.

Fabio worked for more than 20 years as a teacher and education program director, specializing in public, private, and third-sector interventions for at-risk young adults in Rio de Janeiro, Brazil. A learning scientist by training, his research focuses on the development of civic literacies among young learners and the design of analytical reasoning tools for school educators. He holds a Master's degree in Stanford University's Learning, Design, and Technology program, and a BA and MBA from Rio de Janeiro's Federal University (UFRJ).

Mohamed Amine Chatti (mohamed.chatti@uni-due.de) is a professor of computer science and head of the Social Computing Group in the Department of Computer Science and Applied Cognitive Science at the University of Duisburg-Essen, Germany. In his research, he explores the fields of social computing, data science, and learning technologies, with a particular interest in intelligent data-intensive systems, human-centered learning analytics, and visual analytics.

Li Chen (lcheb@mail.uni-mannheim.de) is a PhD student at the University of Mannheim. Based on the background in pedagogy and business education, her research interests are mainly on entrepreneurship education and online collaborative learning, especially online and blended EE and entrepreneurship pedagogy.

Deborah Cockerham (deborah.cockerham@unt.edu) is a lecturer in the University of North Texas Department of Learning Technologies, also directs the Research and Learning Center at the Fort Worth Museum of Science and History. She has been a Visiting Research Scholar at Texas Christian University's Center for Science Communication, where she worked to build communication and connections between research scientists, educators, and the public, and supported multiple museum-university research collaborations. As a learning disabilities specialist for 20 years, she taught children and adolescents with learning and attentional differences. Her work with students who have attention deficit hyperactivity and/or autism spectrum disorder has focused on socioemotional learning, using connections between communication skills and fine arts. She has mentored teachers and trained educators at workshops across the nation, both at conferences (National Council of Teachers of Mathematics; International LDA) and as an invited presenter (Learning Center of North Texas; Colorado Dyslexia Center). Her research interests focus on human relationships with technology, including media multitasking and technology's impact upon family roles and education. Recent studies have investigated and worked to build digital responsibility among adolescents in both formal and informal learning settings. She coedited the book *Mind, Brain, and Technology* and has published in multiple journals.

Ed de Quincey (e.de.quincey@keele.ac.uk) is a Senior Lecturer in Computer Science at Keele University, the Director of Education for the School of Computing and Mathematics, and Senior Fellow of the Higher Education Academy (SFHEA). He has researched and taught in the area of online human behavior for 16 years, looking into the usability and impact of digital products as well as uses of the information that they collect. This has included investigations into the potential of Twitter to detect disease outbreaks such as swine flu and other health-related issues such as hay fever and psychosis. This work is continuing with an AHRC-funded project investigating new strategies for combating online hate speech, and he is also working with medical practitioners at the University Hospital North Midlands looking into interface design guidelines for mobile applications. He has combined his research interests with his teaching, has explored the uses of Web 2.0 tools in learning and teaching, and is now looking at how Learning Analytics can be used to improve student outcomes and curriculum design (funded by HEFCE and Jisc). He has previously worked as an eHealth Researcher at City, University of London, and as a Principal Lecturer at the University of Greenwich.

Ron Dyer (ronald.dyer@sheffield.ac.uk) is a Senior University Teacher/ Programme Director for Sheffield University Management School (EMBA) possessing more than 20 years of project management experience across financial service, education, agriculture, and energy focused on technology transformation initiatives. He has worked on several large IT integration projects at Goldman Sachs, Citibank, and the Inter-American Development Bank. He holds a Doctorate in Business Administration from Grenoble Ecole de Management, France; an MBA in Project Management from Henley Graduate School of Business University; an undergraduate degree from Wilfrid Laurier University, Canada, in Business Administration; and a Certified Quantitative Risk Management Fellowship from the IIPER. His research focuses on the utilization of game-based learning, data visualization, and artificial intelligence technology assets (i.e., artifacts) for improved decision-making and problem-solving within organization.

Martin Ebner (martin.ebner@tugraz.at) is currently head of the Department Educational Technology at Graz University of Technology and therefore responsible for all university-wide e-learning activities. He holds an adjunct professor on media informatics (research area: educational technology) and works also at the Institute for Interactive Systems and Data Science as a senior researcher. His research focuses strongly on seamless learning, learning analytics, open educational resources, maker education, and computer science for children. He has given a number of lectures in this area as well as workshops and keynotes at international conferences. For publications as well as further research activities, please visit his website: http://martinebner.at

Tomáš Effenberger (tomas.effenberger@mail.muni.cz) is a PhD candidate in Computer Science at Masaryk University where he also received his master's degree. After research internships at the University of Oxford and Google AI, he became a member of the Adaptive Learning Group at Masaryk University. His mission is to make learning more efficient and engaging by advancing techniques for improving adaptive learning environments.

Shannon Elkins (srelkins@umich.edu) is a recent graduate of the University of Michigan (BS Information and BA Biopsychology, Cognition, and Neuroscience, 2020), where she studied User Experience Design at the School of Information. She has worked with the My Learning Analytics team since 2018 as a student research assistant and has assisted with data analysis regarding student sentiments surrounding the dashboard. Working with the MyLA team has allowed her to learn extensively about learning analytics and educational technology, a field that she hopes to incorporate into her career. She now resides in St. Louis, Missouri, and works for The Boeing Company in their IT Career Foundation Program as a project manager.

Carrie Demmans Epp (cdemmansepp@ualberta.ca) is an assistant professor in the Department of Computing Science at the University of Alberta, where she leads the Educational Technology, Knowledge, Language, and Learning Analytics (EdTeKLA) research group. Her work has two streams. One focuses on understanding how people use educational technologies through the use of analytics and other methods so that these technologies and their use can be improved. The other focuses on developing adaptive educational technologies and reporting systems to support learning across a variety of contexts.

Sue Folley (s.folley@hud.ac.uk) is an academic developer at the University of Huddersfield, with a remit to support the pedagogic development of staff with the use of digital technologies. Her role involves contributing to the university's strategic developments in this area and providing training and support to academic staff. She has worked in Higher Education for over 20 years. Sue has a PGCE, a master's degree in Multimedia and eLearning, and a doctorate in Education focusing on tutors' experiences of teaching online. She is a senior fellow of the Higher Education Academy, and her research interests include online teaching, digital literacy, and student dashboards.

Hanna Geisswinkler (hanna.geisswinkler@tugraz.at) is part of the organizational unit Higher Education and Programme Development at Graz University of Technology. She is working on communication around making learning analytics known as an essential part of future learning, such as preparing instructions and contributing video tutorials for learning analytic tools.

Anna Gillespie (a.gillespie@open.ac.uk) is an associate lecturer in the Faculty of Wellbeing Education and Languages Studies at the Open University, UK. Her research areas relate to how teachers use learning analytics as part of their practice in supporting students studying at distance.

Mouadh Guesmi is a research assistant and PhD student in the Social Computing Group, Department of Computer Science and Applied Cognitive Science, Faculty of Engineering at the University of Duisburg-Essen, Germany. He has bachelor's degree in computer science and master's degree in intelligent information systems from higher institute of computer science and management in Kairouan, Tunisia.

His research interests include human-centered learning analytics, user modeling and personalization, explainable recommender systems, and visual analytics.

Jackson Hammond (jbhammon@umich.edu) is a graduate of the University of Michigan (M.S. Information, 2020) where he studied human–computer interaction. He previously worked at Epic Systems supporting the dashboard and analytics software at hospitals across the USA and joined the My Learning Analytics team in 2019 to help conduct user research with students who used the MyLA dashboard in their classes at UM. He currently works as a UX designer and front-end developer.

Songhee Han (song9@utexas.edu) is a doctoral student in the Learning Technologies program at the University of Texas at Austin. Her current work at the Knight Center for Journalism in the Americas at Moody College of Communication is developing self-directed online courses and researching effective massive open online course design practices. Prior to her life at the university, she had worked at public elementary schools in Korea for 7 years.

Garth Hasler is Head of Learning Analytics at St Andrew's Cathedral School in Sydney. His role is to advocate for the effective use of quality data to inform teaching practice, assessment, and intervention. He works with leaders throughout the school to help them understand the story their data is telling them and apply their expert knowledge to inform next steps. Far from learning analytics being an imposition, he has seen firsthand how easy access to timely information can make a teacher's work easier.

Mohammad Nehal Hasnine (nehal.hasnine.79@hosei.ac.jp) was awarded his PhD in Engineering from Tokyo University of Agriculture and Technology, Japan, in 2018. Upon completion of his PhD, he worked at Kyoto University as a postdoctoral researcher. Then, he was appointed as an assistant professor at the Tokyo University of Agriculture and Technology. Currently, he is serving as an associate professor at the Research Center for Computing and Multimedia Studies, Hosei University. His research topics are learning analytics, learning systems, pedagogical systems, CALL (Computer-assisted Language Learning), and multimodal analytics. He is a member of IEEE (Institute of Electrical and Electronics Engineers), SOLAR (Society for Learning Analytics Research), APSCE (Asia-Pacific Society for Computers in Education), and IAmLearn (International Association for Mobile Learning).

Christothea Herodotou (christothea.herodotou@open.ac.uk) is an associate professor at the Open University, UK. She has extensive expertise in the design and evaluation of innovative technologies for learning (online platforms, mobile applications, digital games). She holds funding to improve the accuracy of predictive learning analytics of at-risk students, as measured by OU Analyse. She coordinated the four-year evaluation of the Early Alert Indicators project, a university-wide initiative that assessed predictive learning analytics interventions and their impact on students' performance and attainment. This initiative has received multiple awards for research impact and excellence in teaching. She is a Senior Fellow of the Higher Education Academy (SFHEA) and an Honorary Associate of UCL.

Jim Hewitt (jim.hewitt@utoronto.ca) is an associate professor in the Department of Curriculum, Teaching and Learning at the Ontario Institute for Studies in Education, University of Toronto. His research focuses on the educational applications of computer-based technologies, with a particular emphasis on discursive processes in collaborative learning environments. His publications include studies of thread development in asynchronous distance education courses, sociocultural supports for knowledge building in elementary science classrooms, and uses of multimedia and online technologies for teacher development. He is the principal investigator and developer of the web-based learning environment called Pepper. Through these and other research endeavors, he hopes to discover new ways to help students work together creatively to build knowledge.

Sebastian Hobert (shobert@uni-goettingen.de) is a postdoctoral researcher at the University of Goettingen. He works in the interdisciplinary field of computer science, human–computer interaction, and information systems. In his research, he mainly focuses on technology-enhanced learning, chatbots, and wearable computing using design science research. He is particularly interested in conceptualizing, designing, and evaluating software artifacts in innovative fields of research. From a methodic point of view, he takes a design science research perspective by focusing on practice-oriented research problems. Before getting his doctorate in information systems, he studied applied computer science.

Mehmet Barış Horzum (mhorzum@sakarya.edu.tr) is a professor of Computer Education and Information Technologies, head of the Distance Education Center, and Dean of Student at Sakarya University, Turkey. His research focuses on educational technologies, distance education, and technology addiction. He is a project researcher for EU Projects and several TUBITAK (The Scientific and Technological Research Council of Turkey) projects including UZEP (a distance education platform for 12 Turkish Universities). He has widely published on educational technologies and distance education topics. His current research focuses on distance education and educational data mining.

Lingyun Huang (lingyun.huang@mail.mcgill.ca) is a PhD candidate in the Department of Educational and Counselling Psychology at McGill University. He is a member of the Advanced Technologies for Learning in Authentic Settings (ATLAS) Lab. His research focuses on modeling the self-regulated learning (cognitive, metacognitive, and emotional) processes in computer-based environments using learning analytics and educational data mining approaches.

Dirk Ifenthaler (dirk@ifenthaler.info; www.ifenthaler.info) is Professor and Chair of Learning, Design, and Technology at University of Mannheim, Germany, and UNESCO Deputy Chair of Data Science in Higher Education Learning and Teaching at Curtin University, Australia. His research focuses on the intersection of cognitive psychology, educational technology, data analytics, and organizational learning. He is the Editor-in-Chief of the *Technology, Knowledge and Learning*, Senior Editor of *Journal of Applied Research in Higher Education*, and Deputy Editor-in-Chief of *International Journal of Learning Analytics and Artificial Intelligence for Education*.

Shoeb Joarder is a research assistant and PhD student in the Social Computing Group, Department of Computer Science and Applied Cognitive Science, Faculty of Engineering at the University of Duisburg-Essen, Germany. He has a Master's degree in Computer Engineering from the University of Duisburg-Essen. His main research areas involve educational data science, social computing, and learning technologies, with a focus on human-centered learning analytics, visual analytics, and big data.

Rogers Kaliisa (rogers.kaliisa@iped.uio.no) is a doctoral research fellow at the Department of Education, Faculty of Educational Sciences, University of Oslo, Norway. His primary research interests relate to learning analytics, learning design, mobile learning, and technology-enhanced learning.

Matthew Kay (mjskay@northwestern.edu) is an assistant professor in Computer Science and Communications Studies at Northwestern University working in human–computer interaction and information visualization. His research areas include uncertainty visualization, personal health informatics, and the design of human-centered tools for data analysis. He is intrigued by domains where complex information, like uncertainty, must be communicated to broad audiences, as in health risks, transit prediction, or weather forecasting. He codirects the Midwest Uncertainty Collective (http://mucollective.co) and is the author of the tidybayes (https://mjskay.github.io/tidybayes/) and ggdist (https://mjskay.github.io/ggdist/) R packages for visualizing Bayesian model output and uncertainty.

Sinan Keskin (sinankeskin@yyu.edu.tr) is an academic staff at Van Yuzuncu Yil University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education at Gazi University in 2010 and worked as a teacher for one year. He gets his PhD degree in 2019. He has experience in distance education, e-assessment, instructional design, and programming teaching. His research interests relate to e-assessment, feedback design, instructional discussions, adaptive e-learning, learning analytics, and educational data mining.

Pınar Nuhoğlu Kibar (pnuhoglu@hacettepe.edu.tr) is a researcher in the Department of Computer Education and Instructional Technology of Faculty of Education at Hacettepe University. She holds MSc and PhD in Computer Education and Instructional Technology from Hacettepe University. Her research interests include e-learning, multimedia learning, visualization in education, knowledge and information visualization, and visual literacy. Highly interested in educational infographics, she focuses on improving the infographic creation process of learners during teaching-learning process, and her research currently studies the interactive and dynamic form of infographic design in the learning process, which covers animation, video, and dashboards design.

Anders Kluge (anders.kluge@iped.uio.no) is a researcher in technology-enhanced learning at the Department of Education, Faculty of Educational Sciences, University of Oslo, Norway. His research is directed toward how technology can be designed and used to stimulate productive learning processes. In particular, he is engaged in how to strike the balance between user activity and theory presentation in rich digital representations and cocreative processes. He holds a PhD from the Department of Informatics, UiO.

Selay Arkün Kocadere (selaya@hacettepe.edu.tr) is an associate professor at Hacettepe University in Ankara, Turkey. Following her bachelor's degree in Mathematics Education, she received her MSc and PhD in Computer Education and Instructional Technology. She worked as an instructional designer in the private sector before moving into academics. Interested in technology-enhanced mathematics education, online learning, and mentoring, her recent research focuses on gamification. Currently, she is coordinating three international projects on ICT integration into teaching–learning processes and instructional gamification.

Philipp Leitner (philipp.leitner@tugraz.at) is part of Educational Technology at Graz University of Technology and is currently doing his PhD on Learning Analytics with focus on Higher Education at the Institute of Interactive Systems and Data Science (ISDS). Philipp has already published several papers in the field of Learning Analytics and held workshops on this topic. For more information on publications and research activities, please visit his homepage https://philipp-leitner.at.

Grace Lin (gcl@mit.edu) is a Learning Scientist and Assessment Designer at MIT's Scheller Teacher Education Program | The Education Arcade. She is particularly interested in measurement and playful assessments for and of learning. Her research centers around different areas of cognition and how games can be implemented to not just help people learn, but also measure elusive constructs. She received her PhD in Education from the University of California, Irvine; an Ed.M. in Mind, Brain, and Education from Harvard Graduate School of Education; and a BA in Psychology from New York University. She has facilitated teaching assistant and course design professional development workshops for both first-year graduate students and postdocs across various disciplines, and, prior to joining MIT, Grace was a postdoctoral fellow at the University of Oregon, working with nonprofit organizations and on an early childhood measures repository.

Min Liu (mliu@austin.utexas.edu) is a professor of Learning Technologies at the University of Texas at Austin. Her teaching and research interests center on educational uses of new media and other emerging technologies, particularly the impact of such technologies on teaching and learning; and the design of new media enriched interactive learning environments for learners at all age levels. Her current R&D projects include studying the design and effectiveness of immersive, rich media environments on learning and motivation; learning analytics in serious game and other online environments; understanding MOOCs as an emerging online learning tool; examining the affordances and constraints of using mobile technologies in teaching and learning; and using Web 2.0 tools to facilitate instruction.

Athar Mahmoudi-Nejad (athar1@ualberta.ca) is a PhD student in the Department of Computing Science at the University of Alberta. Her doctoral research investigates adaptive virtual reality methodologies.

Marcelo Milrad (marcelo.milrad@lnu.se) is a Full Professor of Media Technology at Linnaeus University (LNU) in Sweden. His research interests include the areas of TEL, advanced HCI, and novel uses of Big Data techniques and mobile technologies in the fields of Education & Health Care. Since March 2020, he acts as the main scientific coordinator of LNU's knowledge environment called "Digital Transformations." He has published over 250 scientific articles. He has also been presenting his work in more than 45 countries worldwide. During the last years, he has been serving as a program committee member in a number of international scientific conferences such as CSCL, ICALT, WMUTE, ICCE, and mLearn. He is also an editorial board member in several scientific journals in the field of technology-enhanced learning. He has acted as an executive member of the IEEE Computer Society Technical Committee on Learning Technology (LTTC), and he is one of the initiators of the IEEE International Conference on Wireless and Mobile Technologies in Education (WMTE). He was one of the steering committee members of the Mobile Learning SIG, a research activity that was part of the European Network of Excellence on Technology Enhanced Learning Kaleidoscope.

Arham Muslim (arham.muslim@seecs.edu.pk) is an assistant professor at the Department of Computing, School of Electrical Engineering and Computer Science at the National University of Sciences and Technology, Islamabad, Pakistan. His main research areas encompass learning technologies, learning analytics, and data science.

Ha Nguyen (thicn@uci.edu) is a PhD candidate in STEM Teaching and Learning at the University of California, Irvine. She applies research in learning sciences, learning analytics, and human–computer interactions to study ways to promote student-centered, equitable learning in STEM through responsive digital environments. She partners with educators and community partners to design interface and computer-supported learning activities, and experiments with ways to systematically process education data. She receives her MA in STEM Teaching and Learning from the University of California, Irvine, and BA in Public Policy, Japanese, and Education from Duke University.

Nuno Otero (nuno.otero@lnu.se) is an associate professor at the Department of Computer Science and Media Technology at Linnaeus University (LNU) in Sweden. He is interested in theories and conceptual frameworks in HCI and technology-enhanced learning. The main question driving his research concerns the understanding of how the properties of distinct devices, computational artifacts, and embedded external representations impact people's activities.

Zilong Pan (panzl89@utexas.edu) is a doctoral student in the Learning Technologies program at the University of Texas at Austin. He earned his master's degree in Middle School Education from the University of Georgia. He had taught in middle schools in the Atlanta area as a science and math teacher for two years. His research interests include learning analytics and integrating learning technology into STEM education.

Teresa Cerratto Pargman (tessy@dsv.su.se) is an associate professor of human–computer interaction at the Department of Computer and Systems Sciences, Stockholm University, Sweden. She is PI for the project responsible LA in Higher Education funded by the Wallenberg Foundations, WASP-HS program. She is interested in the study of ethical issues in education from situated, relational, and dialectical perspectives.

Martyn Parker (martyn.parker@warwick.ac.uk) is a Senior Fellow of the Higher Education Academy (SFHEA), a Fellow of the Institute for Mathematics and its Applications (FIMA), and currently the program director for Mathematics and Statistics at the University of Warwick. He has extensive teaching and scholarly experience working on the transition from school to university mathematics. This work has led to innovations in program and modules design and delivery. He works with national organizations to encourage and facilitate participation in higher education.

Fernando V. Paulovich (paulovich@dal.ca) is an associate professor and Canada Research Chair (Tier 2) in Data Visualization at the Faculty of Computer Science, Dalhousie University, and head of the Visualization and Visual Analytics lab. Before moving to Canada, he was an associate professor for almost a decade at the University of São Paulo, Brazil. His research focuses on integrating machine learning and visualization tools and techniques, taking advantage of the "intelligence" provided by machine learning approaches, and user knowledge through interactions with visual representations to help people understand and take full advantage of complex and massive data collections.

Radek Pelánek (pelanek@fi.muni.cz) received his PhD degree in Computer Science from Masaryk University for his work on formal verification. Since 2010 his research interests focus on areas of educational data mining and learning analytics. Currently, he is the leader of the Adaptive Learning Group at Masaryk University and is interested in both theoretical research in user modeling and practical development of adaptive learning environments.

Niels Pinkwart (niels.pinkwart@hu-berlin.de) completed his PhD studies at the University of Duisburg-Essen with a dissertation on collaborative modelling systems in education. After a post-doctoral researcher position at the Human–Computer Interaction Institute of Carnegie Mellon University, he accepted offers for Assistant Professor and Associate Professor positions at Clausthal University of Technology. In 2013, he moved to Humboldt-Universität zu Berlin where he heads the research group “Computer Science Education/Computer Science and Society,” the ProMINT Kolleg, and the Center of Technology Enhanced Learning located in the Professional School of Education of HU Berlin. In addition to his activities at HU Berlin, he acts as Scientific Director of the Educational Technology Lab at DFKI Berlin and as Principal Investigator at the Einstein Center Digital Future and at the Weizenbaum Institute for the Networked Society (German Internet Institute). Within the German Computer Science Association, he is currently cochair of the working group on Learning Analytics and member of the steering committee of the section on educational technologies.

Eric Poitras (eric.poitras@dal.ca) is an assistant professor in the Faculty of Computer Science at Dalhousie University. His research focuses on the design, implementation, and evaluation of adaptive instructional systems and technologies. He is also interested in the use of educational data mining and learning analytic techniques to model self-regulatory processes in learning about topics in computer science. His work lies at the intersection of computer science education, human–computer interaction, and the learning sciences. Eric has a PhD in the Learning Sciences from McGill University. He spent one year as a postdoctoral researcher in the Learning Environments Across Disciplines (LEADS) research partnership studying intelligent tutoring systems. Before joining the faculty at Dalhousie University, he began his academic career teaching instructional design in the Department of Educational Psychology at the University of Utah.

Jeevan Pokhrel (jeevan.pokhrel@rmit.edu.au) is currently working as a Senior Data Scientist at RMIT University, Melbourne, Australia. He completed his PhD from Institute Mines-Telecom, France, in 2014. He received a Dual Master’s degree from the Institute Mines-Telecom, France, and the Asian Institute of Technology, Thailand in Communication and Network services and Information Communication Technology in 2011. He has contributed to several European and French research projects and coauthored several research articles and book chapters. His topics of interest cover data science, machine learning, learning analytics, performance evaluation, multimedia quality of experience, wireless networks, etc.

Seyedahmad Rahimi (srahimi@ufl.edu) is an assistant professor of Educational Technology in the School of Teaching and Learning at the University of Florida. Previously, he was a postdoctoral researcher at the Department of Educational Psychology and Learning Systems at Florida State University. He worked with Dr. Valerie Shute on several of her research projects. His research focuses on assessing and fostering students' twenty-first-century skills (focusing on creativity) and STEM-related knowledge acquisition (focusing on physics understanding) using educational games. He is also actively researching various aspects of educational games (e.g., game mechanics, game difficulty, cognitive and affective supports, dashboard design, and incentive systems) and how they affect students' motivation, performance, and learning. His research resulted in multiple book chapters, journal articles, and conference presentations. This chapter was written when Seyedahmad was a postdoctoral researcher at FSU.

Bart Rienties (bart.rienties@open.ac.uk) is Professor of Learning Analytics and programme lead of the learning analytics and learning design research programme at the Institute of Educational Technology at the Open University, UK. His primary research interests are focused on learning analytics, professional development, and the role of motivation in learning.

José A. Ruipérez-Valiente ((jruipere@mit.edu) received the BE degree in telecommunications from Universidad Católica de Murcia, and the ME degree in telecommunications and the MSc and PhD degrees in telematics from Universidad Carlos III of Madrid while conducting research with Institute IMDEA Networks in the area of learning analytics and educational data mining. He was a postdoctoral associate with MIT. He has received more than 20 academic/research awards and fellowships, has published more than 70 scientific publications in high-impact venues, and has participated in over 18 funded projects. He currently holds the prestigious Spanish Fellowship Juan de la Cierva with the University of Murcia.

Muhittin Sahin (musahin@mail.uni-mannheim.de; muhittin.sahin@ege.edu.tr) is an academic staff at Ege University, Turkey, and postdoctoral researcher at the University of Mannheim, Germany. His research interests relate to instructional technology, learning analytics, educational data mining, multi-criteria decision making, statistic, sequential analysis, e-assessment, and intelligent learning management systems. He also collaborates on a project about developing an adaptive intelligent tutoring system.

Raghav V. Sampangi (raghav@cs.dal.ca) is a senior instructor at the Faculty of Computer Science, Dalhousie University. He is currently based in K'jipuktuk within the ancestral and unceded territory of the Mi'kmaq known as Mi'kma'ki. K'jipuktuk is also known as Halifax in Nova Scotia, Canada. He is currently serving as the Director of the Master of Applied Computer Science program and as a member of the Curriculum and Teaching Committee at the Faculty of Computer Science. With a background in security and privacy and teaching and learning, his current work explores wellness, equity, inclusion, and accessibility in teaching and learning, and aspects of usable security and privacy in applications for social good. He is a proponent of lifelong learning, is an advocate for mental and emotional health and well-being, and believes that it is essential to be compassionate in our teaching, policies, and our actions.

Sandra Schön (sandra.schoen@tugraz.at) is a senior researcher in the "Educational Technologies" team at the Graz University of Technology (TU Graz), project manager at the "Forum New Media in Teaching Austria" (Graz) within the project "Open Education Austria Advanced," and Adjunct Professor of Innovations in Learning at the Universitas Negeri Malang (Malang State University, Indonesia). Her work focuses on digital innovations for learning and teaching, OER, MOOCs, and maker education. For further information, please visit her website: https://sandra-schoen.de

Clara Schumacher (clara.schumacher@hu-berlin.de) is working as a postdoctoral researcher in the CSES research group at Humboldt-Universität zu Berlin. Clara is working on the LA-DIVA project focusing on adaptive learning analytics for diverse students with emphasis on assessment, collaborative learning, and student profiles. Furthermore, she conducts research on self-regulated learning, informal learning, assessment, and feedback as well as dashboards in the domain of learning analytics. Prior, Clara was a research assistant and completed her doctorate at the chair of Learning, Design, and Technology at the University of Mannheim.

Peixia Shao (pxshao@utexas.edu) is a doctoral student in the Learning Technologies program at the University of Texas at Austin. She was an English as a second language teacher for two years. She got her master's degree in TESOL from the University of Rochester. Her research interests focus on learning analytics in online learning environments and online teaching and learning in K-12 and higher education.

Valerie Shute (vshute@fsu.edu) is the Mack & Effie Campbell Tyner Endowed Professor in Education in the Department of Educational Psychology and Learning Systems at Florida State University. Before coming to FSU in 2007, she was a principal research scientist at Educational Testing Service, involved with basic and applied research projects related to assessment, cognitive diagnosis, and learning from advanced instructional systems. Her general research interests hover around the design, development, and evaluation of advanced systems to support the learning of knowledge, skills, and dispositions. Her research has resulted in numerous research grants, journal articles, chapters in edited books, a patent, and several recent books.

Angela Siegel (siegel@Dal.Ca) is the Program Director, Bachelor of Applied Computer Science and Senior Instructor at Dalhousie University.

Wenting Sun (sunwenti@informatik.hu-berlin.de) completed her master of education at Tongji University, Shanghai, China She joined the research group "Computer Science and Society" of Humboldt-Universität zu Berlin in January 2020 as a PhD student. She joined the research group of "Weizenbaum Institute" (A German Internet Institute) in March 2021. Her research interests are educational psychology, learning analytics, adult education, and learning design.

Brad Swibel is Deputy Head of School at St Andrew's Cathedral School in Sydney. He is responsible for academic, wellbeing, policy, and staffing for the secondary school. He works with the senior executive team on vision development, alignment, and strategy and is involved in cocurricular, risk management, marketing, and budgetary planning. His aspiration is for every student and teacher to be able to reach their personal best. The school's systematic use of data is key to this process by student goal setting, identifying intervention needs, and tracking progress.

Stephanie D. Teasley (steasley@umich.edu) is a research professor in the School of Information at the University of Michigan. Her research focuses on issues of collaboration and learning, looking specifically at how sociotechnical systems can be used to support effective collaborative processes and successful learning outcomes. She is the director of the Learning, Education & Design Lab (LED Lab), an interdisciplinary group of scholars who investigate how instructional technologies and digital media are used to innovate teaching, learning, and collaboration. She was on the executive board for the Society for Learning Analytics Research (SoLAR) from 2012 to 2016 and served as the president of the from 2017 to 2019. She was also on the board of the International Alliance to Advance Learning in the Digital Era (IAALDE) from 2017 to 2018 and served as chair from 2018 to 2020. In 2019, she was selected by the ACM as a distinguished member for outstanding scientific contributions to computing.

Tandra Tyler-Wood (tandra.wood@unt.edu) is a professor in the Department of Learning Technologies at the University of North Texas in Denton, Texas, USA. She has a long-term interest in assessment, and the role assessment plays in providing and denying educational opportunities for students. She conducts individual assessments primarily for gifted children. She works extensively in schools providing technology experiences for at-risk learners. She recently completed a National Science Foundation project, where as principal investigator, she worked with rural and at-risk students to integrate digital fabrication learning opportunities into the curriculum. Currently, se is a principal investigator for Project TRAIL (Teaching Resources to Advance Interest in Law) sponsored by the AccessLex Foundation. Project TRAIL works with students of color interested in attending law school by assisting students to develop skills to perform well on the Law School Aptitude Test (LSAT). The LSAT is a "gatekeeper" in the USA for law school attendance. Students in the project are provided with ongoing assessment as they prepare to take the LSAT. Visualizations of ongoing test score results and dashboards that give feedback to students concerning their progress are used throughout the project.

Mehmet Uysal (mehmetuysal@sakarya.edu.tr) is a research assistant at the Computer Education and Information Technologies and Instructional Designer at Distance Education Center at Sakarya University, Turkey. His research topics include educational technologies, distance education theories, self-regulated learning, and learning analytics.

Johanna Velander (johanna.velander@lnu.se) is a PhD candidate at the Department of Computer Science and Media Technology at Linnaeus University (LNU) in Sweden. She has recently finished her MSc in Media Technology at Linnaeus University investigating student awareness, perceptions, and values related to their university data. She is interested in ethical issues in technologies.

Lorenzo Vigentini (l.vigentini@unsw.edu.au) is a psychologist, an engineer, an educator, and a technology innovation champion. With a wealth of experience in learning and teaching in the higher education sector, in IT/e-learning developments and deployments, and data science applications, his expertise is into learning processes at the crossing between cognitive psychology, differential psychology, education, and human–computer interaction. While working on this project, he was the Academic lead Educational Intelligence and Analytics in the portfolio of the Pro-Vice Chancellor Education at UNSW Sydney where he led a variety of projects across the spectrum of educational innovation, evaluation of the student experience, and learning analytics initiatives. Currently, he holds an adjunct status with the School of Computing Science Engineering at UNSW Sydney and supports LA implementations in Schools.

Leticia Farias Wanderley (fariaswa@ualberta.ca) is a graduate student at the Department of Computing Science at the University of Alberta. Her research work focuses on the application of natural language processing techniques in educational settings.

Yoon Jeon (YJ) Kim (yj.kim@wisc.edu) is an assistant professor of Design, Creative, and Informal Education in the Department of Curriculum and Instruction at UW–Madison. Her work centers on the topic of innovative assessment and application of playful activity design to challenge what and how we are measuring learning. Her playful assessment research ranges from a computer game using evidence-centered design and analytics techniques to paper-based embedded assessment tools for making. The core of her work is close collaboration with practitioners – empowering teachers to innovate around classroom assessment and use playful and authentic assessment tools that can truly impact student learning. She received her PhD in Instructional Systems Design from the Florida State University and a BS in Education Technology from Ewha Womans University.

Volkan Yücepur (volkan.yuecepur@stud.uni-due.de) is a Master's student in the Social Computing Group, Department of Computer Science and Applied Cognitive Science, Faculty of Engineering at the University of Duisburg-Essen, Germany.

Halil Yurdugül (yurdugul@hacettepe.edu.tr) is a professor at Hacettepe University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education in the Department of Statistics at Hacettepe University. He completed PhD degree in 2003 at Hacettepe University. His research interests relate to psychology, psychometry, education, measurement and evaluation in education, statistic, assessment, e-assessment, learning analytics, educational data mining, and intelligent learning management systems.

Part I
Theoretical and Technological Perspectives Linking Visualization and Dashboard Design

Chapter 1
Visualizations and Dashboards for Learning Analytics: A Systematic Literature Review

Muhittin Sahin and Dirk Ifenthaler

1 Introduction

Learning analytics dashboards are customizable control panels displaying personalized learning analytics features which adapt to the learning process in real time (Park & Jo, 2015). Learning analytics features may focus on learning opportunities, self-assessments, recommendations, comparison to peers, social interactions, or additional links (Schumacher & Ifenthaler, 2018). Many learning analytics systems focus on visualizations and outline descriptive information, such as time spent online, access of resources, progress toward the completion of a course, and comparisons with other students (Kim et al., 2016; Verbert et al., 2014), which already helps learners monitor some of their (learning) activities. However, planning upcoming learning activities or adapting current strategies also involves further recommendations based on dispositions of learning, previous behavior, self-assessment results, and learning goals. Dashboards designed to offer beneficial learning analytics features need to be aligned with theory on (self-regulated) learning, feedback, and instruction in order to avoid unfavorable educational consequences (Gašević et al., 2015).

The purpose of this chapter is to present a summary of the dashboard and visualization studies carried out within the scope of learning analytics. For this purpose,

M. Sahin (✉)
Ege University, Bornova, Turkey

University of Mannheim, Mannheim, Germany
e-mail: musahin@mail.uni-mannheim.de

D. Ifenthaler
University of Mannheim, Mannheim, Germany

Curtin University, Perth, Australia
e-mail: dirk@ifenthaler.info

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_1

the systematic literature review was performed. Review methodology has four sequential step: (a) literature review according to the keywords, (b) selecting primary studies, (c) categorizing of the results, and (d) reporting the findings (Gikandi et al., 2011). In the first step, five databases were selected for the review process, and these databases consist of *ACM Digital Library*, *IEEE XPLORE*, *ScienceDirect*, *Wiley*, and *Google Scholar*. After the databases were determined, a literature review was performed with keywords. The search string was used; "Learning Analytics" *and* "Dashboard" and "Learning Analytics" *and* "Dashboard" *or* "Visualization." The literature review was performed on 27 February 2021. On the second step, 76 studies were selected as the primary studies. These studies consist of journal articles and conference papers. Detailed information about the conferences and journals of these papers is presented in Table 1.1. In the third step, categories were determined. These categories consist of (1) keywords, (2) stakeholders (target group) and year, (3) study group (participants), (4) visualization techniques, (5) method, (6) data collection tools, (7) variables, and (8) theoretical background. In the last step, findings were presented according to these eight categories.

Table 1.1 Information about the conferences and journals of the selected papers

Journal/conference titles	Number of papers
IEEE International Conference on Advanced Learning Technologies	3
International Conference on Learning Analytics and Knowledge (LAK)	6
IEEE Global Engineering Education Conference (EDUCON)	3
XI Technologies Applied to Electronics Teaching	1
IEEE Frontiers in Education Conference (FIE)	1
International Conference on Education and Technology (ICET)	1
International Conference on Computers in Education	2
International Conference on New Trends in Computing Sciences (ICTCS)	1
International Conference on Higher Education Advances	1
European Conference on Games Based Learning	1
International Conference on Artificial Intelligence in Education	1
ARTEL@ EC-TEL	1
CHI Conference on Human Factors in Computing Systems	1
Annual ACM Conference on Learning at Scale	1
European Conference on Technology Enhanced Learning	1
International Conference on Learning and Collaboration Technologies	2
L@S 2018	1
International Journal of Computer-Supported Collaborative Learning	2
Asia Pacific Education Review	1
Assessment & Evaluation in Higher Education	1
Behavior & Information Technology	1

(continued)

Table 1.1 (continued)

Journal/conference titles	Number of papers
British Journal of Educational Technology	2
Computers & Education	4
Computers in Human Behavior	3
Educational Technology Research & Development	1
Entertainment Computing	1
Higher Education	1
IEEE Access	1
IEEE Transactions On Learning Technologies	3
Intelligent Tutoring Systems	1
Interactive Learning Environments	1
Interactive Technology and Smart Education	1
International Journal Of Intelligent Systems	1
International Journal of Distance Education Technologies	1
Journal of Applied Research in Higher Education	2
Journal of Children and Media	1
Journal of Computer Assisted Learning	1
Journal of Computing in Higher Education	1
Journal of e-Learning and Knowledge Society	1
Journal of Learning Analytics	2
Journal of Research in Innovative Teaching & Learning	1
Journal of Science Education and Technology	1
Journal of Universal Computer Science	3
Journal of Visual Languages and Computing	1
KSII Transactions On Internet And Information Systems	1
RIED. Revista Iberoamericana de Educación a Distancia	1
International Book Chapter	2
Teaching in Higher Education	1
Technology, Knowledge and Learning	2
The Internet and Higher Education	1
Total	**76**

2 State of Research in Dashboards and Visualizations for Learning Analytics

This section presents a summary of the dashboard and visualization studies carried out within the scope of learning analytics. When we review the literature, some difference names are used for the dashboard such as data dashboard (Roberts et al., 2016; Ahn et al., 2019), learning analytics dashboard (Charleer et al., 2017; Guerra et al., 2020; De Laet et al., 2020), learning dashboard (Leitner & Ebner, 2017; Broos et al., 2020), instructional dashboard (Wise & Jung, 2019), MOOC dashboard

(Dipace et al., 2019; Cha & Park, 2019), visual dashboard (Bektik, 2018), early warning dashboard (Sun et al., 2019), student-facing dashboard (Kia et al., 2020), teacher dashboard (Guenaga et al., 2015; Molenaar & Campen, 2017; van Leeuwen et al., 2019), analytical dashboard (Vaclavek et al., 2018), and student dashboard (Olalde & Larrañaga, 2011).

Findings were categorized including (1) keywords, (2) stakeholders (target group) and year, (3) study group (participants), (4) visualization techniques, (5) method, (6) data collection tools, (7) variables, and (8) theoretical background, and then findings were presented according to these categories.

2.1 *Keywords*

Keywords were chosen as the first category for reporting the findings. In this chapter, both frequencies of the keywords and their relationship with each other were presented. The keywords and their frequencies can be seen in Table 1.2.

Table 1.2 Keywords and frequencies

Keyword	Frequency
Learning analytics	66
Dashboard	52
Visualization	15
Self-regulation learning	13
Higher education	9
Assessment	6
Feedback	6
Educational games	6
Educational data mining	5
Human-computer interaction	3
Achievement	3
At-risk students	2
Decision-making	2
Competency	2
Machine learning	2
Acceptance	2
Learning science	1
Learning process	1
Privacy	1
Ethics	1
Experimental design	1
Motivation	1

It is seen that, respectively, learning analytics, dashboard, visualization, and self-regulation learning are the most common used keywords in the studies. Motivation, experimental design, ethics, privacy, learning process, and learning science are the least used keywords. After the frequencies of the keywords were presented, association rules analysis was conducted in order to determine how often these keywords were used together with each other in the studies. Detailed information about the results of the association rules is presented in Table 1.3.

When the support and confidence values are examined in Table 1.3. Rule 1 is valid for 8% of the studies, and in all the studies that write feedback as a keyword, learning analytics was written as a keyword. Similarly, learning analytics is another keyword in all of the studies that have both dashboard and feedback as keywords. When Rule 4 is examined, this rule is valid for 14% of the studies, and learning analytics is used as another keyword in 91% of the studies that include dashboard and visualization as keywords. It's seen that in Rule 5, this rule is valid for 62% of the studies and learning analytics is used as the other keyword in 89% of the studies that have a dashboard as a keyword. According to Rule 7, this rule is valid for 18% of the studies, and learning analytics is used as a keyword in 87% of the studies that use visualization as a keyword. When the rules are examined, in research where feedback, self-regulation learning, dashboard, visualization, assessment, educational games, or educational data mining are used as keywords, learning analytics has also been used as a keyword.

Table 1.3 Results of association rules according to the keywords

	Antecedent	Consequent	Support	Confidence
Rule 1	Feedback	Learning analytics	0.081	1.000
Rule 2	Dashboard and feedback	Learning analytics	0.042	1.000
Rule 3	Self-regulation learning	Learning analytics	0.162	0.923
Rule 4	Dashboard and visualization	Learning analytics	0.135	0.909
Rule 5	Dashboard	Learning analytics	0.622	0.885
Rule 6	Dashboard and SRL	Learning analytics	0.095	0.875
Rule 7	Visualization	Learning analytics	0.176	0.867
Rule 8	Assessment	Learning analytics	0.068	0.833
Rule 9	Educational games	Learning analytics	0.068	0.833
Rule 10	EDM	Learning analytics	0.054	0.800
Rule 11	Dashboard and higher education	Learning analytics	0.054	0.800
Rule 12	Higher education	Learning analytics	0.095	0.778
Rule 13	Dashboard and educational games	Learning analytics	0.042	0.750
Rule 14	Dashboard and EDM	Learning analytics	0.042	0.750
Rule 15	Dashboard, visualization, and EDM	Learning analytics	0.042	0.750
Rule 16	Dashboard and assessment	Learning analytics	0.028	0.667

2.2 Stakeholder and Year

Dashboards can be designed and developed for different stakeholders such as instructors, learners, researchers, and administrates (Schwendimann et al., 2016). The data which is obtained from digital learning environments includes important information for learners, instructors, institutes, and decision-makers (Yoo et al., 2015). Learners might be compared with peers, monitoring self-achievement level, and self-monitoring via dashboards (Jivet et al., 2017). In addition to these, presenting a visual overview about the learning experiences can be useful for instructors and learners (Duval, 2011). First, the frequency of the studies is presented in Fig. 1.1.

As seen in Fig. 1.1, it seems that the frequency of studies has increased. The literature review does not include the whole of 2021; therefore studies' frequencies seem low in 2021. Dashboard studies and stakeholders by year were presented in Fig. 1.2.

As seen in Fig. 1.2, dashboard designs have been developed specifically for both instructors and learners. It's possible to say that instructors and learners are the most important stakeholders of the dashboard studies. Besides, learning and development managers and administrators are the other stakeholders.

2.3 Study Group

Study group refers to individuals who are included in the research while conducting dashboard research. Various data was obtained from the study group with many data collection tools such as questionnaire, scale, interview, observation, and log data. Many of the stakeholders also contributed to the research as a participant. Findings are presented in Fig. 1.3.

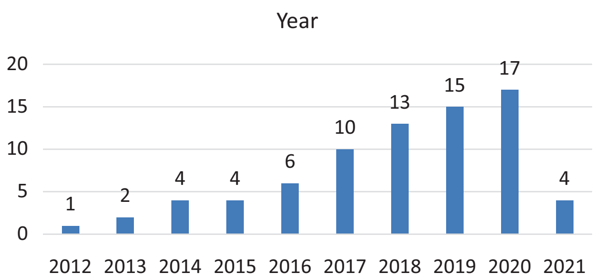


Fig. 1.1 Studies by year

Fig. 1.2 Dashboard studies for stakeholders by year

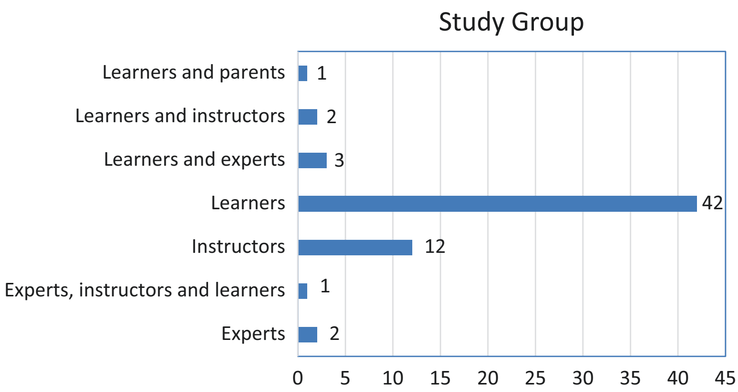


Fig. 1.3 Study groups in the dashboard and visualization researches

As seen in Fig. 1.3, many studies include students as participants. While these students usually consist of undergraduate students (Khan & Pardo, 2016; Bodily et al., 2018; Schumacher & Ifenthaler, 2018; Bennett & Folley, 2019; Russell et al., 2020), there are also studies involving graduate students (Derick et al., 2017; Kuhnel et al., 2018; Jivet et al., 2020) and secondary school students (Tan et al., 2016; Jonathan et al., 2017; Macarini et al., 2020). Second, instructors stand out as the group that participated in the research the most. In addition to these, it's seen that experts (Ullmann et al., 2019; De Laet et al., 2020) and students' family (Roberts et al., 2016) are involved in the studies as a participant in the literature.

2.4 Visualization Technique

Awareness of the learners about the learning process increases through visualization (Khan & Pardo, 2016). Besides this, visual displays have a critical importance role to sense-making if they are presented in meaningful ways (Shemwell, 2005). For this purpose, visualization should be familiar and interesting to the learner in order to help learners understand and interpret data (Kuosa et al., 2016). In the literature, it is seen that various visualization techniques are used to develop dashboard. Information about these techniques and their frequency of use is presented in Table 1.4.

As seen in Table 1.4; in particular, line charts and bar charts are widely used. Then progress bar, textual feedback, timeline, and pie chart are used, respectively. Bubbles, student path, heat map, interaction table, scatter plot, social network analysis, and checklist are seen as the least used visualization techniques. Gamification elements consist of badges, leaderboards, different color flags, scores, etc.

Table 1.4 Visualization techniques and frequencies

Visualization technique	Frequency
Line chart	33
Bar chart	33
Progress bar	24
Textual feedback	23
Timeline	19
Pie chart	15
Spider chart	12
Gamification elements	8
Signal lights	5
Gaussian graph	4
Checklist	2
Social network analysis	2
Scatter plot	2
Interaction table	2
Heat map	1
Student path	1
Bubbles	1

Table 1.5 Research design of the studies

Research design	Frequency
N/A	44
Experimental design	10
Mixed method	8
Qualitative research	7
Quantitative research	3
Usability study	1
Rapid prototyping	1
Longitudinal study	1
Design-based research	1

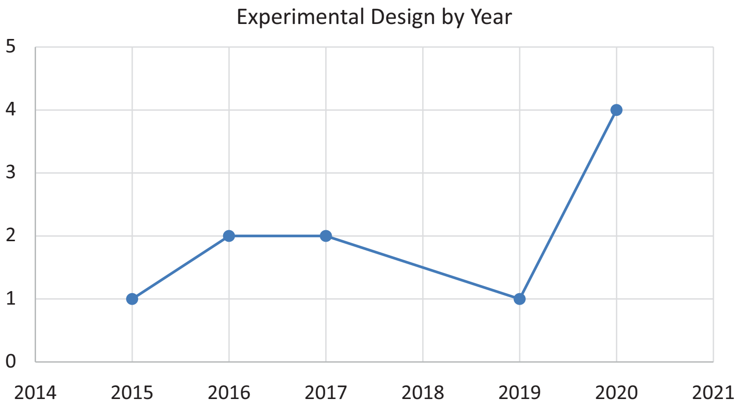


Fig. 1.4 Experimental design by year

2.5 *Research Design*

It is seen that many different research designs were conducted for the dashboard and visualization studies. A summary of these designs is presented in Table 1.5.

The remarkable situation in Table 1.1 is that the research design was not indicated in many studies. Then, respectively, experimental design, mixed method, and qualitative research were used. But in the literature, it's expressed that one of the challenges is lack of sufficient empirical evidence studies in this area (Leitner et al., 2019). Therefore, experimental studies have been examined by the years (Fig. 1.4).

It is seen that experimental studies tend to increase in recent years. It is possible to say that experimental studies are in an increasing trend; however, it is still not sufficient.

Table 1.6 Data collection tools and frequency

Data collection tools	Frequency
Questionnaire/scale	41
Log data	30
Interview	21
Learners performance/test	15
Observations	6
Eye tracking	1

2.6 Data Collection Tools

Due to the fact that the field of study is online learning environments, log data can be used as well as qualitative and quantitative data collection tools. Summary of data collection tools is presented in Table 1.6.

Respectively, questionnaires or scales, log data, and interview are the most used data collection tools. With these data collection tools, many variables were examined such as awareness (Charleer et al., 2013; Lkhagvasuren et al., 2016), reflection (Charleer et al., 2013; Lkhagvasuren et al., 2016), SRL (Cha & Park, 2019; Aguilar et al., 2021), perceived usefulness (Park & Jo, 2015; Sadallah et al., 2020), satisfaction (Arnold & Pistilli, 2012; Kim et al., 2016), achievement (Arnold & Pistilli, 2012; Kim et al., 2016; Cha & Park, 2019; De Laet et al., 2020), perceived ease of use (Sadallah et al., 2020), sense-making (van Leeuwen et al., 2019), and motivation (Aguilar et al., 2021).

2.7 Variables

Examining the variables investigated in studies is important both in order to reveal the current situation and to guide for further researches. For this purpose, information about the variables examined in the studies is presented in Table 1.7.

It's seen in Table 1.7, respectively, that acceptance structures, learner performance, awareness, SRL, usability, and reflection are the most extensive used variables. Contrary to this, metacognitive strategies (Bodily et al., 2018), study skills (Broos et al., 2020), learning strategy (Van Horne et al., 2018), decision-making (Xhakaj et al., 2017), emotional aspects (Zheng et al., 2021), privacy (Schumacher & Ifenthaler, 2018), competency (Tan et al., 2016), and recall (Lkhagvasuren et al., 2016) are the least explored variables.

Table 1.7 Variables that are examined in the dashboard and visualization studies

Variable	Frequency
Acceptance structures	17
Achievement/learner performance	13
Awareness	8
Self-regulation learning	7
Usability	6
Reflection	5
Motivation	4
Behavior change	4
Effectiveness	3
Sense-making	3
Understanding	3
Preferences	2
Attitude	2
Satisfaction	2
Self-efficacy	2
Adoption	2
Engagement	2
Beneficial	2
Cognitive traits	2
Learning style	1
Metacognitive strategies	1
Study skills	1
Learning strategy	1
Decision-making	1
Emotional aspects	1
Privacy	1
Competency	1
Recall	1

2.8 Theoretical Background

Dashboard researches aim to define what data is meaningful to different stakeholders in education and how data can be presented to support meaningful processes (Schwendimann et al., 2016). It is seen that in literature, most of the studies are limited to monitoring learners' performance results, reflection, awareness, and self-evaluation (Bodily & Verbert, 2017). Dashboard studies should be structured bases on the educational theories. Information regarding the examined studies and their theoretical foundations are presented in Table 1.8.

In the literature, it's seen that many studies were structured on the basis of SRL. Besides this, motivation theory and social learning theory were underlain some dashboard and visualization studies.

Table 1.8 Theoretical background, visualization techniques, and variables of the studies

Learning theory	Author(s)	Visualization techniques	Variables
Self-regulation learning	Mejia, Florian, Vatrapu, Bull, Gomez, and Fabregat (2016)	Bar charts, line charts, and pie charts	Reading profiles, learning styles, cognitive traits
Self-regulation learning	Pérez-Álvarez, Maldonado-Mahauad, Pérez-Sanagustín (2018)	Pie chart, textual feedback, bar chart, line chart, progress bar, timeline	Evaluation of usability and usefulness adoption of the dashboard, engagement, performance, effectiveness,
Self-regulation learning	Cha and Park (2019)	Signal lights, bar chart, line chart	SRL Achievement
Self-regulation learning	Russell, Smith, and Larsen (2020)	Bar chart, line chart, textual feedback	Achievement
Self-regulation learning	Jivet, Scheffel, Schmitz, Robbers, Specht, and Drachsler (2020)	Line chart, textual feedback, progress bar	Self-regulated learning, learner goals
Self-regulation learning	Kia, Teasley, Hatala, Karabenick, and Kay (2020)	Bar chart, progress bar, timeline	Achievement, SRL
Self-regulation learning	Sedrakyan, Malmberg, Verbert, Järvelä, and Kirschner (2020)	Bar chart, textual feedback, different types of feedback, timeline, line chart, spider chart	Goal setting and planning, awareness of effectiveness, and efficiency
Self-regulation learning	Aguilar, Karabenick, Teasley, and Baek (2021)	Line chart, bar chart, table	Motivation, academic achievements, SRL
Self-regulation learning	Zheng, Huang, Li, Lajoie, Chen, and Hmelo-Silver (2021)	Timeline, spider chart, progress chart	Emotional, SRL
Motivation theory	Van Horne, Curran, Smith, VanBuren, Zahrieh, Larsen, and Miller (2018)	Bar chart, textual feedback	Learning strategies, academic motivation,
Social learning theory	Smith (2019)	Bar graphs, pie chart, line chart	Motivation, benefit

3 Conclusion

The purpose of this chapter was to present a summary of the dashboard and visualization studies carried out within the scope of learning analytics. For this purpose, 76 studies conducted in the literature were included. These studies were examined in eight categories such as (1) keywords, (2) stakeholders (target group) and year,

(3) study group (participants), (4) visualization techniques, (5) method, (6) data collection tools, (7) variables, and (8) theoretical background.

The first category is keywords used in the studies. According to the results, LA, dashboard, visualization, and SRL are the most used keywords, respectively. Then, it was seen that higher education, assessment, feedback, and educational games were used. Motivation, experimental design, ethics, privacy, learning process, and learning science are the least used keywords. Based on the keywords, it can be suggested to conduct studies about motivation, experimental design, ethics, privacy, learning process, and learning science in the field of dashboard and visualization. Experimental studies have been discussed in the method category. In literature, it is stated that there is a gap between dashboard design and learning sciences in dashboard studies (Sedrakyan et al., 2016, 2019). The learning science deals with designs related to how learning can be done more easily by addressing real-world situations (Carr-Chellman, 2004). In this context, it is recommended to conduct the studies based on motivation, feedback, intervention, and learning theories that affect learning in order to make more effective dashboard designs. In addition to this, association rules analysis was conducted in order to determine how often these keywords were used together with each other in the studies. According to the results, LA keyword is often used together with the keywords feedback, dashboard, SRL, and visualization. It is possible to say that dashboard and visualization are used extensively in LA studies. Furthermore, SRL and feedback are the topics discussed in LA studies.

The second category is the stakeholders of dashboard and visualization studies. As stated in the literature, learners, instructors, administrators, and development managers have been found to be important stakeholders. Considering the years, it is seen that the frequency of studies increases with year by year and studies are carried out for both learners and instructors, especially as stakeholders. In addition to the stakeholders, the participants with whom the studies were conducted were considered as a category. It is seen that as a participant in the studies, respectively, learners, instructors, experts, and families mostly participated in the studies. As can be seen in the keywords, the learner groups generally consist of higher education students. These higher education students consist of undergraduate and graduate students. In addition, studies in which secondary school students are participants are also striking. As an instructor, it consists of individuals working in higher education institutions. In the light of the findings, it is possible to say that the most important participants and stakeholders of the dashboard and visualization studies are learners and instructors. The benefit matrix related to dashboard and visualization studies and their stakeholders is discussed in detail in the last chapter of the book. It is seen that studies work with learners intensively as a participant. Thus, it can be determined that (a) what kind of feedback will be given in dashboard designs for instructors and what kind of suggestions can be given to students, and (b) as for students, it is determined which elements should be for reflection and awareness or where students need intervention. Therefore, data was obtained from the students that were intensively collected, because the ultimate goal of LA is to improve learning and instruction productivity (Elias, 2011).

When the visualization techniques used in dashboard studies are examined, it is seen that, respectively, line chart, bar chart, progress bar, textual feedback, timeline, and pie chart are used. It can be stated that this finding is similar to the literature, because Schwendimann et al. (2016) expressed that bar charts, line graphs, tables, pie charts, and network graphs are the most used visualization techniques. However, dashboards are limited to charts, graphs, or other visuals without providing support to learners' learning experience (Park & Jo, 2015). In order to design an effective dashboard design, it is necessary to establish a theoretical connection with human cognition and perception, situation awareness, and visualization technologies and to be structured based on this theoretical framework (Yoo et al., 2015). In dashboard design, contextually appropriate presentations, visual language, and social framing should be focused on (Sarikaya et al., 2018). On the other hand, it is important to find out which data is valuable to display from students' data (Yoo et al., 2015). Studies of the visualization techniques are better for students, and this situation should be examined (Sedrakyan et al., 2018). In addition to these, one of the important points for dashboard designs is which metric or metrics to display and how to display them. Not only information about learners' performances but also feedback, recommendation, and intervention should be presented to learners via dashboards. Besides, it is recommended that dashboard designs be configured to allow a high degree of individualization (Schumacher & Ifenthaler, 2018). Lastly, using appropriate gamification elements such as leader-board, badges, etc. in dashboard designs can also contribute to the improvement of the digital learning environments. Information on how to use these elements is discussed separately in a chapter.

Looking at the research design of dashboard studies, it is seen that the research design was not expressed in many studies. When we look at the studies involving the research method, it is seen that experimental design, mixed method, and qualitative studies are intense. This finding seems to conflict with the literature, because in the literature it's expressed that one of the challenges is lack of sufficient empirical evidence studies in this area (Leitner et al., 2019). Considering the years of studies, it can be stated that especially the studies for experimental research have increased in recent years, but still there is not sufficient experimental evidence in this area. In addition, it is thought that design-based research can be conducted due to its nature. Design-based research is a systematic and flexible research method that includes analysis, design, development, implementation, and evaluation processes in order to improve educational practices (Wang & Hannafin, 2005). From this perspective, it is considered important in terms of conducting design-based research and examined and developed the effective and efficiency of the systems. It is seen that, respectively, questionnaire, log data, interview, learner performance, observations, and eye-tracking are used as data collection tools in dashboard studies. It is seen that especially awareness, reflection, SRL, perceived usefulness, achievement, perceived ease of use, sense-making, and motivation data are collected with questionnaire or scales. Besides this, lots of information that is valuable determining students' behavior were collected by the online systems (Mazza, 2010), and this data can provide to improve learning experiences (Sin & Muthu, 2015). This data is defined as log data. Analyzing the log data can present some opportunities as supporting self-regulation, more effective learning experience with personalized learning, and increasing awareness of the learning process (Drachsler et al., 2014). With the information contained in the dashboards, students' performance patterns can be discovered, problems can be predicted, problematic topics can be focused on, and motivational elements can be found (Podgorelec & Kuhar, 2011) and provide instant feedback, monitor the weaknesses, and guide to appropriate learning materials (Dumčienė & Lapėnienė, 2010). The lack of quality log data and analyzation of, interpretation of, and understanding the data can be major challenges in e-learning environments (Kuosa et al., 2016). Therefore, it is important to determine the most important metrics that affect students' achievement and to configure designs for them. In this context, feature selection algorithms can be used. With feature selection, the number of variables in the data set can be reduced, one or more of the highly correlated variables can be taken, and latent variables can be obtained by collecting interrelated structures under factors (Şahin & Yurdugül, 2020). Many different algorithms such as Information Gain, Gini Index, Random Forest, and Component Analysis can be used as a feature selection algorithm.

Dashboard designs are developed for various purposes such as (a) metacognitive, (b) cognitive, (c) behavioral, (d) emotional, and (e) self-regulation (Jivet et al., 2017). In order to guide the researchers, the variables investigated in the studies were also examined as another category. According to the results, respectively, acceptance structures, learner performance, awareness, SRL, usability, and reflection are the most extensive used variables. Contrary to this, metacognitive strategies, study skills, learning strategy, decision-making, emotional aspects, privacy, competency, and recall are the least explored variables. In the light of the findings, it is recommended to conduct researches in the areas of metacognitive strategies, study skills, learning strategy, decision-making, emotional aspects, privacy, and competency.

Considering the theoretical foundations of dashboard studies, it is seen that most of the studies, whose theoretical basis is expressed, are based on SRL. In addition, some studies were conducted based on the motivation theory and social learning theory. However, many dashboard studies are conducted without reference to dashboard designs of SRL theories and models (Gašević et al., 2019). In addition, it is stated that dashboard designs are made lack of theories in learning science (Sedrakyan et al., 2016). One of the important challenges in dashboard studies is to eliminate the gap between dashboard designs and the theoretical background. For this purpose, dashboard designs are recommended conducting SRL, motivation theory, social learning theory, feedback intervention theory (FIT), intervention theory, and learning theories. For example, Nicol and Macfarlane-Dick (2006) identified the feedback principles in order to support self-regulation: (a) identify the good performance, (b) use feedback to improve instruction and present high-quality feedback, (c) encourage learners to communicate with peers and instructors, (d) encourage self-esteem and motivation, and (e) give opportunity to close the gap between good and current performances.

In the light of the findings obtained from the literature review, it is possible to summarize the suggestions for researchers and designer for LA dashboard and visualization studies as follows:

- Conduct research on motivation, privacy, ethics, competency, emotional aspects, study skills, and cognitive traits.
- Conduct experimental and design-based researches, although it is observed that experimental research is increasing.
- Study about which metrics are more important to stakeholders in digital learning environments.
- Conduct studies on which or which visualization techniques presented to stakeholders are more effective and efficient.
- In the context of dashboard and visualization, research can be conducted in which the opinions of all stakeholders are received in cooperation.
- Studies should be conducted that fill the gap between learning theories and dashboard design. It is especially recommended to design dashboards based on SRL, motivation, emotion, feedback, intervention, and learning theories and to examine their effectiveness.

References

Aguilar, S. J., Karabenick, S. A., Teasley, S. D., & Baek, C. (2021). Associations between learning analytics dashboard exposure and motivation and self-regulated learning. *Computers & Education, 162*, 104085.

Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6*(2), 70–85.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270).

Arriaran Olalde, I., & Ipiña Larrañaga, N. (2011, July). Indicators needed to design a student dashboard from lecturers' perspectives: A qualitative study. In *HEAD'19. 5th international conference on higher education advances* (pp. 299–305). Editorial Universitat Politècnica de València.

Bektik, D. (2018). XIPIt: Updating the XIP dashboard to support educators in essay marking at higher education. In *Proceedings of the fifth annual ACM conference on learning at scale* (pp. 1–4).

Bennett, L., & Folley, S. (2019). Four design principles for learner dashboards that support student agency and empowerment. *Journal of Applied Research in Higher Education, 12*(1), 15–26.

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418.

Bodily, R., Ikahihifo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598.

Broos, T., Pinxten, M., Delporte, M., Verbert, K., & De Laet, T. (2020). Learning dashboards at scale: Early warning and overall first year experience. *Assessment & Evaluation in Higher Education, 45*(6), 855–874.

Carr-Chellman, A. A. (2004). Instructional systems, learning sciences, design, technology: A more complete pathway. *Educational Technology, 44*(3), 40–44.

Cha, H. J., & Park, T. (2019). Applying and evaluating visualization design guidelines for a MOOC dashboard to facilitate self-regulated learning based on learning analytics. *KSII Transactions on Internet & Information Systems, 13*(6).

Charleer, S., Klerkx, J., Santos, J. L., & Duval, E. (2013). Improving awareness and reflection through collaborative, interactive visualizations of badges. *ARTEL@ EC-TEL*, 1103, 69–81.

Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2017). Learning analytics dashboards to support adviser-student dialogue. *IEEE Transactions on Learning Technologies, 11*(3), 389–399.

Dashboard Analysing First-Year Engineering Students. In: Lifelong Technology-Enhanced Learning – 13th European Conference on Technology Enhanced Learning (V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel, Eds.), *Lecture notes in computer science* (pp. 575–578). Springer.

De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020). Adoption and impact of a learning analytics dashboard supporting the advisor—Student dialogue in a higher education institute in Latin America. *British Journal of Educational Technology, 51*(4), 1002–1018.

Derick, L., Sedrakyan, G., Munoz-Merino, P. J., Kloos, C. D., & Verbert, K. (2017). Evaluating emotion visualizations using AffectVis, an affect-aware dashboard for students. *Journal of Research in Innovative Teaching & Learning, 10*(2), 107–125.

Dipace, A., Fazlagic, B., & Minerva, T. (2019). The design of a learning analytics dashboard: EduOpen Mooc platform redefinition procedures. *Journal of E-Learning and Knowledge Society, 15*(3), 29–47.

Drachsler, H., Dietze, S., Herder, E., d'Aquin, M., & Taibi, D. (2014). The learning analytics & knowledge (LAK) data challenge 2014. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 289–290).

Dumčienė, A., & Lapėnienė, D. (2010). Possibilities of developing study motivation in E-learning products. *Elektronika ir Elektrotechnika, 102*(6), 43–46.

Duval, E. (2011). Attention please! Learning analytics for visualization and recommendation. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 9–17).

Elias, T. (2011). *Learning analytics: Definitions, process and potential*. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.456.7092&rep=rep1&type=pdf. Last access: 04.05.2021.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71.

Gašević, D., Tsai, Y.-S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology, 36*(4), 342–353.

Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers & Education, 57*(4), 2333–2351.

Guenaga, M., Longarte, J. K., & Rayon, A. (2015, March). Standardized enriched rubrics to support competeney-assessment through the SCALA methodology and dashboard. In *2015 IEEE global engineering education conference (EDUCON)* (pp. 340–347). IEEE.

Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M. A., Scheihing, E., Jiménez, A., Broos, T., De Laet, T., & Verbert, K. (2020). Adaptation and evaluation of a learning analytics dashboard to improve academic support at three Latin American universities. *British Journal of Educational Technology, 51*(4), 973–1001.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In *European conference on technology enhanced learning* (pp. 82–96). Springer.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Jonathan, C., Tan, J. P.-L., Koh, E., Caleon, I., & Tay, S. H. (2017). Enhancing students' critical reading fluency, engagement and self-efficacy using self-referenced learning analytics dashboard visualizations. In W. Chen, J.-C. Yang, A. F. M. Ayub, S. L. Wong, & A. Mitrovic (Eds.), *Proceedings of the 25th international conference on computers in education* (pp. 457–462).

Khan, I., & Pardo, A. (2016). Data2U: Scalable real time student feedback in active learning environments. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 249–253).

Kia, F. S., Teasley, S. D., Hatala, M., Karabenick, S. A., & Kay, M. (2020, March). How patterns of students dashboard use are related to their achievement and self-regulatory engagement. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 340–349).

Kim, J., Jo, I. H., & Park, Y. (2016). Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(1), 13–24.

Kuhnel, M., Seiler, L., Honal, A., & Ifenthaler, D. (2018). Mobile learning analytics in higher education: Usability testing and evaluation of an app prototype. *Interactive Technology and Smart Education, 15*(4), 332–347.

Kuosa, K., Distante, D., Tervakari, A., Cerulo, L., Fernández, A., Koro, J., & Kailanto, M. (2016). Interactive visualization tools to improve learning and teaching in online learning environments. *International journal of distance education technologies (IJDET), 14*(1), 1–21.

Leitner, P., & Ebner, M. (2017, July). Development of a dashboard for learning analytics in higher education. In *International conference on learning and collaboration technologies* (pp. 293–301). Springer.

Leitner, P., Ebner, M., & Ebner, M. (2019). Learning analytics challenges to overcome in higher education institutions. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 91–104). Springer.

Lkhagvasuren, E., Matsuura, K., Mouri, K., & Ogata, H. (2016). Dashboard for analyzing ubiquitous learning log. *International Journal of Distance Education Technologies (IJDET), 14*(3), 1–20.

Macarini, L. A., Cechinel, C., Lemos dos Santos, H., Ochoa, X., Rodes, V., Perez Casas, A., Lucas, P. P., Maya, R., Alonso, G. E., & Diaz, P. (2020). Towards the implementation of a countrywide K-12 learning analytics initiative in Uruguay. *Interactive Learning Environments, 28*(2), 166–190.

Mazza, R. (2010). Visualization in educational environments. In C. Romero, S. Ventura, M. Pechenizkiy, & R. S. J. d. Baker (Eds.), *Handbook of educational data mining* (pp. 9–26).

Mejia, C., Florian, B., Vatrapu, R., Bull, S., Gomez, S., & Fabregat, R. (2016). A novel web-based approach for visualization and inspection of reading difficulties on university students. *IEEE Transactions on Learning Technologies, 10*(1), 53–67.

Molenaar, I., & Knoop-van Campen, C. (2017). Teacher dashboards in practice: Usage and impact. In *European conference on technology enhanced learning* (pp. 125–138). Springer.

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218.

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110.

Pérez-Álvarez, R., Maldonado-Mahauad, J., & Pérez-Sanagustín, M. (2018). Design of a Tool to support self-regulated learning strategies in MOOCs. *Journal of Universal Computer Science, 24*(8), 1090–1109.

Podgorelec, V., & Kuhar, S. (2011). Taking advantage of education data: Advanced data analysis and reporting in virtual learning environments. *Elektronika ir Elektrotechnika, 114*(8), 111–116.

Roberts, J. D., Chung, G. K., & Parks, C. B. (2016). Supporting children's progress through the PBS KIDS learning analytics platform. *Journal of Children and Media, 10*(2), 257–266.

Russell, J. E., Smith, A., & Larsen, R. (2020). Elements of success: Supporting at-risk student resilience through learning analytics. *Computers & Education, 103890*.

Sadallah, M., Encelle, B., Maredj, A. E., & Prié, Y. (2020). Towards fine-grained reading dashboards for online course revision. *Educational Technology Research and Development*, 1–22.

Şahin, M. & Yurdugül, H. (2020). Eğitsel veri madenciliğinde veri ön işleme süreci. Eğitsel Veri Madenciliği ve Öğrenme Analitikleri (T. Güyer, H. yurdugül, & S. Yıldırım, Eds., pp. 21–32) Anı Yayıncılık.

Sarikaya, A., Correll, M., Bartram, L., Tory, M., & Fisher, D. (2018). What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics, 25*(1), 682–692.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Sedrakyan, G., Järvelä, S., & Kirschner, P. (2016). Conceptual framework for feedback automation and personalization for designing learning analytics dashboards. In *EARLI SIG 2016, Date: 2016/11/30–2016/12/01,* Location*:* Oulu, Finland.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2018). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*, 105512.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512.

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages, 50*, 19–38.

Shemwell, S. (2005). Futuristic decision-making. *Executive Briefing Business Value from*. Access link: https://www.scribd.com/document/12873609/Dr-Scott-M-Shemwell-Publications-and-Interviews

Sin, K., & Muthu, L. (2015). Application of big data in education data mining and learning analytics – A literature review. *ICTACT Journal on Soft Computing, 5*(4).

Smith, P. (2019). Engaging online students through peer-comparison progress dashboards. *Journal of Applied Research in Higher Education, 12*(1), 38–56.

Sun, K., Mhaidli, A. H., Watel, S., Brooks, C. A., & Schaub, F. (2019). It's my data! Tensions among stakeholders of a learning analytics dashboard. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1–14).

Tan, J. P. L., Yang, S., Koh, E., & Jonathan, C. (2016). Fostering 21st century literacies through a collaborative critical reading and learning analytics environment: User-perceived benefits and problematics. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 430–434).

Ullmann, T. D., De Liddo, A., & Bachler, M. (2019). A visualisation dashboard for contested collective intelligence. Learning analytics to improve sensemaking of group discussion. *RIED: Revista Iboeroamericana de Educación a Distancia (The Ibero-American Journal of Digital Education), 22*(1), 41–80.

Vaclavek, J., Kuzilek, J., Skocilas, J., Zdrahal, Z., &Fuglik, V. (2018). Learning Analytics.

Van Horne, S., Curran, M., Smith, A., VanBuren, J., Zahrieh, D., Larsen, R., & Miller, R. (2018). Facilitating student success in introductory chemistry with feedback in an online platform. *Technology, Knowledge and Learning, 23*(1), 21–40.

van Leeuwen, A., Rummel, N., & Van Gog, T. (2019). What information should CSCL teacher dashboards provide to help teachers interpret CSCL situations? *International Journal of Computer-Supported Collaborative Learning, 14*(3), 261–289.

Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: an overview and future research opportunities. *Personal and Ubiquitous Computing, 18*(6), 1499–1514.
Wang, F., & Hannafin, M. J. (2005). Design-based research and technology enhanced learning environments. *Educational Technology Research and Development, 53*(4), 5–23.
Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics, 6*(2), 53–69.
Xhakaj, F., Aleven, V., & McLaren, B. M. (2017). Effects of a dashboard for an intelligent tutoring system on teacher knowledge, lesson plans and class sessions. In *International conference on artificial intelligence in education* (pp. 582–585). Springer.
Yoo, Y., Lee, H., Jo, I. H., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In *Emerging issues in smart learning* (pp. 145–155). Springer.
Zheng, J., Huang, L., Li, S., Lajoie, S. P., Chen, Y., & Hmelo-Silver, C. E. (2021). Self-regulation and emotion matter: A case study of instructor interactions with a learning analytics dashboard. *Computers & Education, 161*, 104061.

Chapter 2
The Current Landscape of Research and Practice on Visualizations and Dashboards for Learning Analytics

Min Liu, Songhee Han, Peixia Shao, Ying Cai, and Zilong Pan

1 Introduction

Research on learning analytics (LA) has increased significantly in recent years (Liu et al., 2019b). The field is moving forwards from just understanding the benefits and challenges of LA to a more mature level to gain a deeper understanding of students' learning experiences through analytics (Viberg et al., 2018). Stakeholders such as university instructors and administrators, K-12 teachers and students, and corporations are interested in LA applications, especially how to make sense of big data and how to utilize the data to make evidence-based decisions. With rapid changes in technology, the use of visualizations and dashboards as learning analytics applications shows potentials to provide visual information based on learner-generated data to help stakeholders better understand the data. While progress has been made in this field, much is still to be understood to achieve the benefits of using LA to optimize learning and to improve learning environments for teachers and students.

The purpose of this chapter is to examine the research and practice of using visualizations as an analytic technique in LA research and explore the practice of dashboard designs as a means to communicate the research findings to stakeholders (Alhadad, 2018). This paper has two goals:

Goal 1: To conduct a synthesis on the current literature, 2016–2020, on how visualizations and dashboards are utilized in learning analytics research, both at research and practice levels

Goal 2: To present a case study of our R&D efforts in creating an immersive problem-based learning program for middle school science where we use

M. Liu (✉) · S. Han · P. Shao · Y. Cai · Z. Pan
The University of Texas at Austin, Austin, TX, USA
e-mail: mliu@austin.utexas.edu; song9@utexas.edu; pxshao@utexas.edu; yingcai@utexas.edu; panzl89@utexas.edu

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_2

visualizations to report research outcomes and our efforts in designing a dashboard of this program for teachers as a supporting teaching tool

In the following sections, we will first report our synthesis on the current literature, 2016–2020, on how visualizations and dashboards are utilized in learning analytics research, both at research and practice levels. We will then present a case study of our R&D efforts when we use visualizations to report research outcomes and create a dashboard for teachers to use as a supporting teaching tool.

2 Goal 1: Review of Related Literature

2.1 Method

For Goal 1, we conducted a synthesis of the current literature from 2016 to present regarding how data visualizations and dashboards were utilized in LA research. The selection criteria were based on two previous literature reviews on LA in education (Liu et al., 2017, 2019b), but with a focus on LA data visualization and dashboard use in this study. We adhered to the PRISMA literature review methodology and followed the four steps including identification, screening, eligibility, and included (Moher et al., 2009). In this study, we adopted three criteria in selecting articles for consideration: (a) empirical study articles published in peer-reviewed journals, excluding conference proceedings, book chapters, literature reviews, and theoretical papers, (b) research published between 2016 and September 2020 when we started the review on this study, and (c) articles that we could find with the search query: "learning analytics" AND dashboard OR visuali*. The selection of the included articles went through three-rounds of the examination process.

First, we went over the previously selected peer-reviewed journals that were used from the previous literature review (Liu et al., 2019b) and found four journals (*British Journal of Educational Technology; Computers & Education; Computers in Human Behavior; Technology, Knowledge and Learning*) from the previous list were actively producing articles matching our criteria for this study. After including these four journals to our list of journals to review, we added four more journals on educational technology and learning analytics (*Educational Technology Research and Development; International Review of Research in Open and Distributed Learning; IEEE Transactions on Learning Technologies; Journal of Learning Analytics*). After searching each journal for all possible articles during the timeframe from 2016 to September 2020, we came up with a total of 44 articles by this point in the identification step.

Then in the screening step, we excluded articles investigating the effectiveness of visual learning analytics tools, having less focus on the use of data visualization or dashboard in the learning analytics aspect but emphasizing the use of interactive visualizations in teacher professional development programs. Each article was verified by at least two research team members for deciding its inclusion. Next in the eligibility step, we went through the selected articles pertaining to the purpose of this study and Goal 1 of this chapter. We selected those articles that met our review purpose: how data visualizations and dashboards are utilized in LA research and eliminated the articles only focused on the practice-level data visualization and the practitioner articles that only focused on the specific subject matter-based data visualization even though they included the keyword “learning analytics” (e.g., medical studies used data visualization techniques to improve specific medical practices for practitioners). This iterative and selective process produced 37 articles in total for further analysis.

As a result of the above iterative selection process, we created a spreadsheet containing the categories of our research focus in this review which included research questions, data visualization techniques or dashboards for LA researchers as a research methodology, and dashboard use for instructors and learners as a communication tool in the included step. Having read each article for inclusion at a broad level, it became clear to us the articles can be categorized into two big categories (Alhadad, 2018): (a) data visualization technique or dashboard as a research methodology and (b) dashboard use for instructors and learners as a communication tool. To examine the research of using data visualization or dashboard use in LA research more closely from the selected articles, we used three subcategories (type; data; benefit) for “data visualization technique or dashboard for LA researchers as a research methodology” (Alhadad, 2018, p. 62) and three subcategories (data; target user; benefit) for “dashboard use for instructors and learners as a communication tool” (Alhadad, 2018, p. 62). We extracted information to fill these categories in the spreadsheet from each of the 37 articles with its key findings. The information added to each category was double-checked by two team members, and changes were made until all team members reached a consensus on those changed items. In the following, we will discuss the findings of our synthesis.

2.2 Findings

Alhadad (2018) elicits the value of visualizing data largely in two domains from cognitive psychology and visualization science standpoints: as a research methodology and as a means of communication tools. To define the terminologies, the research methodology refers to the use of data visualization or dashboard to enlighten researchers’ inquiry process as an analytic technique, whereas a means of communication tools indicates the employment of visualizations by learners or instructors to inform about their educational practices (Alhadad, 2018). For LA researchers, either data visualization technique or dashboard—sometimes both—was used as a research methodology, but dashboard, sometimes it was just called as a tool, was mainly used as a means of communication tool for learners and instructors in our literature review. We found most ($n = 36$ out of 37) of the LA data visualization or dashboard articles used either data visualization techniques or dashboard as a research methodology or a communication tool, including some studies that

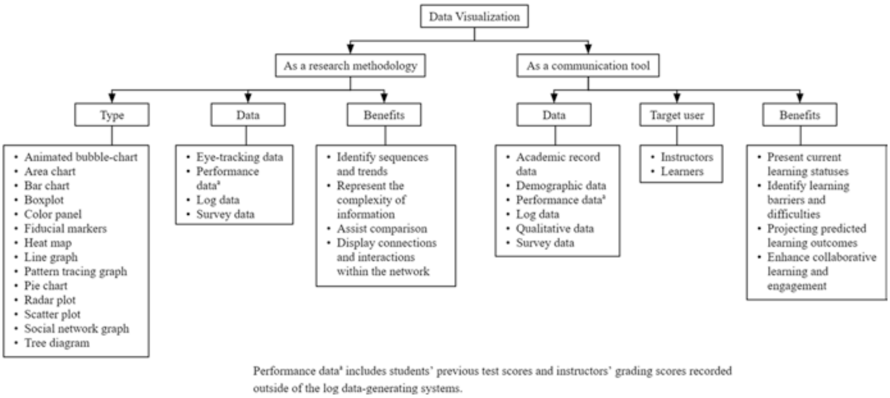


Fig. 2.1 Findings of data visualization uses from the reviewed articles

used both. Figure 2.1 presents the findings from the selected articles and exhibits the structure of the following sections on the findings of this review of literature. In the following, we will discuss the specific findings under each category.

2.2.1 The Use of Data Visualization Technique or Dashboard as a Research Methodology

There has been much effort in research communities to represent research data in a more intuitive way to permeate their findings widely while avoiding the common belief that data themselves are neutral and objective (Alhadad, 2018; Gelman & Hennig, 2017; Woodward, 2011). We have found most of the LA researchers ($n = 20$, see Table 2.1 for the details) used various data visualization techniques for straightforward but rich representations of their research findings. Therefore, we examined what kind of data visualization techniques or dashboards researchers used (i.e., type), what kind of data sources they used (i.e., data), and the reasons for them to choose specific techniques or dashboards over others (i.e., benefit) in the following sections as represented by Table 2.1.

Type A number of recent LA studies used graphs or charts ($n = 9$). To represent the quantitative data comparison in a more intuitive way, many researchers used graphs or charts in lieu of showing tables of variables and numbers. For example, Avila et al. (2020) used a bar chart to show the different levels of web accessibility by type of HTML elements such as links or images. A pie chart was also used to show the proportion of accessibility per Web Content Accessibility Guidelines in the study. In another study, Sedrakyan et al. (2020) used multiple pattern tracing graphs to show students' required items for their choice of learning goals. These graphs contained learning resources, time, and performance requirements per chosen goal using bar and layered graphs in one visualization.

Table 2.1 Details of the reviewed articles used data visualization technique or dashboard as a research methodology

Author (year)	Type (data)	Benefit
Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019)	Scatter plot (Log data)	Compare the multivariate analysis of variance (MANOVA) in a single shot
Avila, C., Baldiris, S., Fabregat, R., & Graf, S. (2020)	Proportional bar chart; pie chart (Survey data)	Show the different accessibility across different tools on the web like links or images; the pie chart shows the proportion of accessibility
Caprotti, O. (2017)	Markov chain diagram (Log data)	Visualize student progress in the information space of a course as a graph
Crick, R. D., Knight, S., & Barr, S. (2017)	Heatmap; line graph (Survey data)	Be more explicit about what is uncertain about the questionnaire result data
De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020)	Boxplot; bar panel (Log data)	Examine the average interaction time in minutes; the impact of new modules on the dashboard on perceived support of the advisor, relation between perceived support and average time of the new dashboard, and changes in workload between certain periods of time; visualize the identified themes in the 14 staged advising dialogues
Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018)	Heatmap (Log data)	Represent the intuitive comparison of teachers' gaze behavior between exploratory versus explanatory visualizations
Fiel, J., Lawless, K. A., & Brown, S. W. (2018)	Scatter plot (Log data)	Identify and investigate various patterns of timing behavior that might emerge in an actual course. Also enables an easy division of groupings of "early starters" or "late starters" relative to their peers and not necessarily restricted by course raw time
Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M. A., Scheihing, E., Jiménez, A., Broos, T., … & Verbert, K. (2020)	Proportional bar chart with different color (Survey data)	Show the different proportion per group
Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020)	Box plot; bar plot (Survey data)	Overlay the expert and student responses with different colors for easier comparisons
Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019)	Gradient color panel (log data)	Show the percentage of teachers who actually accessed the system in relation to those who were originally given access to the system

(continued)

Table 2.1 (continued)

Author (year)	Type (data)	Benefit
Liu, M., Lee, J., Kang, J., & Liu, S. (2016)	Area chart; line chart (Log data)	Represent multiple layers of information in a single view which enables researchers to understand how the patterns may vary according to students' learning characteristics
Liu, M., Kang, J., Zou, W., Lee, H., Pan, Z., & Corliss, S. (2017)	Radar plot; area chart and scatter plot (Performance data[a])	Compare high- and low-performance groups' learning patterns in an intuitive way
Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017)	Fiducial marker (Eye-tracking data)	Generate reliable footprints of collaboration quality and separate productive from less productive groups of students
Nagy, R. (2016)	Animated bubble chart (Performance data[a])	Select and watch the path of a single student while conducting a one-on-one interview about their efforts
Pardos, Z. A., & Horodyskyj, L. (2019)	Scatter plot (Log data)	Not specified
Pardos, Z. A., Whyte, A., & Kao, K. (2016)	moocRP dashboard (Log data)	Prepare data for developing instructor and researcher-oriented interfaces
Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018)	Bar chart (Log data)	Help teachers/teaching staff make informed design alterations and interventions based upon learning analytics data
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020)	Pattern tracing graph (Log data)	Present the pattern for all groups and indicate which group has the pattern of expected or unexpected
Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017)	Radar plot; bar graph, social learning network graph; line graph (Log data)	Show each student's 21c skills strength compared to her/his peers; show each student's mindset soundness compared to peers; reflects students' position and influence within the WiREAD learning network; show each student's reading achievement compared to peers
Van Horne, S., Curran, M., Smith, A., VanBuren, J., Zahrieh, D., Larsen, R., & Miller, R. (2018)	Bar graph; boxplot (Log data)	Show the distribution of the dashboard; shows course grade for matched triplets

[a]Performance data include students' previous test scores and instructors' grading scores recorded outside of the log data-generating systems

Other than graphs or charts, plots were the second most popular type ($n = 7$) in data visualization types in LA studies followed by mappings ($n = 3$). To name some examples of plot and mapping uses, Gutiérrez et al. (2020) showed their survey results through box and bar plots. By overlaying expert and student responses with different colors, the researchers facilitated the comparison between the two groups. In addition, Echeverria et al. (2018) visualized four teachers' gaze behaviors through heatmaps and explored the different learning analytics use patterns influenced by whether data storytelling elements were added to the data visualization or not. The example heatmaps of exploratory and explanatory visualizations depicted in this study better showed data storytelling elements had the potential to assist teachers in exploring visualizations easily.

One noteworthy finding was that other than these conventional data visualization techniques mentioned above, some studies introduced a new data visualization technique and dashboard aiming to show their unique findings even more prominently, which also promoted a more convenient way of data analysis sharing. For example, Pardos et al. (2016) developed moocRP model/dashboard utilizing standardized data streaming based on Caliper and xAPI. By streaming data from multiple platforms and standardizing it in advance to feed it to the analysis visualizing sharing tool, known as moocRP in this case, this model not only facilitated learning activity visualization but also eased the data analysis, distribution, and research analytics module reuse. One of the most significant features of this model-based dashboard is integrating data request, authorization, and distribution processes embedded for instructors and researchers in the system. This enables other researchers to apply and adapt the data analysis conducted by third parties to their own datasets without any violation of data ethics such as transparency or privacy. Using this dashboard, researchers simply add or delete the dataset they need from multiple data sources through a few mouse clicks, and they can also utilize visual analytic modules such as Bayesian Knowledge Tracing or course structure visualizer with their selected datasets.

Data In our literature review, we found log data from either learning management systems or educational games were the most dominantly used data source ($n = 14$) for the methodological purposes of visualization. Besides, we found most of the researchers utilized various data visualization techniques to make their findings more accessible to larger audiences because raw log data tend to be too unobtrusive to render any distinct collective patterns or groupings. For example, Aljohani et al. (2019) used a correlational matrix comparing the multivariate analysis of variance (MANOVA) from the log data in a single visualization and showed the distinct positive correlations between multiple variances. In another study, Fiel et al. (2018) used a box plot to identify and investigate various patterns of students' timing behaviors from the log data they collected. This visualization enabled the researchers to detect the different group emergence easily which was divided into four groups by the combination of the students' timing index and their spacing counts.

The second most popularly used data source was using surveys ($n = 4$), and survey results were visualized mainly for the apparent comparison in proportions per different group or individual. To name a few, Guerra et al. (2020) visualized the students' different perceptions regarding the dashboard and their number of special requests by semester in the proportional bar charts with different colors to make the comparison more explicit. Likewise, Gutiérrez et al. (2020) displayed their survey data in the box and bar plots overlaying the survey responses from the pairs (expert versus laymen and expert versus students) for representing the evident differences in those pairs with different colors. Other than log data or survey data, students' performance scores or instructors' grading scores were also included for representation and comparison purposes. For example, Liu et al. (2017) showed students' test scores in radar plots to compare high- and low-performance groups' learning patterns, and Nagy (2016) visualized the teachers' grading scores based on the rubrics per student to assist teachers to track their grading scores of the students.

Infrequently but not rarely, eye-tracking data were collected from separate tools detached from learning management system (LMS) to be compared with the LMS-generated log data or another preexisting dataset to make a better sense of the meaning of teacher or student's behaviors recorded in the log data. For instance, teachers' eye-tracking data were used to match them with the LMS-generated data to find the different teacher behavior patterns upon the exploratory and explanatory visualizations (Echeverria et al., 2018), or students' eye-tracking data were collected to track students' gaze data with them to produce real-time references for teachers to easily decide who or which group needs teacher's support most at the moment (Martinez-Maldonado et al., 2017). In summary, the use of eye-tracking data in our review demonstrated the researchers' intention to enhance their data analysis by adding more contexts to the log data themselves.

Benefit The goal of data visualization is to enable researchers to explain the data in more clear and understandable forms (Chen et al., 2007). Data visualization also delivers a comprehensible picture for researchers to grasp the gist of the outcomes, provides an approach to explore data, and sometimes even generates insightful research results (Chen et al., 2007). In this review, four significant benefits of using data visualization techniques emerged: (a) presenting research results indicating trends; (b) demonstrating multilayered information in a single view; (c) promoting comparisons; and (d) displaying research participants' relationships and interactions within the network identified in a study.

First, data visualizations can present research results in a sequence for researchers to identify trends. For example, Sedrakyan et al. (2020) used a bar chart to show a sequence of trials of completing a chosen learning goal. Specifically, each bar demonstrates an achievement level for each trial, and arrows indicate time spent between the trials, which gives a representative time sequence to show the trend. Also, in the same study, line charts are applied to reveal students' time spent across different trails. In another study, Rienties et al. (2018) selected bar charts to show the changes in assessment submission rate over time, making it easier for researchers to see the trends. A dynamic chart is also used to show the progress as time elapses in the study. In Nagy's (2016) study, he used a three-dimensional motion chart with animated bubbles to track users' achievement paths over time. Since different colors (girls in blue and boys in green) were used to visualize their dissimilar paths, the trends between boys and girls looked more salient. Furthermore, this dynamic and interactive motion chart also allowed researchers to track each individual's behavioral change over time and presented the fluctuation of the academic efforts that students put into, which reveals the diverse individual-level trends within the collective trends categorized by gender. Besides, Fiel et al. (2018) used a scatter plot to present the various timing behavior patterns among the four different groups. The plot showed the unique singularities in the four different groups' trends, especially focusing on each group's timing index and spacing counts about when and how often they completed their coursework.

Second, the data visualization technique allows the representation of multiple layers of information in a single view. For example, Liu et al. (2016) used area graphs with lines to demonstrate the average frequency and duration of tools usage by students across various problem-solving stages from two science knowledge groups. Each tool used by each group was presented in a separate graph but organized consistently in an integrated view: the x-axis is used for showing log time, while the y-axis is used for showing the total duration. Additionally, Liu et al. (2017) used radar plots to represent the multivariate data about the high- and low-achieving groups. By representing five variables in a two-dimensional plot per subject and module, the multiple series of radar plots enriched the contexts of the two groups' distinctive tool-usage patterns.

Third, data visualization can promote comparisons. Using different colors is a common technique for researchers to show the contrast between groups. For example, Sedrakyan et al. (2020) overlaid both expert and student responses with different colors to compare the difference between the planned performance on a goal-specific task and a student's actual outcomes. Also, radar plots and bar charts are popularly used to show comparisons. For instance, Tan et al. (2017) used a radar plot to show each student's skills strength compared to their peers, and they also used a bar graph for showing each student's mindset soundness compared to their peers. For a small number, heatmaps are also utilized by researchers to make comparisons. In the study conducted by Echeverria et al. (2018), 24 heatmaps correspond to 4 teachers' inspection episodes were created to help researchers perform a rapid visual comparison between 2 types of gaze behaviors (exploratory and explanatory).

Lastly, data visualization can display participants' relationships and interactions within the network. Specifically, Tan et al. (2017) used social network maps to reflect students' positions and their influences on others within the learning network. Each student was represented by a node, and the total nodes were connected by arrows which represented the connections among students as well as the direction of each interaction. The more replies a student received, the larger the node would be. By the visualization represented in this manner, researchers were able to observe the degree of each student's participation and interaction pattern in the course easily. Similarly, Caprotti (2017) used the social network map to display the resources such as quizzes, peer-assessed workshops, and the discussion forum posts that students visited in the course. Each resource that appeared in the log file was displayed as a node, and each node's size corresponded with the students' visit frequency in the visualization. In this way, the researchers were able to explore the students' activity patterns easily, and they discovered that only graded activities that contributed to their final grades were frequently visited by the students.

2.2.2 The Use of Dashboards for Instructors and Learners as a Communication Tool

Dashboard, as a platform for presenting the visualized educational information, has been widely used to empower instructor-learner interaction and support learning practices (Alhadad, 2018). The reviewed articles revealed diverse types of dashboard applications in various educational contexts ranging from online learning environments (e.g., Moreno-Marcos et al., 2019) to face-to-face advising (De Laet et al., 2020). To take a closer look at the dashboard implementation, in the following sections we examined the data sources for the dashboard to convey educational information (i.e., data), the target users that the dashboard was designed for (i.e., target user), and, lastly, the benefits that a dashboard brought to instructors and learners (i.e., benefit) (see Table 2.2).

Data Based on the reviewed articles, log data are the most common data type utilized by the dashboards ($n = 19$) as a communication tool. In fact, instead of simply presenting the raw log data, many dashboards firstly processed the log data using some machine learning models or algorithms and then presented the outcomes. For example, Herodotou et al. (2019) collected students' usage log data such as assignment submission status from a LMS and constructed a prediction model. The outcomes of the prediction were presented on the dashboard to visualize the predictive information on which student was at risk or not of submitting an assignment. In another study, Mavrikis et al. (2019) applied artificial intelligence (AI) techniques to create a series of indicators using students' log data generated in an exploratory learning environment. The indicators were then presented on the dashboard for teaching assistants to monitor students' real-time learning progress. A noteworthy finding was that many dashboards, although the log data provided the bulk of the data source, also integrated with other types of data. For example, Russell et al. (2020) collected and visualized students' performance data such as assignment grades integrated with the log data to present students' learning progress, which provided instructors with a more comprehensive view of the learners' progress in the course.

Other than log data, students' academic records such as course-taking behaviors were also applied to the dashboard design. Guerra et al. (2020) used students' academic record data such as previous course-taking information, the progress of the program, and performance scores to build dashboards to support academic advising in higher education contexts. A similar dashboard design was also applied in the studies of De Laet et al. (2020) and Gutiérrez et al. (2020). After adding more information such as the demographic background to the dashboard, the dashboards in

Table 2.2 Details of the reviewed articles that used dashboard as a communication tool

Author (year)	Data	Target users	Benefit
Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019).	Log data	Instructors	Compare patterns across classes and sections
Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019)	Log data; performance data[a]	Learners	Show the best students' performance averages for each factor to other students
Avila, C., Baldiris, S., Fabregat, R., & Graf, S. (2020)	Qualitative data	Instructors	Help teachers easily identify accessibility failures and quality items that need to be improved before its delivery to students
Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2018)	Log data	Learners	Support the dialogue between adviser and student through an overview of study progress, peer comparison, and by triggering insights based on facts as a starting point for discussion and argumentation
Crick, R. D., Knight, S., & Barr, S. (2017)	Survey data; performance data[a]	Instructors and learners	Help teachers to make decisions to improve outcomes
De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Visualize the students' pathway and supports for making study plan
Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018)	Log data	Instructors	See the stories behind the data
Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M. A., Scheihing, E., Jiménez, A., Broos, T., … & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Provide the first-year key moments and profiles
Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Provide various visualizations for academic progress
Han, J., Kim, K. H., Rhee, W., & Cho, Y. H. (2020)	Log data; qualitative data	Learners	Monitor students learning status
Hernández-García, Á., Acquila-Natale, E., Chaparro-Peláez, J., & Conde, M. Á. (2018)	Log data	Learners	Detect students' cooperation work achievement using LMS data

(continued)

Table 2.2 (continued)

Author (year)	Data	Target users	Benefit
Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019)	Log data; demographic data	Instructors	Predict on a weekly basis whether (or not) a given student will submit their assignments
Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017)	Log data	Instructors and learners	Gain a better understanding of student's learning paths
Mavrikis, M., Geraniou, E., Gutierrez Santos, S., & Poulovassilis, A. (2019)	Log data	Instructors	Provide eight traits of this dashboard that mentioned in the paper
Mejia, C., Florian, B., Vatrapu, R., Bull, S., Gomez, S., & Fabregat, R. (2017)	Survey data; demographic data	Learners	Create awareness among students about their reading difficulties, learning style, and cognitive deficits to facilitate reflection and encourage their self-regulated learning skills
Michos, K., & Hernández-Leo, D. (2018)	Log data	Instructors	Not specified
Molenaar, I., & Knoop-van Campen, C. A. N. (2019)	Log data	Instructors	Display real-time data on learner performance to teachers, and it impacted the pedagogical actions of teachers
Moreno-Marcos, P. M., Alario-Hoyos, C., Munoz-Merino, P. J., Estevez-Ayres, I., & Kloos, C. D. (2019)	Qualitative data	Learners	Support the proposed 3S methodology
Pardos, Z. A., Whyte, A., & Kao, K. (2016)	Log data	Instructors	Provide support for instructional actions
Park, Y., & Jo, I. H. (2019).	Log data	Learners	Detect students' behavior pattern on dashboard
Roberts, L. D., Howell, J. A., & Seaman, K. (2017)	Log data	Learners	Support students' learning experience
Russell, J. E., Smith, A., & Larsen, R. (2020)	Log data; performance data[a]	Learners	Show students' weekly progress and grade
Sadallah, M., Encelle, B., Maredj, A. E., & Prié, Y. (2020)	Log data	Instructors	Detect the reading barriers that learners face with content and to identify how their courses can be improved accordingly

(continued)

Table 2.2 (continued)

Author (year)	Data	Target users	Benefit
Schumacher, C., & Ifenthaler, D. (2018)	Log data	Learners	Understand one's learning habits, track the progress towards goals, optimize one's learning paths, or adapt to recommendations
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020)	Log data	Not specified	Enhance students' motivation
Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017)	Log data; qualitative data	Learners	Foster greater self-awareness, reflective, and self-regulatory learning dispositions; enhancing learning motivation and engagement; nurturing connective literacy among students

[a]Performance data include students' previous test scores recorded outside of the log data-generating systems

these studies presented detailed information of undergraduate students' academic path in the institute, which provided advisors a holistic view about students' overall progress, thus enabling them to deliver better instructions through more personalized advising.

Last but not least, some dashboards also collected and processed qualitative data such as the posts students composed in the discussion forums. For example, Moreno-Marcos et al. (2019) applied sentiment analysis techniques to categorize students' forum posts and replies in a MOOC. The dashboard could present the proportion of each sentiment category (positive, negative, neutral) of the forum each day and the trend across the time to inform further instruction design. In another study, Tan et al. (2017) collected students' comments generated in an online learning environment—WiREAD—and used the length of comments to create radar charts as indicators to identify the students' different levels of participation. The radar charts presented the learning behavior patterns for an individual student as well as the whole class, which provided insights for the future learning analytics dashboard design.

Target User In the reviewed literature, dashboards were designed for two groups of target users: learners (n = 14) and instructors (n = 14). For learners, some dashboards were developed to promote their self-reflective learning process through visualization in the dashboard. For example, Charleer et al. (2018) used the dashboard to provide key moments of students' performance, such as exam scores. Roberts et al. (2017) also applied a feature to the dashboard to compare each individual to the overall performance of the class, supplemented by the progress bars for showing the number of site visits, engagement level, the number of assessments submitted, and the grade level for each subject. In addition, some dashboards were designed to draw students' attention to their possible at-risk behaviors. In this respect, Herodotou et al. (2019) designed a predictive dashboard to identify students' at-risk behaviors such as not submitting assignments. Gutiérrez et al. (2020)

also designed a similar predictive system using predictive algorithms to display students' academic risk on the dashboard.

Dashboards designed for instructors could help them visualize learners' performance to gain a better understanding of current academic development. For example, Guerra et al. (2020) designed the dashboard for advisors to visualize students' past and current performance and progress, which supported instructors to advise on students' study plans and help students achieve content knowledge mastery. Also, De Laet et al. (2020) used a dashboard to enhance the communication between advisors and students in developing study plans. Sometimes, dashboards were also designed for instructors to monitor learners' learning behavior and academic progress. For example, Sedrakyan et al. (2020) processed students' log data to provide the visualization of their learning trends in radar graphs. In addition, some dashboards were designed to enable instructors to offer academic recommendations. In this regard, Sadallah et al. (2020) applied an assistant mechanism to empower instructors with the data of remediation suggestions once the dashboard identified learners' academic issues.

Benefit The reviewed articles showed the benefits of using data visualization or dashboards as a communication tool in the following four aspects: (a) presenting current learning status; (b) identifying learning barriers and difficulties; (c) projecting predicted learning outcomes; and (d) enhancing collaborative learning and engagement.

A number of studies indicated dashboards were beneficial for presenting learners' current learning status. For instance, Han et al. (2020) provided a student dashboard informing students about how many comments a student had posted, which peers the student had interacted with, and what argumentation elements such as reason(s) or claim(s) were included in their comments. To better support students, the researchers also inserted help buttons for the students to use so that instructors would be notified once the students requested help. This dashboard enabled students to own autonomy in managing their own learning pace and provided them with a comprehensive image of their learning progress. In another study, Aljohani et al. (2019) implemented a student dashboard called "Analyse my Blackboard Activities (AMBA)" to reveal the hidden patterns of learner's behaviors and attitudes. Using the students' log data from their blackboard LMS, this tool provided each student his/her own learning statistics with other comparatives selected by the instructors, such as class average, average of active students, and average of best student performance. Supported by the dashboard, the students were able to see their current learning progress and performance versus the whole class. Moreover, some studies focused on the use of dashboards to demonstrate students' learning progress. For instance, Park and Jo (2019) provided a dashboard using students' online learning log data to present learners' status such as how long and how often they accessed certain learning materials. In this case, students were able to get a better sense of their own learning behavior patterns and be informed about what learning activities were yet to be explored.

In addition, dashboards are beneficial for identifying learning barriers and difficulties. Avila et al. (2020) used an analytic tool, Analytics Tool to trace the Creation and Evaluation of OERs (ATCE), to trace the creation and evaluation of open educational resources embedded in the ATutor LMS. They concluded that ATCE allowed the instructors to identify what they needed to improve for their courses and the visualizations helped instructors identify their failures in preparing quality learning materials in advance of the student's use in a real scenario. While Avila et al. (2020) used ATCE to help teachers identify the barriers for improvement, Mejia et al. (2017) used another dashboard called Panel de Analíticas de Aprendizaje de Dislexia en Adultos (PADA) to help students create awareness about their reading difficulties and cognitive deficits. PADA was designed to facilitate students' reflections on the reading process and encourage them to develop self-regulated learning skills in the study.

Moreover, dashboards are used for projecting predicted learning outcomes. The learning analytic system in the study of Herodotou et al. (2019) used a traffic light system to predict whether the students at risk were submitting their assignments. Specifically, the red color in the system indicated students at risk of not submitting their next assignment. In this way, students could receive early intervention if they were at risk; as a result, it prevented students from missing assignment dues and falling behind their peers. In another study, Russell et al. (2020) examined the effects of the LA dashboard use with at-risk students and showed the benefits of using such a dashboard. They found this dashboard use was effective not only for students' overall progress but also for enhancing final grades of the at-risk students.

Finally, dashboards can also promote learning engagement and enhance collaborative learning. Tan et al. (2017) demonstrated how a dashboard—WiREAD—was used to support collaborative critical reading and discussion. This dashboard provided an interface for students to peer review and critique each other's writing, which fostered greater self-awareness and collaborative learning disposition and also nurtured connective literacy among the students. In another study, Aljohani et al. (2019) implemented a dashboard, allowing students to see their learning statistics from the blackboard LMS. The comparison feature of the dashboard enabled students to compare their personal learning behavior frequency with the average frequency in the most active group in the class. This comparison raised every student's awareness about the most active students' work and contributed to the increased students' engagement as a whole in the study.

3 Goal 2: A Case Study

In this section, we present a case where we use visualizations to report research outcomes and our efforts in designing a dashboard for teachers as a supporting teaching tool. This case study serves as an example to support the review of literature in the previous section by illustrating how researchers and designers can use visualizations and dashboards both at the research and practical levels.

3.1 Context of the Case Study

This case study is situated in the context of Alien Rescue, a virtual technology-enriched program for 6th grade space science (AR, https://alienrescue.edb.utexas.edu). This program is designed by the researchers and designers at the University of Texas at Austin. The goal of the program is to engage middle school students in solving a complex problem that requires them to use tools, procedures, and knowledge of space science as scientists and to apply processes of scientific inquiry while learning about our solar system. Students who act as young scientists are charged to find new planet homes for six displaced aliens. It uses problem-based learning pedagogy and aims to enhance middle school students' problem-solving skills. It is aligned with national science standards and Texas Essential Knowledge and Skills (https://alienrescue.education.utexas.edu/teacher/) and has been used by schools in at least 30 states in the USA and 4 countries. Delivered entirely online, the program is designed for 12–15 days with 45-min class session each day. But with appropriate adaption, it can be used from grades 5th to 9th according to schools' curriculum needs and time available.

3.2 Using Visualization as a Research Tool to Communicate Research Findings

As researchers and designers, we have published numerous research studies relating to the Alien Rescue program. In publishing our research findings, we have used visualizations as a research tool to communicate the research findings (Alhadad, 2018). For example, in Liu et al. (2015), we used visualizations to show how learners accessed different tools in Alien Rescue. Figure 2.2 presented multiple layered information showing tool use frequency and duration over a time period by four conceptual categories in one single visualization. The study by Liu et al. (2019b) used visualizations to illustrate the differences in using the tools based upon the log data between different groups over a period of time (see Fig. 2.3). More recently, Kang and Liu (2020) used visualizations to present the problem-solving workflow by students at risk vs. students not at risk in 1 day (see Fig. 2.4).

While the visualizations from the above studies drew upon the log data, in a study by Liu et al. (2019a), visualizations were also used to present findings from the qualitative data regarding students' perceptions of their experience in using Alien Rescue. Figure 2.5a showed students' interview responses to compare their experience with Alien Rescue to other science classes, evaluating whether they were able to learn science better, the same, or worse through Alien Rescue. The keywords describing why they learned better with Alien Rescue are displayed in Fig. 2.5b. Together, these examples illustrate visualizations can be effective in communicating research findings not only among researchers but also to a general audience.

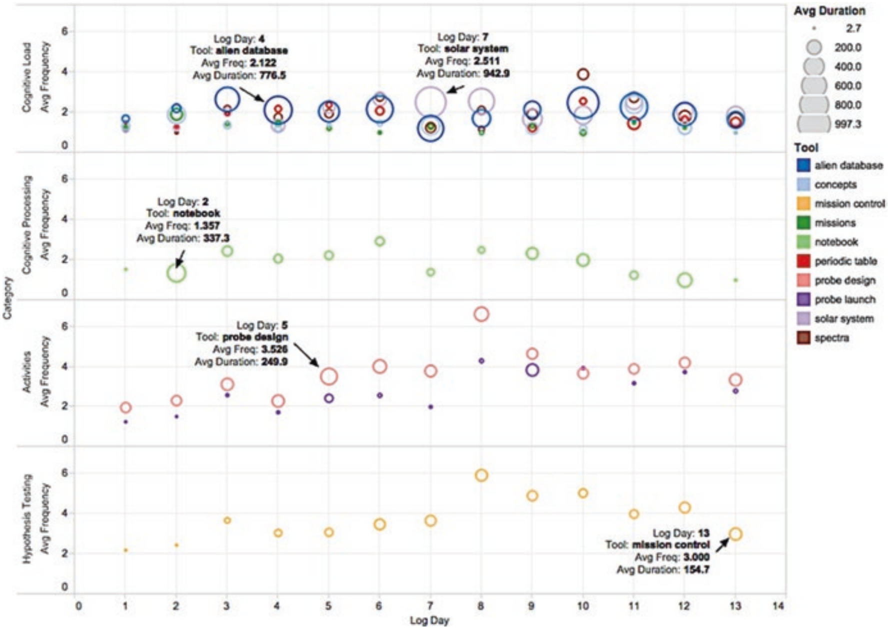


Fig. 2.2 Average frequency and duration of tool use over 14 days by four conceptual categories

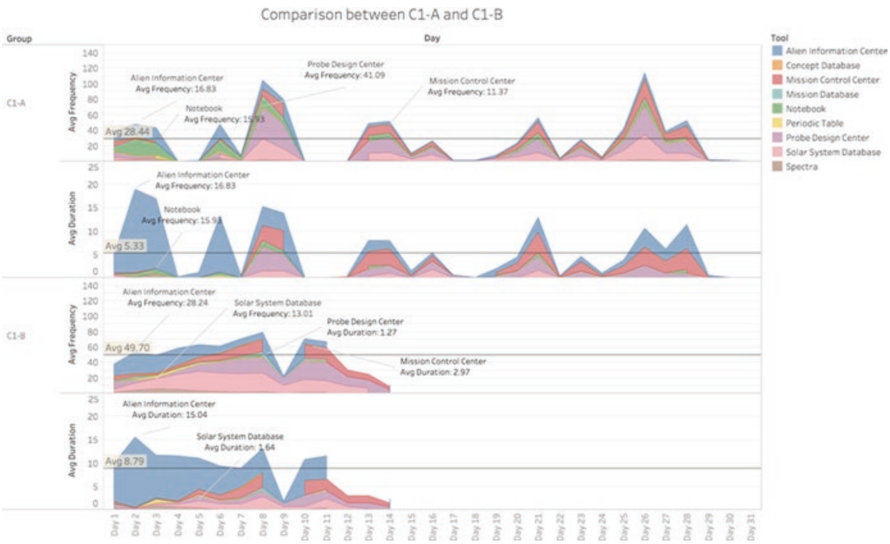
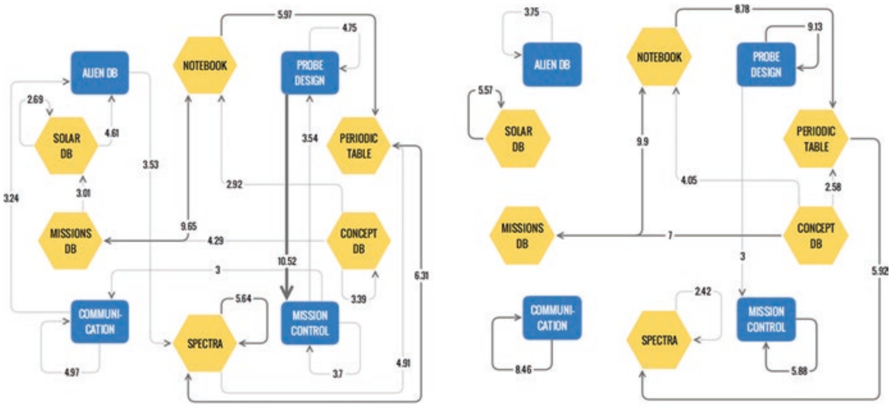
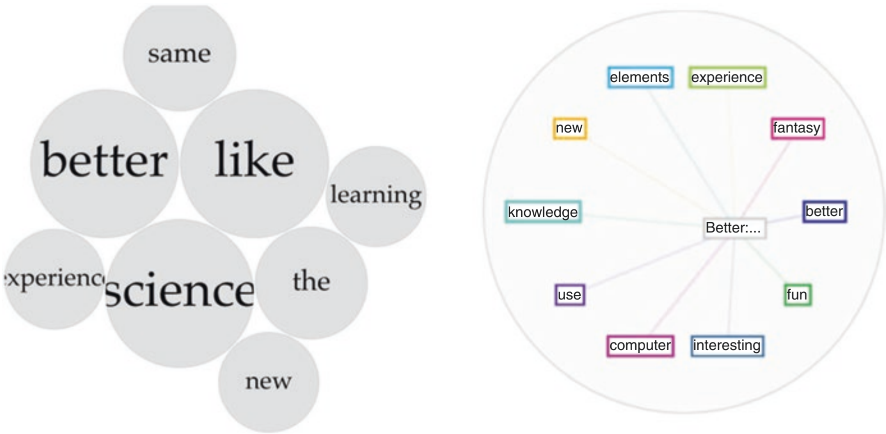


Fig. 2.3 Comparison of tool usage by Group A and Group B over individual days



(a) Day 4: Non-at-risk Students ($n = 104$) (b) Day 4: At-risk Students

Fig. 2.4 How non-at-risk students (**a**) vs. at-risk students (**b**) navigate through Alien Rescue on a specific day



(a) Terms Berry Visualization (b) Mandala Visualization

Fig. 2.5 Students stated they learned science better in (**a**) and the reasons for learning better with Alien Rescue in (**b**)

3.3 Using Dashboard with Visualizations as a Means to Communicate Research Findings to Teachers So as to Inform Their Educational Practices

We are the designers and developers of the Alien Rescue program. In our R&D efforts, we aim to incorporate the research findings into the design as guided by the design-based research framework (Barab & Squire, 2004; Design-Based Research

Collective, 2003). In doing so, we have created a dashboard as a way to communicate our research findings to teachers so as to inform their use of Alien Rescue more effectively (Alhadad, 2018). Here we describe two examples to illustrate how we use the dashboard together with visualizations to translate our research findings to practitioners. The data source of these two examples is a dataset of 7,006,045 lines of log data from 8537 students who used the program during a 2-year time span.

The dashboard as an accompanying tool for Alien Rescue is designed for teachers, who are a key stakeholder using the program. The main purpose of this dashboard is to help teachers use the information from the dashboard to monitor students' learning progress more effectively. A key aspect of the problem-solving process in Alien Rescue is a simulation allowing students to design probes where students research various scientific equipment used in both past and present NASA probe missions and construct probes by selecting appropriate probe type, communication, power source, and instruments. While appropriately constructed, probes will provide useful information to further problem solving. Incorrectly equipped probes can malfunction and waste valuable money. As students write justifications of why they need to design a probe in a certain way and in what way the destination planet is suitable for the alien species they are finding a home, providing just-in-time scaffolding to the students can significantly increase their chances of solving the problem. Therefore, one main feature of the dashboard is to auto-classify students' justifications from poorly justified arguments to well-justified arguments (Pan et al., 2021a). An example of this auto-classification feature is presented in Fig. 2.6. Since one justification is required each time a student sends a probe, this example figure shows that in this class students sent more probes on Oct. 20th than the other 2 days. There are more justifications categorized as specific inquiry (dark blue) and random (red) on this day. Using this just-in-time visual representation, teachers can quickly see students' justifications and intervene as needed to assist their students' inquiry processes. For example, seeing a relatively large portion of randomly written justifications displayed in Fig. 2.6, teachers can remind students about the importance of writing the justification and ask them to compose the scientific justification carefully.

Another example is to incorporate a machine learning model as guided by Csikszentmihalyi's flow theory (1975) to provide teachers visual images to show their students' real-time problem-solving status (Pan et al., 2021b). The three problem-solving states classified based upon the flow theory are flow, anxiety, and boredom (see Fig. 2.7). If a student is identified as in the flow state, it means the student is engaged and is using the tools provided in the environment wisely to solve the problem. If a student is identified as in the anxiety state, it means the student is encountering some difficulties and teachers might need to provide some suggestions or guidance. If a student is identified as in the boredom state, it means the student is gaming in the environment such as clicking random places without specific purposes. In this case, teachers can intervene and remind students to stay on task. Using this information, teachers can easily get a sense of how each student is progressing and be more efficient in checking and providing personalized scaffoldings when necessary.

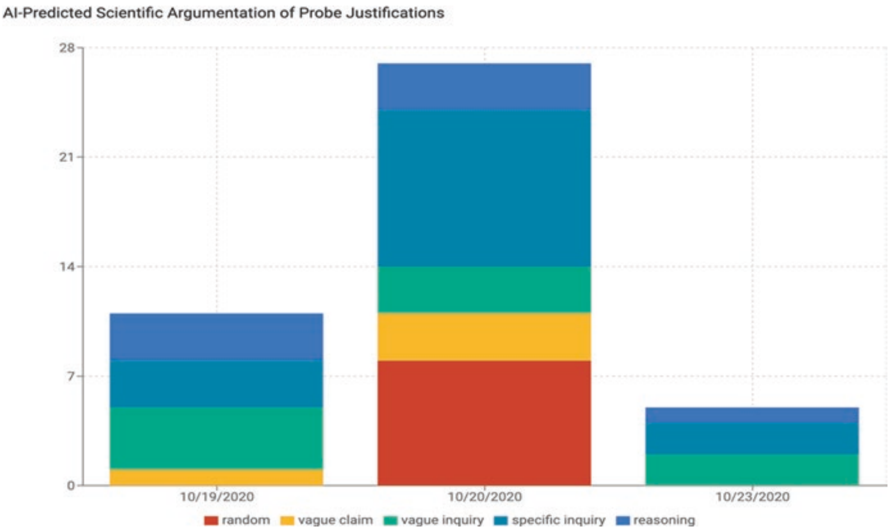


Fig. 2.6 A visual representation of classified students' probe justifications using machine learning techniques (y-axis indicating number of justifications)

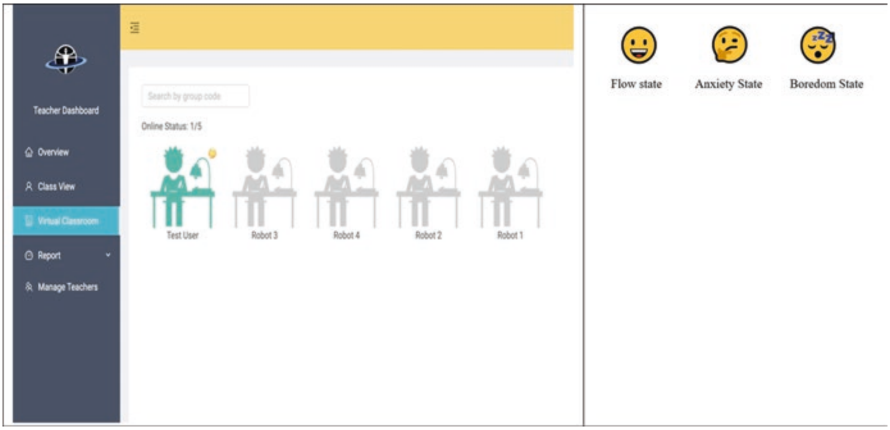


Fig. 2.7 An example showing students' emotional states (**a**) using emojis (**b**) based on Csikszentmihalyi's flow theory

4 Discussion and Summary

In this chapter, we aimed to accomplish two goals. For Goal 1, we conducted a review of literature from 2016 to 2020 on how visualizations and dashboards are utilized in learning analytics research, both at research and practical levels. The findings of our review showed nearly 100% of the included studies used data visualization techniques or dashboards as a research methodology to display findings effectively or as a communication tool to inform learning processes in time. For the use of research methodology, log data from either LMS or educational simulations/games were the dominant data source. For the use of a communication tool, the reviewed articles also revealed diverse data sources with log data being the most common type. Learning analytics dashboards were used to translate a large amount of usage data into interpretable formats to assist users, who were mostly instructors and learners.

For Goal 2, we presented our own R&D efforts in creating an immersive problem-based learning program for middle school science as a case to illustrate how we used visualizations to report research outcomes. The visualizations examples presented here reflected the trends as discussed in Goal 1 in support of the findings of the review of literature. The data source for our research was primarily log data with interview responses as secondary data source. We used visualizations to demonstrate multilayered information in a single view (Fig. 2.2) to illustrate group comparisons (Figs. 2.3 and 2.4) and to display research participants' relationships as they navigated the program (Figs. 2.2 and 2.4). We also discussed how we have designed a dashboard with visualizations to communicate our research findings to practicing teachers so as to support their teaching. The dashboard shows current learning status (Fig. 2.6) and identifies each student's learning barriers and difficulties (Fig. 2.7). Together, this chapter provides a picture of the current landscape of research and practice of visualizations and dashboards for learning analytics.

There are several implications for designing dashboards effectively. First, it is important to provide instructors with information about both individual and group levels. In other words, teachers should receive a more holistic picture of learning progress when they access the information from the dashboard. The information from both individual students and the whole class can help teachers' decision-making related to future lesson planning. Second, instructors play a multitasking role when facilitating problem-solving activities. Instead of delivering large amount of learner-generated behavioral data to instructors, it would be more useful to aggregate and process the data first and then present the information in more easily understandable representations on the dashboard. In our case study, it is not feasible to expect teachers to go through every justification students have composed during each class session. Yet, by presenting the justifications auto-classified into interpretable categories, teachers will be able to take advantage of this processed information in monitoring their students' progress. Third, the dashboard should provide instructors with real-time information which cannot be easily captured via conventional classroom facilitation strategies. That is, if all students are looking at their devices while working on their tasks, it will not be possible for teachers to know which students might need help by simply observing students' physical behaviors or their screens. However, if teachers have access to a dashboard which provides them with real-time information (e.g., students' potential mental status in our case), teachers will be better informed in terms of who and when to provide scaffolding. In conclusion, this chapter shows there are many potentials to use LA-supported dashboards for teaching and learning purposes. We are only at the beginning stage of discovering such potentials.

References[1]

*Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6(*2), 70–85. https://doi.org/10.18608/jla.2019.62.5

Alhadad, S. S. J. (2018). Visualizing data to support judgement, inference, and decision making in learning analytics: Insights from cognitive psychology and visualization science. *Journal of Learning Analytics, 5*(2), 60–85. https://doi.org/10.18608/jla.2018.52.5

*Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019). An integrated framework for course adapted student learning analytics dashboard. *Computers in Human Behavior, 92*, 679–690. https://doi.org/10.1016/j.chb.2018.03.035

*Avila, C., Baldiris, S., Fabregat, R., & Graf, S. (2020). Evaluation of a learning analytics tool for supporting teachers in the creation and evaluation of accessible and quality open educational resources. *British Journal of Educational Technology, 51*(4), 1019–1038. https://doi.org/10.1111/bjet.12940

Barab, S., & Squire, K. (2004). Design-based research: Putting a stake in the ground. *Journal of the Learning Sciences, 13*(1), 1–14. https://doi.org/10.1207/s15327809jls1301_1

*Caprotti, O. (2017). Shapes of educational data in an online calculus course. *Journal of Learning Analytics, 4*(2), 76–90. https://doi.org/10.18608/jla.2017.42.8

Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2018). Learning analytics dashboards to support adviser-student dialogue. *IEEE Transactions on Learning Technologies, 11*(3), 389–399. https://doi.org/10.1109/TLT.2017.2720670

Chen, C. H., Härdle, W. K., & Unwin, A. (Eds.). (2007). *Handbook of data visualization*. Springer Science & Business Media.

*Crick, R. D., Knight, S., & Barr, S. (2017). Towards analytics for wholistic school improvement: Hierarchical process modelling and evidence visualization. *Journal of Learning Analytics, 4*(2), 160–188. https://doi.org/10.18608/jla.2017.42.13

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety*. Jossey-Bass.

*De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020). Adoption and impact of a learning analytics dashboard supporting the advisor—Student dialogue in a higher education institute in Latin America. *British Journal of Educational Technology, 51*(4), 1002–1018. https://doi.org/10.1111/bjet.12962

Design-Based Research Collective. (2003). Design-based research: An emerging paradigm for educational inquiry. *Educational Researcher, 32*(1), 5–8, 35–37. http://www.designbasedresearch.org/reppubs/DBRC2003.pdf

*Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018). Exploratory versus explanatory visual learning analytics: Driving teachers' attention through educational data storytelling. *Journal of Learning Analytics, 5*(3), 73–97. https://doi.org/10.18608/jla.2018.53.6

*Fiel, J., Lawless, K. A., & Brown, S. W. (2018). Timing matters: Approaches for measuring and visualizing behaviours of timing and spacing of work in self-paced online teacher professional development courses. *Journal of Learning Analytics, 5*(1), 25–40. https://doi.org/10.18608/jla.2018.51.3

Gelman, A., & Hennig, C. (2017). Beyond subjective and objective in statistics. *Journal of the Royal Statistical Society: Statistics in Society Series A, 180*, 1–31. https://doi.org/10.1111/rssa.12276

Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M., Scheihing, E., Jiménez, A., Broos, T., De Laet, T., & Verbert, K. (2020). Adaptation and evaluation of a learning analytics dashboard to improve academic support at three Latin American universities. *British Journal of Educational Technology, 51*(4), 973–1001.

[1] **Included in the review of literature section.*

*Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*, 105826–105826. https://doi.org/10.1016/j.chb.2018.12.004

*Han, J., Kim, K. H., Rhee, W., & Cho, Y. H. (2020). Learning analytics dashboards for adaptive support in face-to-face collaborative argumentation. *Computers & Education, 163*, 104041–104041. https://doi.org/10.1016/j.compedu.2020.104041

*Hernández-García, Á., Acquila-Natale, E., Chaparro-Peláez, J., & Conde, M. Á. (2018). Predicting teamwork group assessment using log data-based learning analytics. *Computers in Human Behavior, 89*, 373–384. https://doi.org/10.1016/j.chb.2018.07.016

*Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019). Empowering online teachers through predictive learning analytics. *British Journal of Educational Technology, 50*(6), 3064–3079. https://doi.org/10.1111/bjet.12853

Kang, J. & Liu, M. (2020). Investigating Navigational Behavior Patterns of Students Across At-Risk Categories Within an Open-Ended Serious Game. *Technology, Knowledge and Learning*. https://doi.org/10.1007/s10758-020-09462-6.

*Liu, M., Kang, J., Zou, W., Lee, H., Pan, Z., & Corliss, S. (2017). Using data to understand how to better design adaptive learning. *Technology, Knowledge and Learning, 22*(3), 271–298. https://doi.org/10.1007/s10758-017-9326-z

*Liu, M., Lee, J., Kang, J., & Liu, S. (2016). What we can learn from the data: A multiple-case study examining behavior patterns by students with different characteristics in using a serious game. *Technology, Knowledge and Learning, 21*(1), 33–57. https://doi.org/10.1007/s10758-015-9263-7

Liu, M., Liu, S., Pan, Z., Zou, W., & Li, C. (2019a). Examining science learning and attitudes by at-risk students after they used a multimedia-enriched problem-based learning environment. *Interdisciplinary Journal of Problem-Based Learning., 13*(1). https://doi.org/10.7771/1541-5015.1752

*Liu, M., Pan, Z., Pan, X, An. D, Zou, W., Li, C., & Shi, Y. (2019b). The use of analytics for educational purposes: A review of literature from 2015 to present. In M. S. Khine (Ed.), *Emerging trends in learning analytics* (pp. 26–44). Brill Publishers.

Liu, M., Kang, J., Lee, J., Winzeler, E. & Liu, S. (2015). Examining through visualization what tools learners access as they play a serious game for middle school science. Serious Games Analytics: *Methodologies for Performance Measurement, Assessment, and Improvement* (pp. 181–208). Switzerland: Springer. https://doi.org/10.1007/978-3-319-05834-4.

*Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017). Learning analytics for natural user interfaces: A framework, case studies and a maturity analysis. *Journal of Learning Analytics, 4*(1), 24–57. https://doi.org/10.18608/jla.2017.41.4

*Mavrikis, M., Geraniou, E., Gutierrez Santos, S., & Poulovassilis, A. (2019). Intelligent analysis and data visualisation for teacher assistance tools: The case of exploratory learning. *British Journal of Educational Technology, 50*(6), 2920–2942. https://doi.org/10.1111/bjet.12876

*Mejia, C., Florian, B., Vatrapu, R., Bull, S., Gomez, S., & Fabregat, R. (2017). A novel web-based approach for visualization and inspection of reading difficulties on university students. *IEEE Transactions on Learning Technologies, 10*(1), 53–67. https://doi.org/10.1109/TLT.2016.2626292

*Michos, K., & Hernández-Leo, D. (2018). Supporting awareness in communities of learning design practice. *Computers in Human Behavior, 85*, 255–270. https://doi.org/10.1016/j.chb.2018.04.008

*Molenaar, I., & Knoop-van Campen, C. A. N. (2019). How teachers make dashboard information actionable. IEEE Transactions on Learning Technologies, 12(3), 347–355. https://doi.org/10.1109/TLT.2018.2851585

*Moreno-Marcos, P. M., Alario-Hoyos, C., Munoz-Merino, P. J., Estevez-Ayres, I., & Kloos, C. D. (2019). A learning analytics methodology for understanding social interactions in MOOCs. *IEEE Transactions on Learning Technologies, 12*(4), 442–455. https://doi.org/10.1109/TLT.2018.2883419

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2009). Reprint—Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Physical Therapy, 89*(9), 873–880.

*Nagy, R. (2016). Tracking and visualizing student effort: Evolution of a practical analytics tool for staff and student engagement. *Journal of Learning Analytics, 3*(2), 165–193. https://doi.org/10.18608/jla.2016.32.8

Pan, Z., Chenglu, L., Zou, W., & Liu, M. (2021a, April). *The development of an automatic text classifier enhanced dashboard in supporting teacher's facilitation of virtual problem-based learning activities*. Presentation accepted to the annual conference of American Educational Research Association (AERA). Orlando, FL.

Pan, Z., Li, C., Zou, W., & Liu, M. (2021b). *Learning analytics strategy for supporting teachers in tracking students' problem-solving status*. Manuscript submitted for publication consideration.

*Pardos, Z. A., & Horodyskyj, L. (2019). Analysis of student behaviour in "Habitable" worlds using continuous representation visualization. *Journal of Learning Analytics, 6*(1), 1–15. https://doi.org/10.18608/jla.2019.61.1

*Pardos, Z. A., Whyte, A., & Kao, K. (2016). moocRP: Enabling open learning analytics with an open source platform for data distribution, analysis, and visualization. *Technology, Knowledge and Learning, 21*(1), 75–98. https://doi.org/10.1007/s10758-015-9268-2

*Park, Y., & Jo, I. H. (2019). Factors that affect the success of learning analytics dashboards. *Educational Technology Research and Development, 67*(6), 1547–1571. doi:https://doi.org/10.1007/s11423-019-09693-0

*Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018). Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers. *International Review of Research in Open and Distributed Learning, 19*(5). https://doi.org/10.19173/irrodl.v19i5.3493

*Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*(3), 317–333. https://doi.org/10.1007/s10758-017-9316-1

*Russell, J. E., Smith, A., & Larsen, R. (2020). Elements of success: Supporting at-risk student resilience through learning analytics. *Computers & Education, 152*, 103890–103890. https://doi.org/10.1016/j.compedu.2020.103890

*Sadallah, M., Encelle, B., Maredj, A. E., & Prié, Y. (2020). Towards fine-grained reading dashboards for online course revision. *Educational Technology Research and Development, 68,* 3165–3186. https://doi.org/10.1007/s11423-020-09814-0

*Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

*Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512–105512. https://doi.org/10.1016/j.chb.2018.05.004

*Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017). Learner dashboards a double-edged sword? Students' sense-making of a collaborative critical reading and learning analytics environment for fostering 21st century literacies. *Journal of Learning Analytics, 4*(1), 117–140. https://doi.org/10.18608/jla.2017.41.7

*Van Horne, S., Curran, M., Smith, A., VanBuren, J., Zahrieh, D., Larsen, R., & Miller, R. (2018). Facilitating student success in introductory chemistry with feedback in an online platform. *Technology, Knowledge and Learning, 23*(1), 21–40. https://doi.org/10.1007/s10758-017-9341-0

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110.

Woodward, J. F. (2011). Data and phenomena: A restatement and defense. *Synthes, 182*(1), 165–179. https://doi.org/10.1007/s11229-009-9618-5

Chapter 3
Designing Theory-Driven Analytics-Enhanced Self-Regulated Learning Applications

Mohamed Amine Chatti, Volkan Yücepur, Arham Muslim, Mouadh Guesmi, and Shoeb Joarder

1 Introduction

Self-regulated learning (SRL) is one of the most important areas of research within educational psychology over the last two decades. SRL refers to self-generated thoughts, feelings, and behaviors that are oriented to attaining learning goals (Zimmerman, 2000). Self-regulation researchers attributed individual differences in learning to students' lack of self-regulation and provided methods to help students develop key SRL processes, such as goal setting, adoption of learning strategies to attain the goals, self-evaluation, time management, and seeking help or information (Zimmerman, 2002). In recent years, there has been a growing interest regarding the role of learning analytics (LA) to support how students regulate their own learning processes (Winne, 2017). LA aims at turning educational data into insights, decisions, and actions to improve learning. In LA systems, data is traditionally displayed through dashboards with indicator visualizations developed from traces that learners leave when they interact with different learning spaces. Various LA dashboards and indicators were proposed to support crucial SRL processes, such as planning, awareness, self-reflection, self-monitoring, feedback, and motivation (Bodily & Verbert, 2017; Jivet et al., 2018; Matcha et al., 2019; Schwendimann et al., 2017). However, current design of LA dashboards and indicators to support SRL suffers from two main limitations. First, the design of the dashboards and

M. A. Chatti (✉) · V. Yücepur · M. Guesmi · S. Joarder
University of Duisburg-Essen, Duisburg, Germany
e-mail: mohamed.chatti@uni-due.de; volkan.yuecepur@stud.uni-due.de;
mouadh.guesmi@stud.uni-due.de; shoeb.joarder@uni-due.de

A. Muslim
National University of Sciences and Technology, Islamabad, Pakistan
e-mail: arham.muslim@seecs.edu.pk

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_3

indicators is often without reference to SRL theories and models (Gašević et al., 2019; Jivet et al., 2018; Matcha et al., 2019). Second, the designed dashboards and indicators are often not well aligned with learners' needs and expectations. In fact, there is still a divide between those who design LA dashboards (i.e., researchers, developers) and those who are expected to use these dashboards or are most affected by them (i.e., learners) (Chatti et al., 2020a; Ifenthaler & Schumacher, 2016; Jivet et al., 2020; Rodriguez-Triana et al., 2017). In order to design LA dashboards and indicators that meet learner's needs and expectations, it is crucial that LA researchers and developers conduct qualitative user studies (e.g., interviews, focus groups) where they go to the learners, observe their activities, and try to understand what they really need to support their SRL activities (Jivet et al., 2020; Schumacher & Ifenthaler, 2018). Thereby, it is important to find the right set of questions to ask in the study in order to generate the right set of indicators. To get at this, there is a need to draw on SRL theories and models as a theoretical foundation to guide the design of the qualitative user studies. The next step would be to design the indicators themselves. Here also, having the learners in the loop and empowering them to take control of the indicator design process is crucial in order to effectively meet their needs and expectations (Chatti et al., 2020a).

In the LA research community, there is a lack of theoretically sound methodologies to guide the systematic design and development of LA indicators to scaffold SRL. Several methodologies are established in different disciplines to support the systematic design of user interfaces (Norman, 2013), information visualizations (Munzner, 2014), visual analytics interfaces (Thomas & Cook, 2006), and information systems (Peffers et al., 2007). However, these methodologies are not enough in the LA discipline because they do not take account of the learning context (Martinez-Maldonado et al., 2015). While LA researchers have long been interested in learning theory-driven design of LA dashboards, most of this work has been conducted in conceptual terms (Jivet et al., 2018). And, despite the fact that research on human-centered learning analytics (HCLA) has been gaining momentum in recent years, approaches that involve learners in the design of LA indicators remain scarce in the literature (Buckingham Shum et al., 2019; Chatti et al., 2020a; de Quincey et al., 2019; Ochoa & Wise, 2020; Prieto-Alvarez et al., 2020). Thus, there is a need for a complete methodology that provides us guidance on how to conduct theory-driven LA-enhanced SRL research.

In this paper, we argue that in order to design LA dashboards and indicators that effectively support SRL activities, it is essential to (1) **understand** learners' needs and expectations from LA-enhanced SRL and (2) **empower** learners to steer the indicator design process. The guiding questions for this work are as follows: Which LA indicators are needed to support SRL? How to systematically design these indicators? To answer these questions, we propose and develop a **S**tudent-**C**entered **L**earning **A**nalytics-enhanced **S**elf-**R**egulated **L**earning (**SCLA-SRL**) methodology that provides a process model to conduct theory-driven research on LA-enhanced SRL. The primary aim of SCLA-SRL is to guide the systematic design of LA indicators that support SRL by (1) linking the design to well-established SRL models as well as human-computer interaction (HCI) and information visualization (InfoVis) guidelines and (2) actively involving learners throughout the entire indicator design process. The SCLA-SRL methodology is illustrated with a case study of the systematic design and development of LA indicators to support novice programmers' SRL in a higher education context.

The paper proceeds as follows: The next section provides an overview of the current related work on LA-enhanced SRL, LA dashboards, and student-centered LA. Then, we present and discuss our methodology for Student-Centered Learning Analytics-enhanced Self-Regulated Learning (SCLA-SRL). Next, we demonstrate an example of SCLA-SRL application by utilizing it in a higher education SRL scenario. Finally, we conclude by summarizing the contributions of the work.

2 Related Work

This work aims at providing a methodology to guide the systematic design and development of LA indicators that support SRL. So far, no complete, generalizable process model exists for LA-enhanced SRL research; however, if we develop such a process model, it should build upon the strengths of prior efforts. There is a substantial body of research, both within the LA literature and in related disciplines, that provides us with principles, practices, and procedures to support such a process. Below, we present this related work and discuss how our proposed methodology for conducting LA-enhanced SRL research builds on this work and integrates its principles, practices, and procedures.

2.1 SRL Meets LA

Self-regulated learning (SRL) is generally defined as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2000). It includes the cognitive, metacognitive, behavioral, motivational, and emotional/affective aspects of learning (Panadero, 2017). Panadero (2017) provides an excellent analysis and comparison of different SRL models (e.g., Boekaerts, 1992; Efklides, 2011; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). The author points out that although these models address different aspects and use different terminologies, all of them view SRL as a cyclical process, composed of three main phases: (a) *goal setting* (forethought, task analysis, planning, activation of goals, self-motivation); (b) *executing* (performance, processing); and (c) *evaluating* (self-reflection, feedback, monitoring, controlling, appraisal, regulating, adapting, reacting).

Recently, there is an increased interest in the application of LA to promote SRL. Several researchers stressed the need to bring LA into SRL research. For instance, Roll and Winne (2015) pointed out that LA offers exciting opportunities for analyzing and supporting SRL. According to the authors, LA can provide affordances and interventions for learners to more productively regulate their learning. Winne and Baker (2013) also stressed that educational data mining (EDM) – a research field closely related to LA – can play a significant role to advance research on motivation, metacognition, and SRL. Bodily et al. (2018) linked student-facing LA dashboards (LADs) to open learner models (OLMs), as both have similar goals. The authors further stated that OLMs can be used as awareness tools to help learners monitor, reflect on, and regulate their own learning.

Winne (2017) noted that a framework is useful to conceptualize LA for SRL. There are few examples of case studies that integrate LA and SRL by following a theory-driven approach. For example, Nussbaumer et al. (2015) pointed out that LA can provide personalized scaffolds that assist learners in a self-regulated manner. Building on SRL theory, the authors designed and implemented an architecture composed of different learning methodologies for supporting students' SRL in a variety of activities. Similarly, Marzouk et al. (2016) adopted self-determination theory (SDT) as a framework for designing LA that promote SRL as a function of content studied, reasons to adapt learning processes, and the presentation of analytics. Molenaar et al. (2020) presented a learning path app that combines three personalized visualizations to support young learners' SRL in adaptive learning technologies, following the COPES model as a theoretical basis (Winne & Hadwin, 1998).

Chatti and Muslim (2019) pointed out that, while SRL theory has been used to inform the design of LA tools, there remain important gaps in the theory from which to conduct research on LA-enhanced SRL in a systematic manner. Particularly, there is a lack of theoretically sound frameworks to guide the systematic design and development of LA indicators to promote SRL. To address this challenge, the authors proposed the personalization and learning analytics (PERLA) framework that provides a process model to guide the design of qualitative user studies attempting to collect requirements for LA indicators that can support different SRL processes. The proposed framework, however, is at the conceptual level and is still not applied and validated in a real learning setting. In this paper, we build on the PERLA framework and augment it with another process model enabling to move from requirement elicitation to the concrete design and development of LA indicators that support SRL.

2.2 Learning Analytics Dashboards

A variety of dashboards presenting data to various LA stakeholder groups were proposed in the LA literature (Jivet et al., 2018; Verbert et al., 2013). LA dashboards (LADs) are "single displays that aggregate different indicators about learners, learning processes and/or learning contexts into one or multiple visualisations" (Schwendimann et al., 2017). They aim at supporting students and teachers in making informed decisions about the learning and teaching process (Jivet et al., 2020). Current reviews of LAD research (e.g., Bodily & Verbert, 2017; Schwendimann et al., 2017; Verbert et al., 2014) tried to identify design considerations about what data is presented to different LA stakeholders, how data can be visualized, and why is the data presented.

In particular, research on student facing LADs traditionally has a strong focus on visualizing data to support different crucial SRL processes, such as goal setting and planning (Jivet et al., 2020), (self-)monitoring (Molenaar et al., 2020; Schwendimann et al., 2017), awareness and reflection (Ahn et al., 2019; Bodily & Verbert, 2017; Jivet et al., 2017; Scheffel et al., 2017; Verbert et al., 2013), metacognition (Bodily et al., 2018; Jivet et al., 2018; Karaoglan Yilmaz & Yilmaz, 2020), and feedback (Jivet et al., 2021; Molenaar et al., 2020; Sedrakyan et al., 2020). However, little attention has been paid to the systematic design of the LA indicators to support the intended goals. Indicators represent a core part of any dashboard. An indicator can be defined as "a specific calculator with corresponding visualizations, tied to a specific question" (Muslim et al., 2017). In general, the current design of LA indicators suffers from two main limitations, thus hindering their acceptance and adoption. First, the design of the indicators is rarely grounded in learning theories (Chatti & Muslim, 2019; Gašević et al., 2015, 2017, 2019; Jivet et al., 2018; Kelly et al., 2015; Marzouk et al., 2016; Matcha et al., 2019; Molenaar et al., 2020; Sedrakyan et al., 2020), human-computer interaction (HCI) (Verbert et al., 2013), and information visualization (InfoVis) (Alhadad, 2018; Chatti et al., 2020b; Ritsos & Roberts, 2014). Second, the indicators are designed about and not with their users and are thus often not well aligned with user needs. Consequently, users do not see the added value of these indicators (Chatti et al., 2020a; de Quincey et al., 2019). For example, Jivet et al. (2020) note that in many cases, what students report as relevant to see and use on a dashboard differs from what LADs provide. Thus, there is a crucial need for a framework that (1) draws from existing theories, principles, and practices to inform the design of useful LA indicators that support SRL and (2) put learners in the driver's seat and actively involve them in the design of the indicators that really meet their needs.

2.3 Student-Centered Learning Analytics

LA research has recently begun to investigate how HCI principles can be adopted and adapted to support the development of human-centered learning analytics (HCLA) as a way to mitigate the misalignment between LAD designs and their intended uses with diverse stakeholders and as a key to user trust, acceptance, and adoption of LA systems (Ahn et al., 2019; Buckingham Shum et al., 2019; Chatti et al., 2020a; de Quincey et al., 2019; Dollinger & Lodge, 2018; Holstein et al., 2018; Prieto-Alvarez et al., 2020). HCLA is an approach that emphasizes the human factors in LA and aims at bringing HCI to LA in order to involve users throughout the whole LA process (Chatti et al., 2020a). In recent years, some researchers succeeded in bringing design thinking and human-centered design (HCD) into the LA research community. Design thinking is an HCI approach to problem forming and solving that is focused on who we are designing for. HCD – a powerful tool for design thinking – is a user-centered process that starts with the user, creates design artifacts that address real user needs, and then tests those artifacts with real users (Norman, 2013; Giacomin, 2014). However, research on HCLA is still in the early stages of development (Buckingham Shum et al., 2019; Chatti et al., 2020a).

While there is a growing interest in involving stakeholders in the design, development, and implementation of LA, there are only few papers which provide mature examples of how HCI approaches (e.g., design thinking, HCD, participatory design, co-design, value-sensitive design) can be applied to LA to overcome the challenge of designing LA tools that lack the voice of the end users. These works mainly present case studies that target teachers or institutions as stakeholders. For instance, Dollinger et al. (2019) compare different approaches of human-centered design (HCD) and provide an overview of participatory frameworks in LA (co-design, co-creation), followed by a case study of how designers co-created LA platforms with teachers. Martinez-Maldonado et al. (2015) propose the LATUX workflow to engage teachers in iterative prototyping and evaluation cycles before deploying an LA system. Holstein et al. (2019) argue that the co-design of LA systems requires new kinds of prototyping methods and introduce Replay Enactments (REs) as a prototyping method to address unique challenges of co-prototyping LA tools. The authors exemplify this method through a case study of the iterative co-design of augmented reality glasses for K-12 teachers. This work demonstrates how non-technical stakeholders can participate throughout the design process of an LA system. Ahn et al. (2019) report on their design experience developing dashboards to support middle school teachers' pedagogical practices and offer ways to adapt common HCD methods, such as contextual design and design tensions, when developing visual analytics systems for educators. Rehrey et al. (2019) suggest implementation strategies that consider the human factor in adopting new technologies by practitioners. The authors use action research strategies to engage faculty, staff, and administrators across a university with LA. To support ethical considerations and human values in LA systems, Chen and Zhu (2019) introduce two cases of applying value sensitive design methods (e.g., stakeholder analysis, value analysis) to LA design. The authors note that engaging stakeholders in the early stages of the design and using stakeholders' insights and feedback to guide the system development are important to increase their acceptance and perceived impacts of the system.

Notably, these case studies present co-design processes with teachers or institutions as stakeholders. Examples of HCLA research involving learners within the design process remain very rare in the LA literature. Exceptions include the work by Prieto-Alvarez et al. (2018) where the authors stress the critical role of giving voice to learners in the LA design process and provide a case study focused on co-designing LA tools with learners using different co-design techniques such as focus groups, storyboarding, and prototyping. Based on this work, Prieto-Alvarez et al. (2020) propose a deck of design cards (LA-DECK) to facilitate co-design sessions and ensure that all stakeholders have an active voice in the design process of LA tools. In the same vein, de Quincey et al. (2019) present a project that has employed a user-centered design (UCD) approach to engage students in the design, development, and evaluation of a student facing LAD.

In general, this research encourages the active learner involvement in the LA design process and provides demonstrations of successful co-design processes for LA tools with learners. However, existing learner-centered design workflows provide limited methodological guidance for effectively involving learners throughout the entire LA design process, including understanding user needs, idea generation, prototyping, and testing. Moreover, the reported case studies are focused on the participatory design of LA tools and platforms (macro design level) rather than the systematic design of the underlying indicators (micro design level). Furthermore, most of the current work on HCLA is not informed by well-established InfoVis design guidelines. To fill this gap, Chatti et al. (2020a) proposed the Human-Centered Indicator Design (HCID) as an HCLA approach that targets learners as end users by involving them in the systematic design of LA indicators that fit their needs, based on conceptual models from the HCI and InfoVis fields. This approach, however, is not linked to theories from learning science.

In this paper, we focus on student-centered learning analytics (SCLA), i.e., the branch of HCLA that targets learners (Ochoa & Wise, 2020). We extend the HCID approach proposed in (Chatti et al., 2020a) by integrating SRL theories and models with the aim of providing a theoretically sound methodology to help LA researchers and developers systematically design and develop LA indicators for and with learners to effectively support their SRL activities. In the next sections, we provide the conceptual details of the proposed methodology and put it into practice through a concrete case study in a higher education context.

3 The SCLA-SRL Methodology

The Student-Centered Learning Analytics-enhanced Self-Regulated Learning (SCLA-SRL) methodology is a learner-first approach to indicator design that starts with an understanding of the learners' real needs and goals and then designs indicators that best address these needs and goals. The methodology integrates principles, practices, and procedures required to carry out systematic research on LA-enhanced SRL. It is consistent with established theoretical frameworks in SRL, HCI, and InfoVis and provides a theory-driven process model for designing and developing LA indicators and dashboards that support SRL. The final objective of the SCLA-SRL methodology is to give answers to the following questions: Which LA indicators are needed to support SRL? How to systematically design these indicators? This is achieved through two cyclical processes aiming at (1) **understanding**

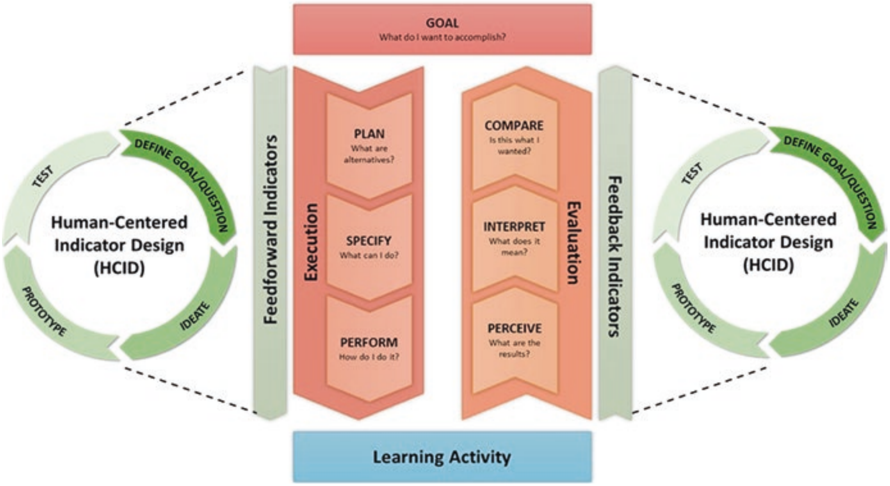


Fig. 3.1 The SCLA-SRL methodology (understand and empower)

learners' needs and expectations from LA-enhanced SRL and (2) **empowering** learners to take control over the indicator design process, as depicted in Fig. 3.1.

3.1 Understand: Feedforward and Feedback Indicators for SRL

Which LA indicators are needed to support SRL? It is obvious that in an SRL scenario, the set of required indicators is unpredictable, because the indicators depend on the context, and different learners have different needs. It is therefore important to conduct qualitative user studies (e.g., interviews, focus groups) with learners to **understand** what they expect from LA-enhanced SRL and what are the LA indicators that they really need to support their SRL activities. Getting the right set of indicators would require asking the right set of questions. The different phases of the SRL process can provide a systematic way to ask the right set of questions and categorize the required LA indicators (Chatti & Muslim, 2019).

SRL is a cyclical process, composed of three general phases: (a) *goal setting*, (b) *executing*, and (c) *evaluating* (see Sect. 2.1). In an HCI context, Norman (2013) discusses seven stages of action that provide a guideline for developing usable and understandable new products or services, following a human-centered design (HCD) approach. By associating the typical three phase SRL model and Norman's seven stages of the action cycle, the SRL process can be modeled as a cyclical seven stages activity, as shown in the middle part of Fig. 3.1. In detail, there are three major phases to an SRL activity: *goal setting*, *executing*, and *evaluating*. The execution phase is further subdivided into three stages that follow from the goal: *plan*, *specify*, and *perform*. The evaluation phase is further broken down into three stages: *perceive*, *interpret*, and *compare*.

The SRL activity cycle starts from the top with the learning goal (goal) and then goes through the three stages of execution: planning the possible learning activities to achieve those goals (plan), specifying a learning activity path (specify), and performing the learning activity (perform). The cycle then goes through the three stages of evaluation: perceiving the results of the learning activity (perceive), trying to make sense of it (interpret), and comparing the learning outcome with the goal (compare). It is important to stress that most SRL activities require multiple feedback loops in which goals lead to subgoals, and the results of one activity are used to trigger further ones. Moreover, SRL activities do not always have to include all stages, nor do they have to proceed in a linear manner across all stages.

Each of the seven stages represents a possible question to ask towards an SRL activity. The seven-stage SRL activity cycle provides a useful tool for guiding the design of indicators for SRL. The role of LA is to help learners by conveying the information required to answer the learner's question at each stage of the execution and evaluation phases through appropriate indicators. Indicators that provide information that helps answer questions of execution (the left side of the middle part of Fig. 3.1) are **feedforward indicators**. These include indicators for planning, awareness, and recommendation. Indicators providing information that aids in answering questions of evaluation (the right side of the middle part of Fig. 3.1) are **feedback indicators**. These include indicators for self-monitoring, self-reflection, assessment, feedback, and motivation. The use of appropriate indicators at each stage enhances the overall SRL process. In the following, we summarize the questions related to the stages of the execution and evaluation phases along with the description of the indicators needed to answer these questions:

- *Goal* (What do I want to accomplish?): Provide information about the defined goals of the learning activity.
- *Plan* (What are alternatives?): Provide information needed to understand the possible actions that can be taken in order to reach the goals.
- *Specify* (What can I do?): Provide information to help learners decide on the appropriate learning activity path.
- *Perform* (How do I do it?): Provide information on best strategies in order to perform a task in an effective and efficient way.
- *Perceive* (What are the results?): Provide information to communicate the results of the performed tasks and the current state of the learning activity.
- *Interpret* (What does it mean?): Provide information to help learners understand the results and the impact of the learning activity in context.
- *Compare* (Is this what I wanted?): Provide information about progress towards goals.

The seven stages of the SRL activity cycle provide a guideline for developing structured interviews with learners to understand which indicators they really need to support their SRL activities. Rather than asking learners in an ad hoc manner about their abstract expectations of LA indicators, it is more effective to systematically ask about what they would do at each of the seven stages and then co-generate requirements for potential feedforward/feedback indicators that can support each stage.

3.2 Empower: Human-Centered Indicator Design

The question that might be raised now is: Once we have co-generated requirements for potential indicators, how to systematically co-design these indicators with learners? To get at this, we adopt the Human-Centered Indicator Design (HCID) approach proposed in (Chatti et al., 2020a). HCID brings together Norman's human-centered design (HCD) process (Norman, 2013) and Munzner's what-why-how visualization framework (Munzner, 2014) to provide a theory-informed approach for the systematic design of LA indicators, thus enabling to "get the right indicator" and to "get the indicator right." The main aim of HCID is to **empower** users to take control of the indicator design process in order to effectively meet their needs and goals. The HCID process encompasses four iterative stages: (1) define goal/question, (2) ideate, (3) prototype, and (4) test, as shown in the outer parts of Fig. 3.1.

3.2.1 Define Goal/Question

The HCID process begins with a good understanding of users and the needs that the design is intended to meet. To achieve this, the initial stage in HCID is to define the goal/question to be addressed/answered by the indicator. These goals and questions are the results of the qualitative user study conducted based on the seven-stage SRL activity cycle, as discussed in the previous section.

3.2.2 Ideate

In the ideate stage, designers and learners come together to co-generate indicator ideas and concretize them in a systematic manner, using Indicator Specification Cards (ISC). An ISC describes a systematic workflow to get from the why (i.e., user goal/question) to the how (i.e., visualization). An example ISC is shown in Fig. 3.4. It consists of two main parts, namely, Goal/Question and Indicator. The Goal/Question part refers to the results of the previous stage of the HCID approach. The Indicator part is further broken down into three sub-parts, namely Task Abstraction (Why?), Data Abstraction (What?), and Idiom (How?), which reflect the three dimensions of Munzner's what-why-how visualization framework (Munzner, 2014).

3.2.3 Prototype

The next stage in the HCID process is to co-create indicator prototypes with learners based on the generated ISCs. The goal of this stage is to understand which of the visualization idioms proposed in the ideation stage are more effective for the tasks and data at hand. Paper or software prototypes can be used in this stage.

3.2.4 Test

The final stage in the HCID process is to get feedback from learners on the indicator prototypes. The aim is to verify that these prototypes effectively address/answer the goal/question defined in the first stage of the HCID process. Ideally, the evaluators should not be the same learners who participated in the previous HCID stages.

4 Case Study

To demonstrate the use of the SCLA-SRL methodology, we applied it to design LA indicators to support SRL activities of bachelor students attending an introductory Python programming course, offered in the winter semester 2019/2020 at the University of Duisburg-Essen, Germany. This course was relevant for our study, as a high degree of self-regulation was required from students who were expected to plan and carry out their learning independently and also monitor and evaluate their progress throughout the course.

4.1 Understand

The first step was to follow the seven stages of the SRL activity cycle to understand learners' needs and goals and co-generate requirements for potential feedforward and feedback indicators that can support novice programmers' SRL. Authentic learning scenarios were constructed and validated to focus the interview conversation towards specific and realistic problems in the context of the programming course. An initial set of 14 scenarios were brainstormed by the authors together with tutors of the programming course, because they are familiar with the difficulties faced by the students in this course, such as lack of motivation and frustration, insufficient learning time, avoidance of help seeking, and lack of conceptual understanding. These scenarios covered the three phases of the SRL process: (a) goal setting (before learning), (b) executing (during learning), and (c) evaluating (after learning). The scenarios were constructed, tested, refined, and tested again in order to keep only the scenarios that are clear, desirable, feasible, measurable, and realistic from a student perspective. In order to observe the target group in their natural environment, we visited the exercise classes on different dates at the beginning of the semester and asked students (*n* = 5) to give feedback on the scenarios in terms of the dimensions above by rating the scenarios on a 5-point Likert scale from "strongly disagree" to "strongly agree." Each interview took between 1 and 3 h, including introduction to the topic, presenting and discussing each of the 14 scenarios, and rating them. The resulting six most important scenarios along with their refined final descriptions are summarized in Table 3.1.

After the construction and validation of the learning scenarios, we conducted new interviews with other students from the same course (*n* = 11) in order to co-generate requirements for potential feedforward and feedback indicators that can support these learning scenarios. All interviews were about 90 min long. The seven stages of the SRL activity cycle were used as a template to guide the interviews. For the analysis of the interview results, we followed the phases of thematic analysis process proposed in (Braun and Clarke, 2006). We started by familiarizing ourselves with the depth and breadth of the qualitative data. Next, we coded each answer and clustered the codes with the aim of identifying patterns within the data set. The analysis was rather deductive (i.e., theoretically driven) as we aimed to use theoretical concepts from SRL and metacognition research (e.g., planning, strategy selection, help/information seeking, awareness, monitoring, self-reflection, motivation) as pre-existing coding frames and themes to categorize the indicators. The findings of this round of interviews has led to a first set of nine feedforward (FF) and eight feedback (FB) indicators as summarized in Table 3.1. Each indicator is described as a triplet of the form **indicator type and id**, *indicator category*, and indicator description, for example, **FF1**, *Help Seeking*: As a feedforward indicator of whether help is needed to solve a task.

4.2 Empower

The next step was to use the requirements for the potential feedforward and feedback indicators as input to the HCID loop to systematically co-design these indicators. We organized two co-design workshops with the same group of students that were interviewed before. However, only six students (n = 6) were able to attend the workshops. The workshops were held online via an online video conferencing tool and were 4 h long each.

The aim of the first workshop was to brainstorm together with students ideas for possible visualizations to illustrate the potential feedforward and feedback indicators and to co-develop paper prototypes for the indicators, based on Indicator Specification Cards (ISCs) (see Sect. 3.2.2). Figure 3.4 shows an example ISC to describe the feedforward indicator FF5. In practice, this step turned out to be too complex and at times confusing to the participants, since in general, bachelor students do not have a strong background in InfoVis theory. During this step we noticed how important the role of the moderator was. The moderator can provide

Table 3.1 SRL scenarios and potential feedforward/feedback indicators

SRL phases	SRL scenarios	Feedforward (FF) and feedback (FB) indicators
Before learning (G = goal setting)	**G1**: Get familiar with the Python programming concepts discussed in the course **G2**: Successfully solve the tasks in all assignment sheets to prepare for the exam	
During learning (Ex = executing)	**Ex1**: You read the task on the assignment sheet. You believe that you have understood the task correctly. But you do not know how to solve it. You give yourself 15 minutes to try to understand it better	**FF1**, *Help Seeking*: As a feedforward indicator of whether help is needed to solve a task **FF2**, *Strategy Selection*: As a feedforward indicator for using promising strategies and avoiding others to solve a task **FF3**, *Information Seeking*: As a feedforward indicator of which resources are suitable as references to solve a task **FF4**, *Information Seeking*: As a feedforward indicator to reuse certain code **FF5**, *Planning*: As a feedforward indicator of whether one should learn more about a topic or concept
	Ex2: While you try to solve a programming task, error messages appear. You want to fix the error messages to be able to solve the task. You give yourself 15 minutes to deal with the error	**FF6**, *Information Seeking*: As a feedforward indicator of which websites can be used to search for a solution **FF7**, *Help Seeking*: As a feedforward indicator of how helpful was a specific website in solving a problem **FF8**, *Help Seeking*: As a feedback indicator of how helpful was an exercise class in solving a problem **FF9**, *Information Seeking*: As a feedforward indicator of which questions are suitable for finding answers to a problem

(continued)

Table 3.1 (continued)

SRL phases	SRL scenarios	Feedforward (FF) and feedback (FB) indicators
After learning (Ev = evaluating)	**Ev1**: You have solved several programming tasks so far. Now you take 30 minutes to figure out which programming concepts (looping, recursion, sorting, etc.) you still have problems with	**FB1**, *Monitoring (Learning Success)*: As a feedback indicator of how adequately one has dealt with a problem **FB2,** *Monitoring (Learning Difficulties)*: As a feedback indicator of how difficult a task was perceived **FB3**, *Monitoring (Learning Difficulties)*: As a feedback indicator of which mistakes you make more often in which context **FB4**, *Monitoring (Learning Success)*: As feedback indicator for the distance to the learning goal G1 **FB5**, *Motivation*: As a feedback indicator of how strong is your motivation to learn a new concept **FB6**, *Monitoring (Learning Success)*: As a feedback indicator of how well one has understood a particular concept **FB7**, *Monitoring (Learning Difficulties)*: As a feedback indicator for which concepts one still has difficulties with
	Ev2: You have solved all assignment sheets so far and want to prepare for the exam. Now you take 30 minutes to figure out whether you have learned enough for the exam or whether you should continue learning	**FB8**, *Monitoring (Learning Success)*: As feedback indicator for the distance to the learning goal G2

explanation when participants are not aware of why specific visualizations are more effective than others or when someone needs more background information about the used what-why-how visualization framework (Munzner, 2014). For instance, the moderator explained that the information visualization literature suggests that the idioms (how?) depend heavily on the underlying tasks (why?) and data (what?) of the visualization and provides guidelines related to "what kind of idioms is more effective for what kind of tasks (mapping why? → how?)" and "what kind of idioms is more effective for what kind of data (mapping what? → how?)." For example, scatterplots and parallel coordinates are effective idioms to visualize correlation tasks. And, stacked bar charts and heatmaps are effective idioms to visualize data with two categorical and one quantitative attributes. We provided the participants with a summary of these InfoVis design guidelines to advance their understanding of the topic and help them choose the right visualization for the task and data at hand, as depicted in Figs. 3.2 and 3.3. The participants found these illustrations helpful to learn more about InfoVis theory and decide on the appropriate visualization. Despite the complexity of this step, the ISCs enabled to get the indicators right by following state-of-the-art InfoVis design practices.

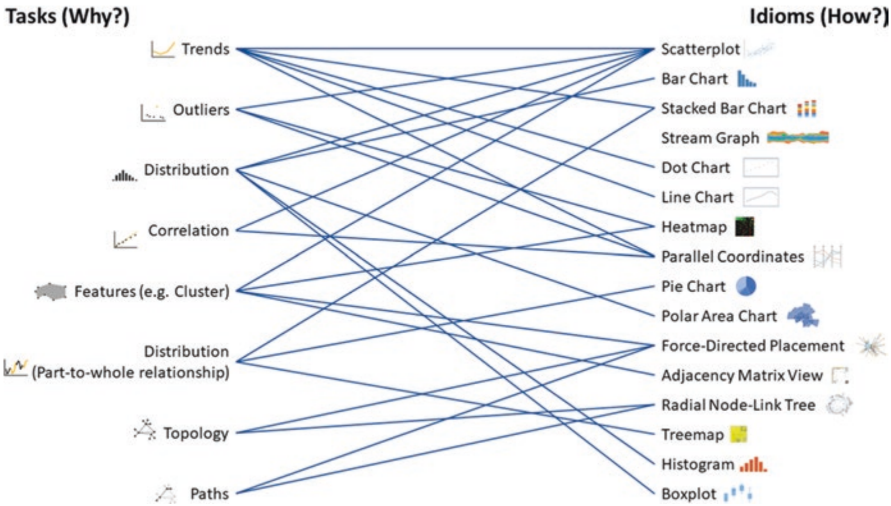


Fig. 3.2 InfoVis design guidelines: Mapping why? → how? (tasks → idioms)

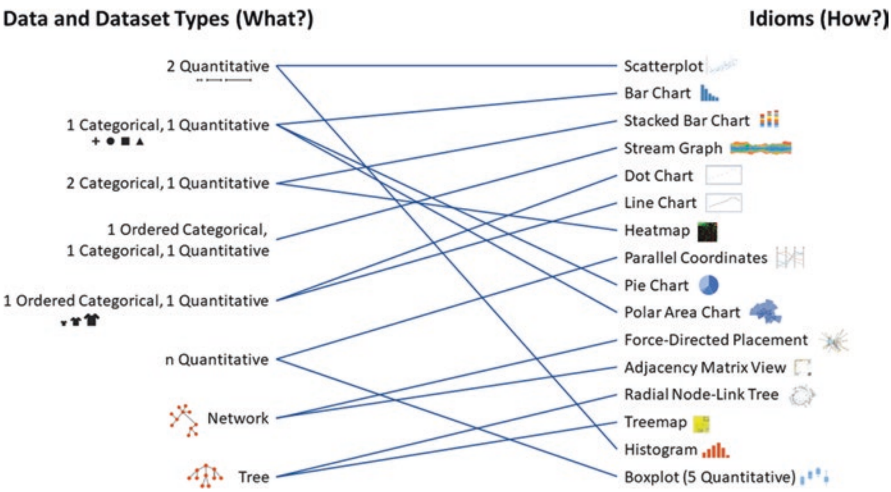
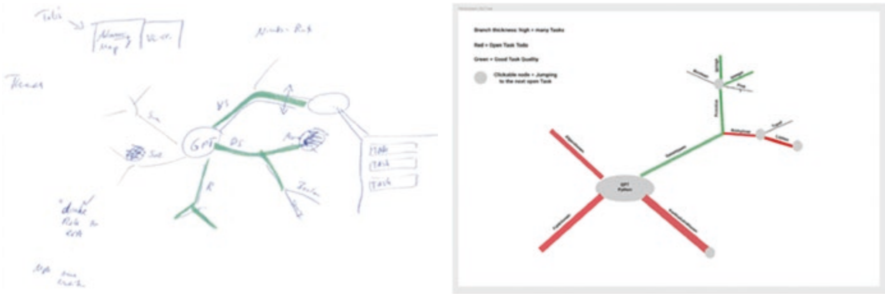


Fig. 3.3 InfoVis design guidelines: Mapping what? → how? (data → idioms)

Goal/Question	
Goal: Plan the next learning activity **Question:** What are the programming concepts that I need to learn for this course? How do they relate to each other? What is the next concept that I need to learn about?	
Indicator	
Task Abstraction (Why?) *Identify* the concept structure (*topology*) of the course *Identify* relationships (*features*) between the course concepts *Identify* possible learning *paths*	
Data Abstraction (What?)	
Raw data Course data: • Concepts (categorical attribute) • Concept mastering level (categorical attribute)	***Derived data*** Course tree: • Nodes: Concepts • Links: Sub-concept.of
Idiom (How?)	
How to encode? Radial Node-Link Tree Color	***How to interact?*** *Manipulate: select* (concept), *zoom, pan*

(a)



(b) **(c)**

Fig. 3.4 (**a**) Indicator Specification Card (ISC), (**b**) paper prototype, and (**c**) software prototype for feedforward indicator FF5

Based on the ISCs, paper prototypes were co-produced with students (see Fig. 3.4 for an example).

The goal of the second workshop was to test these prototypes regarding the effectiveness of the visualizations to illustrate the related indicators. To prepare for this workshop, the paper prototypes were converted to Figma software prototypes by the authors (see Fig. 3.4). To evaluate the initial prototypes, the students were asked for their feedback first on the importance of the different indicators to meet the learning goals G1 and G2 and second on the usefulness of the associated prototypes and how to improve them. Feedback addressed, for example, the need to make simple visualizations (e.g., bar charts, tables) and to remove some of the prototypes and combine others. This resulted in nine prototypes (FF1, FF5, FB1, FB2, FB3, FB4, FB6, FB7, FB8) that were perceived to be effective for G1 and G2 and were thus adopted for the next round. Feedback has been used to improve the design of the indicators and merge some of them,

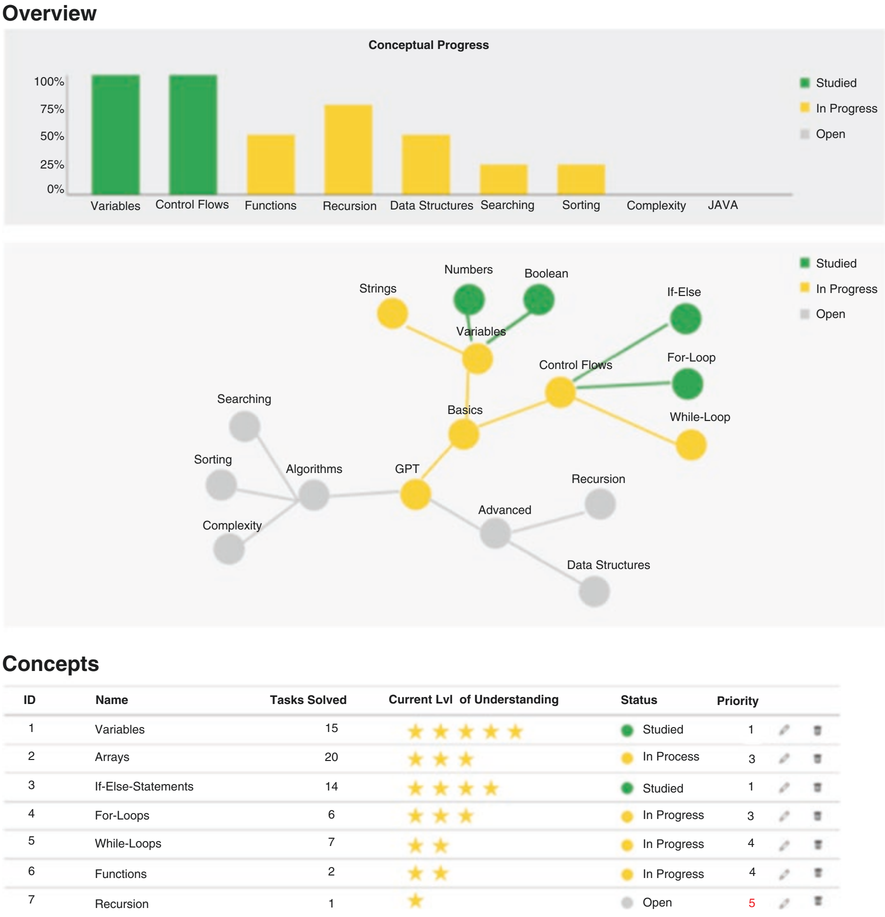


Fig. 3.5 Final prototypes (part 1)

as well as to adapt the arrangement of the indicators in a dashboard by following an overview-detail approach. Figures 3.5 and 3.6 show the final dashboard with the various indicators that have been developed. The first two indicators use bar chart and concept map to provide an overview of the learning progress at an abstract level, allowing students to monitor their progress (FB4), see the relationships between the concepts, and plan their next learning activities (FF5). The next three indicators use table and heatmap to provide more details at the concept, task, and solution levels to help students monitor their progress towards learning goals at a more granular level and assess their learning success (FB1, FB6) and difficulties (FB2, FB3, FB7) and eventually seek help (FF1). The last two indicators use bar chart and table to help students monitor their learning performance to prepare for the exam (FB8, FF5).

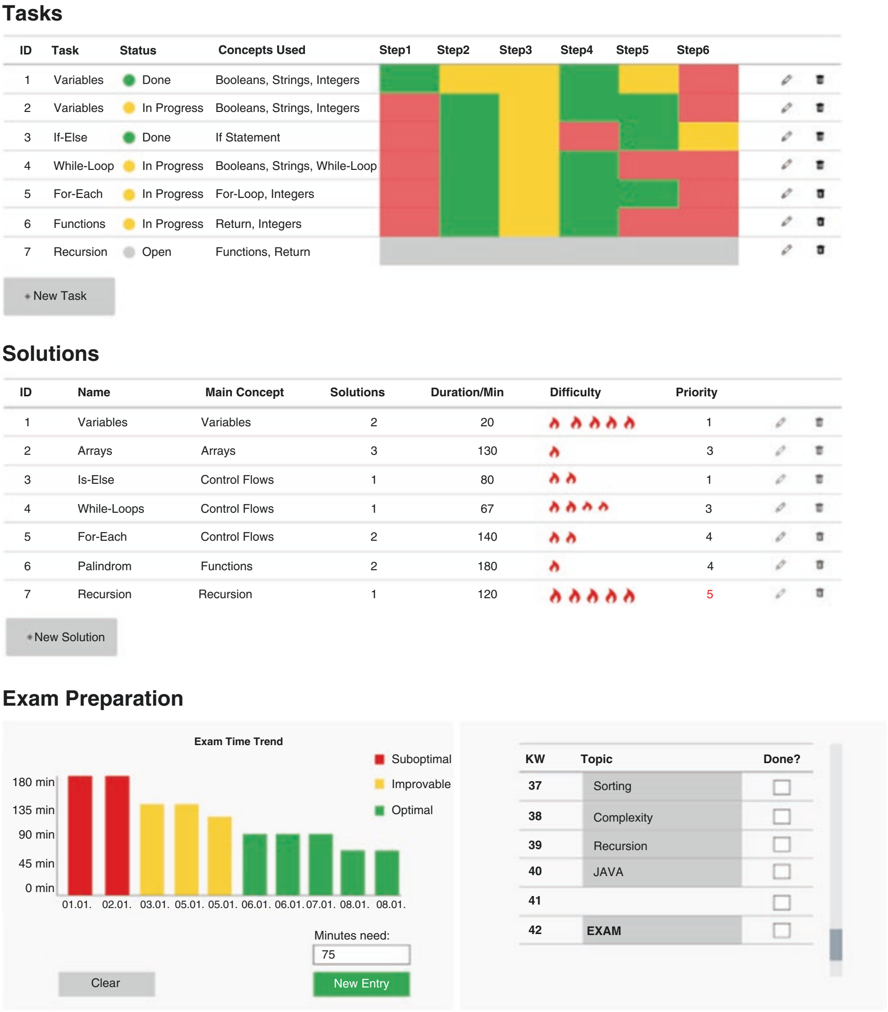


Fig. 3.6 Final prototypes (part 2)

5 Conclusion

Learning analytics (LA) is opening up new opportunities for promoting self-regulated learning (SRL). In this paper, we stressed the need for a methodology to serve as a commonly accepted framework for LA-enhanced SRL research and a template for the systematic design of LA indicators to support SRL. We argued that for LA dashboards and indicators to be accepted and adopted by learners, their design and development need to be much more linked to sound theories and models in learning science, human-computer interaction (HCI), and information visualization (InfoVis). Moreover, learners have to be involved throughout the whole design process. To this end, we proposed the Student-Centered Learning Analytics-enhanced Self-Regulated Learning (SCLA-SRL) methodology to guide the systematic design of LA indicators that support SRL. We then presented a case of applying this methodology to design and develop LA indicators to support novice programmers' SRL in a higher education context. In our study, we experienced that following an SCLA approach for LA indicator design is a complex, time consuming, and resource-intensive task. We believe, however, that designing LA indicators for and with their users is essential to increase value, build trust, and push forward the acceptance and adoption of LA.

We expect that this case study will provide a useful template for LA researchers and developers who want to apply SCLA-SRL to their efforts. The novelty of the SCLA-SRL methodology resides in the fact that it instantiates design guidelines from the HCI and InfoVis areas and combines them with SRL models. This effort contributes to LA research by providing a theoretically sound framework for successfully carrying out LA-enhanced SRL research and a template to systematically design LA indicators and dashboards that support SRL.

References

Ahn, J., Campos, F., Hays, M., & Digiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6*(2), 70–85.

Alhadad, S. S. (2018). Visualizing data to support judgement, inference, and decision making in learning analytics: Insights from cognitive psychology and visualization science. *Journal of Learning Analytics, 5*(2), 60–85.

Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., & Verbert, K. (2018). Open learner models and learning analytics dashboards: A systematic review. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 41–50).

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418.

Boekaerts, M. (1992). The adaptable learning process: Initiating and maintaining behavioural change. *Applied Psychology, 41*(4), 377–397.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centred learning analytics. *Journal of Learning Analytics, 6*(2), 1–9.

Chatti, M. A., & Muslim, A. (2019). The PERLA framework: Blending personalization and learning analytics. *The International Review of Research in Open and Distance Learning, 20*(1).

Chatti, M. A., Muslim, A., Guesmi, M., Richtscheid, F., Nasimi, D., Shahin, A., & Damera, R. (2020a). How to design effective learning analytics indicators? A human-centered design approach. In *European conference on technology enhanced learning* (pp. 303–317). Springer.

Chatti, M. A., Muslim, A., Guliani, M., & Guesmi, M. (2020b). The LAVA model: Learning analytics meets visual analytics. In *Adoption of data analytics in higher education learning and teaching* (pp. 71–93). Springer.

Chen, B., & Zhu, H. (2019). Towards value-sensitive learning analytics design. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 343–352).

de Quincey, E., Briggs, C., Kyriacou, T., & Waller, R. (2019). Student centred design of a learning analytics system. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 353–362). ACM.

Dollinger, M., Liu, D., Arthars, N., & Lodge, J. M. (2019). Working together in learning analytics towards the co-creation of value. *Journal of Learning Analytics, 6*(2), 10–26.

Dollinger, M., & Lodge, J. M. (2018). Co-creation strategies for learning analytics. In *Proceedings of the 8th international conference on learning analytics and knowledge (LAK '18), 5–9 March 2018, Sydney, NSW, Australia* (pp. 97–101). ACM.

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist, 46*(1), 6–25.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–75.

Gaševic, D., Kovanovic, V., & Joksimovic, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice, 3*(1), 63–78.

Gašević, D., Tsai, Y.-S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology, 36*(4), 342–353.

Giacomin, J. (2014). What is human centred design? *The Design Journal, 17*(4), 606–623.

Holstein, K., Hong, G., Tegene, M., McLaren, B. M., & Aleven, V. (2018). The classroom as a dashboard: Co-designing wearable cognitive augmentation for K–12 teachers. In *Proceedings of the 8th international conference on learning analytics and knowledge (LAK '18), 5–9 March 2018, Sydney, NSW, Australia* (pp. 79–88). ACM.

Holstein, K., McLaren, B. M., & Aleven, V. (2019). Co-designing a real-time classroom orchestration tool to support teacher-ai complementarity. *Journal of Learning Analytics, 6*(2), 27–52.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In *European conference on technology enhanced learning* (pp. 82–96). Springer.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40). ACM.

Jivet, I., Wong, J., Scheffel, M., Valle Torre, M., Specht, M., & Drachsler, H. (2021). Quantum of choice: How learners' feedback monitoring decisions, goals and self-regulated learning skills are related. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 416–427).

Karaoglan Yilmaz, F. G., & Yilmaz, R. (2020). Learning analytics as a metacognitive tool to influence learner transactional distance and motivation in online learning environments. *Innovations in Education and Teaching International*, 1–11.

Kelly, N., Thompson, K., & Yeoman, P. (2015). Theory-led design of instruments and representations in learning analytics: Developing a novel tool for orchestration of online collaborative learning. *Journal of Learning Analytics, 2*(2), 14–43.

Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J., & Clayphan, A. (2015). LATUX: An iterative workflow for designing, validating, and deploying learning analytics visualizations. *Journal of Learning Analytics, 2*(3), 9–39.

Marzouk, Z., Rakovic, M., Liaqat, A., Vytasek, J., Samadi, D., Stewart-Alonso, J., Ram, I., Woloshen, S., Winne, P. H., & Nesbit, J. C. (2016). What if learning analytics were based on learning science? *Australasian Journal of Educational Technology, 32*(6), 1–18.

Matcha, W., Gašević, D., & Pardo, A. (2019). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 13*(2), 226–245.

Molenaar, I., Horvers, A., Dijkstra, R., & Baker, R. S. (2020). Personalized visualizations to promote young learners' SRL: The learning path app. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 330–339).

Munzner, T. (2014). *Visualization analysis and design* (AK Peters Visualization Series). CRC Press.
Muslim, A., Chatti, M. A., Mughal, M., & Schroeder, U. (2017). The goal-question-Indicator approach for personalized learning analytics. In *CSEDU* (Vol. 1, pp. 371–378).
Norman, D. (2013). The design of everyday things: Revised and expanded edition. *Basic books*.
Nussbaumer, A., Hillemann, E. C., Gütl, C., & Albert, D. (2015). A competence-based service for supporting self-regulated learning in virtual environments. *Journal of Learning Analytics, 2*(1), 101–133.
Ochoa, X., & Wise, A. F. (2020). Supporting the shift to digital with student-centered learning analytics. *Educational Technology Research and Development*, 1–5.
Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*(422). https://doi.org/10.3389/fpsyg.2017.00422
Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems, 24*(3), 45–77.
Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 452–502). Academic.
Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Anderson, T. D. (2018). Co-designing learning analytics tools with learners. In *Learning analytics in the classroom: Translating learning analytics for teachers*. Routledge.
Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Buckingham Shum, S. (2020). LA-DECK: A card-based learning analytics co-design tool. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 63–72). ACM.
Rehrey, G., Shepard, L., Hostetter, C., Reynolds, A., & Groth, D. (2019). Engaging faculty in learning analytics: Agents of institutional culture change. *Journal of Learning Analytics, 6*(2), 86–94.
Ritsos, P. D., & Roberts, J. C. (2014). Towards more visual analytics in learning analytics. In *Proceedings of the 5th EuroVis workshop on visual analytics* (pp. 61–65).
Rodriguez-Triana, M. J., Prieto Santos, L. P., Vozniuk, A., Shirvani Boroujeni, M., Schwendimann, B. A., Holzer, A. C., & Gillet, D. (2017). Monitoring, awareness and reflection in blended technology enhanced learning: A systematic review. *International Journal of Technology Enhanced Learning, 9*, 126–150.
Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics, 2*(1), 7–12.
Scheffel, M., Drachsler, H., Toisoul, C., Ternier, S., & Specht, M. (2017). The proof of the pudding: Examining validity and reliability of the evaluation framework for learning analytics. In *Proceedings of the 12th European conference on technology enhanced learning (EC-TEL 2017), 12–15 September 2017, Tallinn, Estonia* (Lecture Notes in Computer Science) (pp. 194–208). Springer.
Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407.
Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512.
Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. *Computer Graphics and Applications, IEEE, 26*(1), 10–13.
Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509.
Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal and Ubiquitous Computing, 18*(6), 1499–1514.

Winne, P. H. (2017). Learning analytics for self-regulated learning. In *Handbook of learning analytics* (pp. 241–249).

Winne, P. H., & Baker, R. S. J. D. (2013). The potentials of educational data mining for researching metacognition, motivation and self-regulated learning. *Journal of Educational Data Mining, 5*(1), 1–8.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Erlbaum.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–40). Academic. https://doi.org/10.1016/b978-012109890-2/50031-7

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70.

Chapter 4
Data Visualizations to Foster Self-regulated Learning with Intelligent Programming Tutors

Towards an Instructional Design Framework

Lingyun Huang, Eric Poitras, Angela Siegel, Raghav V. Sampangi, and Fernando Paulovich

1 Introduction

Over the past three decades, research has shown that students face significant challenges in understanding code while learning a programming language (Qian & Lehman, 2017; Sorva, 2012). Program comprehension requires knowledge of the features of a programming language and how to write proper syntax. Although students often make errors while writing a program such as mismatched parentheses, brackets, and quotation marks, these compilation errors are relatively easy to find and fix (Altadmri & Brown, 2015; Sirkiä & Sorva, 2012). To write meaningful code that satisfies a stated purpose is much more difficult. Students are expected to engage in a range of different strategies, including efforts to trace the program execution to infer the flow of data across operations, infer the function of program statements, and add new statements in their efforts to solve a problem. The processes or mechanisms by which a student arrives at a mental representation of a program as he or she proceeds from statement to statement determine the outcome of successful comprehension. However, students may fail in their attempts to construct a mental representation of the program. At the core of these difficulties is the process of combining elements of the program with elements from the students' own prior knowledge through their semantic relations, or at least to do so in an efficient manner (Malmi et al., 2020; Schulte et al., 2010). In doing so, students may

L. Huang
Faculty of Education, McGill University, Montreal, Canada
e-mail: lingyun.huang@mail.mcgill.ca

E. Poitras (✉) · A. Siegel · R. V. Sampangi · F. Paulovich
Faculty of Computer Science, Dalhousie University, Halifax, Canada
e-mail: eric.poitras@dal.ca; siegel@dal.ca; raghav@cs.dal.ca; paulovich@dal.ca

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_4

incorrectly trace the execution of the program and understand the data and control flow (Vainio & Sajaniemi, 2007) or fail to recognize or confuse features of a programming language (Altadmri & Brown, 2015). The resulting discrepancies between evolving mental representation of the program and its actual behavior are manifested in the form of either major or minor fixes to the code, including the addition, movement, or deletion of statements to perform a given task or changes to specific expressions in statements (de Souza et al., 2017).

The main assumption in this chapter is that visual representations of information that are properly designed can help a student engage in the processes that underlie success and failure in program comprehension. Understanding the nature of such processes during programming and how they interact with the way the program is represented to the student is essential for theories of program comprehension and early-stage programming skill acquisition (Kaczmarczyk et al., 2010; Ma, 2007; Sorva, 2012). It is common for decisions about how to design visual representations to reflect underlying assumptions for how students process information. For example, when syntax highlighting displays code in different colors, this design choice assumes that text corresponds to categories of distinct information and should thus be presented in a different manner to ensure comprehensibility. Several examples reviewed in this chapter refer to visual representation, including words or syntax specific to a programming language read by students, but also static or dynamic graphics and illustrations, such as words marked or highlighted by the text editor. The purpose of these representations is to make implicit information readily available in a comprehensive manner, and that would otherwise be inferred by the students.

This chapter explores this assumption from the theoretical perspective of self-regulated learning and discusses the design implications for intelligent programming tutors. The first section lists and classifies several examples of visual representations in the domain of computing education to define the term. The second section describes program comprehension processes from an information processing perspective, where we outline a model of self-regulatory processes, explain how representation modality interacts with such processes, and draw recommendations for instructional design. The third section illustrates how these principles inform the design of intelligent programming tutors in terms of supporting students in different facets of program comprehension during learning and task performance. The fourth section compares the use of visual representations in the context of intelligent programming tutors and learning analytic dashboards. To conclude this last section, we summarize the broader implications of our claims in terms of bridging the gap between learning sciences researchers and computing education practitioners.

2 Definition of Visual Representation

Technological advances have led to significant affordances in representing code in pictorial forms, ranging from simple syntax highlighting to more abstract depictions of conceptual notions in programming. It is necessary here to clarify exactly what is meant by the term visual representation. Although a considerable amount of literature has been published on visualizations in computing education (Hundhausen et al., 2002; Kelleher & Pausch, 2005; Maletic et al., 2002; Sorva et al., 2013), researchers examining visualizations in the context of intelligent programming tutors have yet to synthesize different approaches into a taxonomy. In Table 4.1, we break down this notion into two categories, including software visualizations and visual environments. Software visualizations refer to representations about the running behavior of computer programs and are further partitioned into sub-categories that capture the different levels of granularity of a representation (see Fig. 4.1). A program may contain a single or multiple algorithms to solve a problem. Whereas an algorithm is used to refer to a set of interrelated instructions that are interrelated with one another in a purposeful manner to solve a problem, data refers to information that is processed or stored given the instructions defined in an algorithm. Visual environments refer to the design of tools to read and write programs and are partitioned further into visual programming and user interface design constraints (see

Table 4.1 Taxonomy of visual representations

Type	Definition	Example
Software – representation of runtime program behavior and environment		
Program	A single or multiple algorithms to solve a problem	Static diagram of the relationship between classes and objects
Algorithm	A set of interrelated instructions that are interrelated with one another in a purposeful manner to solve a problem	Static graph of control flow or branching scenarios in a series of operations
Data	Information that is processed or stored given the instructions defined in an algorithm	Static image of variable value held in memory at a given state of program execution
Environment – representation of program features and elements		
Software	Visual notation of program instructions	Visual programming languages where program statements are represented as blocks manipulated by students
Interface	Visual graphics of text editor	Visualization features of text editors that allow students to recognize structure, selectively hide or display, or fill-in program statements

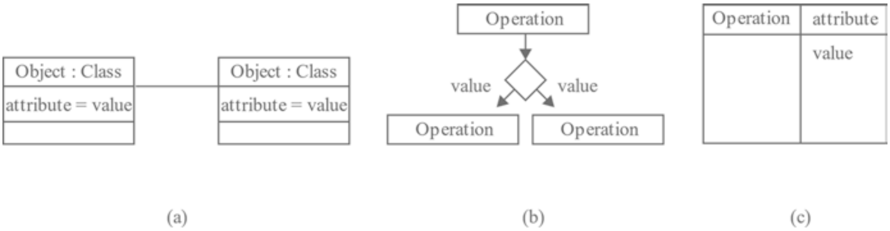


Fig. 4.1 Example visual representations of (**a**) program, (**b**) algorithm, and (**c**) data

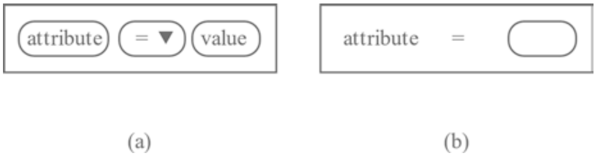


Fig. 4.2 Example visual representations of (**a**) software, (**b**) interface

Fig. 4.2). The act of designing, implementing, and debugging a computer program can be made more explicit through visual entities that are meant to represent program instructions as in visual programming environments. Another substantial area of research concerns visual design elements of user interfaces that structure the various tasks involved in programming, commonly referred to as instructional scaffolds for learning (Quintana et al., 2004; Reiser, 2004).

Many different types of visualizations for software are designed to teach novice programmers about the runtime behavior of programs at different levels of granularity, including parameter passing (Naps & Stenglein, 1996), expression evaluation (Brusilovsky & Loboda, 2006), objects (Kölling, 2008), recursion (Velázquez-Iturbide et al., 2008), and assignment (Ma, 2007). These visual representations capture different aspects of the dynamics of program execution to support students to reason about programs and design their behavior during runtime (Sorva et al., 2013; Thuné & Eckerdal, 2010). In 1986, Du Boulay (Du Boulay, 1986) introduced the term notional machine to refer to an abstraction of the computer and its role in executing different types of programs to explain misconceptions about their inner workings. For instance, a notional machine for Java programs may specify abstract memory areas such as the call stack and the heap as well as control flow rules dictated by certain types of statements. Student misconceptions or the lack of an appropriate mental model of a notional machine is often attributed to excessive cognitive load due to the large amount of interrelated program instructions (Fitzgerald et al., 2008). Students may also fail to mentally simulate the execution of programs, a skill referred to as tracing program execution, relying instead on drawing analogies between solutions to problems with shared surface features (Thomas et al., 2004).

Examples of such visual representations include but are not limited to analogies to something that is familiar to students such as classes and objects represented as a diagram of a file drawer (Gries, 2008). Cunningham et al. (2017) instructed students to sketch diagrams of program execution for notional machine components. Students may also trace memory usage within programs using established templates for memory visualization that lists variable names and values (Dragon & Dickson, 2016; Xie et al., 2018). Given the time-consuming nature of hand-drawn approaches to tracing program execution, many software tools have been used over the past 30 years to visualize program execution to support program comprehension processes. These systems may emphasize relationships between classes and objects as abstract diagrams (Ben-Ari et al., 2011; Bruce-Lockhart et al., 2007; Cross et al., 2011; Huizing et al., 2012) or animations of the data and control flows (Ma et al., 2011; Sorva, 2012; Wang et al., 2012). Of importance, a great deal of modern systems focuses on simulation, enabling students to move backwards and forwards through an execution, while visualizing stack frames and variables, heap object contents, and memory (Guo, 2013; Moons & De Backer, 2013; Nelson et al., 2017; Sirkiä & Sorva, 2015).

Visual environments by comparison provide help to students by structuring certain aspects of the programming task to facilitate comprehension. Visual notations, commonly referred to as block-based languages, including Scratch (Resnick et al., 2009), Snap! (Harvey & Mönig, 2010), and Blockly (Fraser, 2015) often rely on visual representations to simplify syntax and convey features of textual languages. In doing so, visual programming editors help structure the learning task by enabling students to perform tasks that they could not otherwise handle, as is common with dealing solely in fixing syntactic errors. Weintrop and Wilensky (2017) showed that using either isomorphic blocks or textual representations, students with the benefit of visual notations are more capable of correctly tracing the execution of selection statements as the shapes of blocks make explicit each branch. Students are also exposed to representations that intersperse visual and textual notations (Bau et al., 2015), allowing them to read the same program, but displayed interchangeably in either one or another notation (Homer & Noble, 2014).

Visual programming environments make use of the design of its interface to constrain how students interact with programs and build a mental representation of their execution. This is perhaps most evident in the use of environments where students control avatars that may represent objects in the execution of object-oriented programs (Jimenez-Diaz et al., 2012) or are instructed to complete programming tasks (Park et al., 2020). Worked examples of programs can be structured and sequenced by the system to help the students to attain successful comprehension. Gajraj and colleagues (Gajraj et al., 2011) designed such a tool that relies on graphical metaphors of instructions written in multiple steps through the guidance of the system to illustrate the runtime semantics of a program. Assessment quizzes may also be embedded through visualizer plugins to allow tools to provide instruction with automated feedback (Bruce-Lockhart et al., 2009). Students may lack the knowledge required to interpret feedback from debuggers or to effectively rely on strategies to debug programs (Fitzgerald et al., 2008). Game-based learning environments have been used to support students in acquiring debugging strategies (Miljanovic & Bradbury, 2017) and generating test cases (Tillmann et al., 2014), allowing for a variety of game mechanics to promote active interaction and engaging experiences.

3 Mental Representation of Visualizations

Much of the interest in making explicit and visible different aspects of the programming task as well as the program themselves is that students gain more robust understanding of their behavior and function. A much debated question is whether certain forms of visual representations are more effective in facilitating program comprehension during learning and task performance. It is unclear exactly how program comprehension processes interact with visual representations in building a mental representation. Likewise, although researchers assume that the visual representations lead to the outcome of a mental representation of a program, they rarely specify in what manner the visualizations do so. This section provides a framework for conceptualizing several program comprehension processes that take place during learning and the way these lead to and, at the same time, depend on visual representations of the code. This is done in three sub-sections, concerning the processes, modalities of representation, as well as their interactions and affordances towards instruction. Figure 4.3 provides a schematic description of the different mechanisms

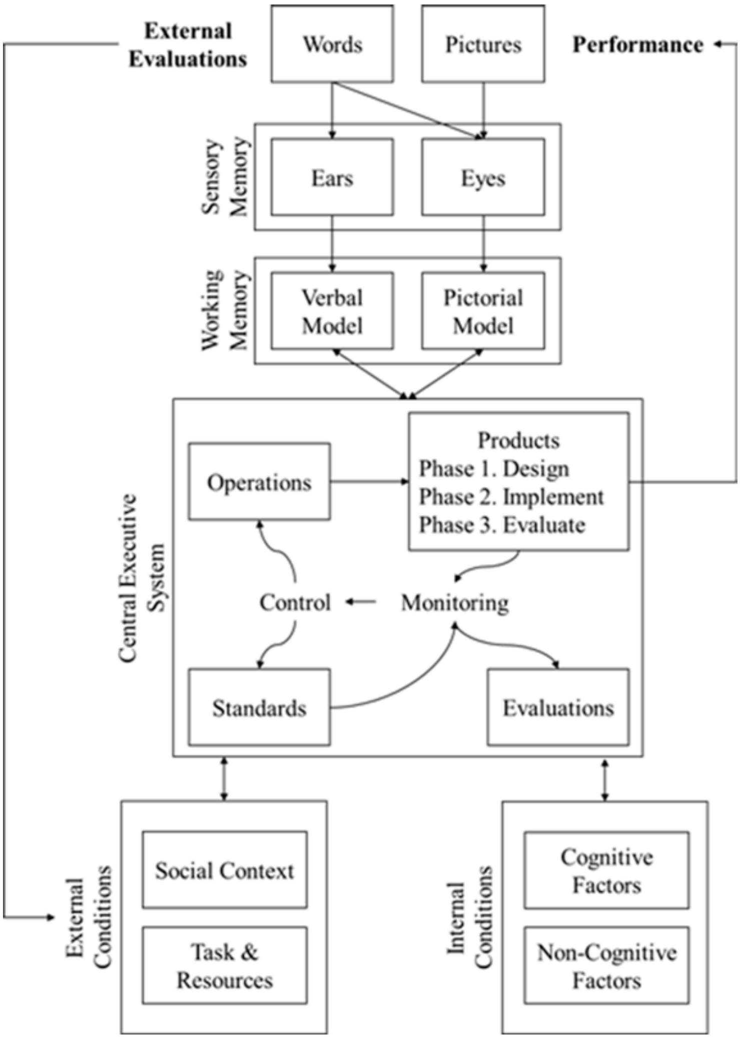


Fig. 4.3 Integrated model of program comprehension processes during learning and programming task performance

that underlie program comprehension given the modality in which information is presented to students.

Self-regulation refers to the knowledge that is required for a student to be aware of their own thoughts and take corrective actions when and if necessary, to attain a goal (Schraw, 2006). As various terms and models are used to conceptualize self-regulation (Dinsmore et al., 2008; Efklides, 2008; Lajoie, 2008), there is no consensus among researchers regarding its components. It is generally characterized as a theory that accounts for how students coordinate cognitive, metacognitive, motivational, and affective processes given contextual factors that underlie learning and performance (Pintrich, 2000; Schunk & Zimmerman, 2008; Winne, 2001; Winne & Hadwin, 1998; Zimmerman, 2000). The assumption is that successful learning requires students to metacognitively monitor and control certain aspects of their own learning and adaptively modify behavior (Greene & Azevedo, 2007). Extensive research across several academic domains has shown that self-regulatory processes during learning are critical in building sophisticated mental representations of complex topics (Panadero, 2017). The following sections elaborate further on the function of self-regulatory processes in program comprehension during learning from different representations of instructional content.

3.1 Modality of Program Representation

Visual representations include elements of words (e.g., on-screen text) and pictures (e.g., hue, shape, position, connection, containment, area), which can be converted to a verbal representation as in sounds or verbalizations of words in working memory (Mayer & Moreno, 2003). Extensive research has shown that student learning involves cognitive operations that include linking verbal and pictorial information in a coherent manner. This assumption of active processing is a fundamental tenet of multimedia learning theory (Mayer, 2005, 2008) and is consistent with information processing models for how central executive functions in working memory regulate representations stored in the phonological loop and visuospatial sketchpad (Baddeley, 1998; Mayer, 2001). The assimilation process by which students build a mental representation of a program thus requires the coordination of a substantial number of operations that is subject to the limited capacity of working memory and that are prone to failure (Schulte et al., 2010). Due to the cognitive load caused by the inherent complexity of the programming task and the number and interactivity of abstract elements that must be processed by the student, the executive control system has a critical role in allocating attentional resources through a coordinated set of cognitive and metacognitive processes to assimilate information. These higher-order processes are referred to as self-regulatory processes as students can engage in or fail to monitor these processes that underlie understanding to take remedial actions when comprehension breaks down.

3.2 Program Comprehension Processes

In the domain of computing education, a few studies have begun to examine self-regulation as a mechanism that underlies program comprehension during learning and task performance (see Prather et al., 2020). It is yet unclear exactly how students' knowledge of programming mediates their efforts to monitor and control certain aspects of learning (Malmi et al., 2020). Loksa and Ko (2016) however provide a comprehensive description of how students coordinate several cognitive and metacognitive processes during different facets of programming tasks. The sections below elaborate further on each of these facets as defined in Robins et al. (2003), including (1) students' efforts to understand the task and plan a solution while designing a program; (2) assimilating information and monitoring their comprehension while generating a program; and (3) tracing and appraising solutions while evaluating a program. We further assume that solving such problems involves cyclical and iterative phases to characterize how students monitor and control the products of these efforts given a cognitive architecture outlined below. It is evident from the findings of Loksa and Ko (2016) that students with low prior knowledge often fail to regulate certain aspects of their comprehension of a program during learning. Furthermore, students that do engage in such efforts lack the ability to do so efficiently, leading to difficulties and potentially even misconceptions.

3.2.1 What Are the Cognitive and Metacognitive Processes in Designing Programs?

Knowledge of methods for planning, problem-solving, and designing algorithms are applied in the beginning of a programming task (Robins et al., 2003). When a student is presented with a problem, they typically begin by processing information relevant to understanding the task demands and solution requirements. This understanding of problem requirements or the cognitive representation of the problem is reinstated to organize the work and reevaluated as the student engages in metacognitive activities. Namely, students engage in questioning the details of the problem prompt by engaging in process and comprehension monitoring. Process monitoring refers to attempts made by the student to track whether programming sub-goals are completed. Comprehension monitoring refers to student reflections about their own understanding of the program and problem prompts. Although students who engage in process and comprehension monitoring are expected to identify knowledge gaps that may hinder program comprehension, Loksa and Ko (2016) showed that novice programmers seldom engage in such activities during problem-solving such as drawing examples to evaluate understanding or noting relevant information and constraints. Rather, students often begin to implement solutions without fully understanding the problem that causes them to address these gaps later by reinterpreting the problem.

3.2.2 What Are the Cognitive and Metacognitive Processes in Implementing Programs?

Knowledge of programming languages, libraries, and tools is required to successfully implement algorithms and construct the desired program during the programming task (Robins et al., 2003). To begin this process, students make efforts to identify similarities between the current problem and other problems or solutions. This search for analogous problems involves metacognitive activities such as process monitoring and self-explanation. Although students with prior knowledge are more capable to draw analogies across structural rather than surface features of problems, novices tend to verbalize to a greater extent than more experienced students while searching for analogous problems. Furthermore, students draw on knowledge of related problems encountered in the past to better define the computational aspects of the solution as well as to identify what needs to be changed about a prior solution to solve the current problem. Adaptation of previous solutions involves a variety of metacognitive activities, including comprehension monitoring to understand the previous solution and the current problem, planning the adaptations necessary, and monitoring their progress. Students are expected to reflect about their own understanding of the solution and problem, express intent to adapt parts of the code, and track completion of each sub-goal while performing these tasks. Loksa and Ko (2016) has shown that novice programmers often fail to verbalize efforts to adapt previous solutions, although those with more experience may exhibit more confidence and less need for comprehension monitoring.

3.2.3 What Are the Cognitive and Metacognitive Processes in Evaluating Programs?

Knowledge of debugging tools and methods for tracing and repairing algorithms are necessary to reduce discrepancies between the actual and desired program in the later stages of a programming task (Robins et al., 2003). Evaluation of a solution, including analysis, testing, and debugging, is key to iteratively converge towards a successful solution to a programming problem. Loksa and Ko (2016) found that students engage in a metacognitive activity referred to as reflection on cognition. In doing so, students make metacognitive judgments about the quality and limitation of not only their own recall of analogous solutions but also their own reasoning in how well the solution addresses the problem. These judgments of misconceptions and errors are also expected to lead to comprehension monitoring by identifying knowledge gaps in initial understanding of the task. Novice students seldom engage in verbalizing evaluations of solutions, including the intent to do so or the result of an evaluation. For those students that do engage in such activities, however, they often report increased confidence in their solutions or might return to reinterpreting the problem to clarify ambiguities or locate an error that should be fixed in their program.

3.3 Cognitive Architecture

A fundamental hypothesis underlying self-regulated learning research is that to be successful in any programming tasks, students must employ a variety of cognitive and metacognitive activities such as planning, reflection, and strategy use (Azevedo, 2009; Veenman, 2007; Zimmerman, 2008). These operations, and their products, have been further described by Loksa and Ko (2016) and are herein assumed to occur within a cognitive architecture referred to by the acronym COPES (Winne, 2001). The COPES acronym states that learning results from the interaction of conditions, operations, products, evaluations, and standards. Conditions refer to both the students' prior knowledge about the topic, motivational and affective states, attitudes, and beliefs about programming, as well as external factors in the surrounding environment that influence the learning task. External conditions include among others physical representations in the form of auditory or visual stimuli presented to students. Operations refer to cognitive processes to assimilate information in working memory, ranging from basic operations to higher-order patterns of such activities, such as tactics and strategies to read and write programs. Products are the result of operations during learning, including student-produced program elements, including comments, pseudocode, and code. Evaluations refer to the process of comparing these different products to standards. Standards for products constitute a plan for either forwards or backwards development of the program, which are tied to the goal of the programming task for solving a given problem (Rist, 1989, 1991).

We claim that self-regulated learning theory provides a nuanced account of program comprehension processes during learning through this cognitive architecture that includes metacognitive monitoring and control processes. A higher-order strategy such as self-explanation, as described by Loksa and Ko (2016), can therefore be decomposed in terms of its constituent lower-order operations. Namely, students pay attention to on-screen text for a given program statement, and parts of the image will be represented in working memory along with mentally created sounds corresponding to the image. Operations on the representation in working memory are required to connect the syntactic elements of the program with prior knowledge of semantics (i.e., operation on data and control flow) and the intended function (i.e., sub-goal of the statement in attaining a broader objective of solving a problem). The resulting observable product or novel representations in working memory differ based on the phase for task performance and may be evaluated against standards for task performance. For example, students who design a solution may write a goal label as an in-line comment, while those who evaluate a solution might lead to rewriting a statement to attain the goal. This implies that evaluations resulting from metacognitive monitoring led to control processes that change the relevant strategies to better attain the standards for a given task. We elaborate further on the notion of modality of representation in the following section, where we discuss the implications for the design of effective instruction to facilitate program comprehension during learning.

4 Framework for Instructional Design of Visualizations

Few studies have systematically examined how different modalities may be combined to support information processing, avoid irrelevant information, or highlight relevant information (Sorva et al., 2013). We claim that a more nuanced understanding of self-regulatory processes involved in using different representations can offer important insights for the design of instruction. From an instructional design perspective, the question is how best to represent instructional content in the form of visual representations (i.e., on-screen text, graphic, illustrations) that stands to facilitate processing of essential information and reduce processing attributed to nonessential aspects as well as in holding representations in working memory with limited capacity (Mayer & Moreno, 2003). In this chapter, we limit our review to three different tutoring systems to illustrate our claims regarding the use of visual representations in facilitating assimilation of information and self-regulation during program comprehension, as summarized in Table 4.2.

Table 4.2 Instructional design principles for visual information processing

Principle	Description	Phase	Category	Sub-category	Tutor
Signaling	Representing information in a visual representation with embedded cues that direct students how to process information in a manner that is consistent with program behavior to ease comprehension	Implement	Software	Algorithm	Explaining and monitoring program comprehension with Problets (Kumar, 2016)
Mapping	Transforming information from a verbal representation in working memory to an external visual representation or on-screen text to reduce the need to hold the information over an extended period	Evaluate	Software	Data	Tracing code execution with PLTutor (Nelson et al., 2017)
Translating	Transforming information from a visual representation in working memory to an external visual representation or on-screen text organized in a different form to reduce nonessential processing	Design	Environment	Interface	Task understanding and planning with ProPL (Lane & VanLehn, 2003)

Students' comprehension of a program requires the retrieval of prior knowledge while learning from a representation of a given program and building a mental representation. Reading a program involves conscious efforts to link elements of the program that are new or unfamiliar, which may be difficult when the relevant knowledge is missing or difficult to recall. The operations that mediate assimilation of information can be facilitated by making explicit the information that should be extracted by students, including relevant aspects of the operations, control and data flow, program state, and function of relevant statements. This presentation of the material lessens the need for students to engage in operations to interpret its function and infer the resulting execution of the program based on properties of the text, which may be just beyond their current capability. Visual cues in the form of indenting, positioning, and syntax highlighting as well as comments that highlight function can be provided to students to help them select properties of the text and infer their relationships, a technique called signaling. The signaling effect supports the dual process of abstraction and inferences by providing cues for students on how to process the information in the manner that the visual representation is presented. Furthermore, the positioning of on-screen text coincides with the visual cues to ease comprehension of program behavior by integrating both visual and verbal information in a coherent manner.

Students also hold a substantial amount of visual and verbal information in working memory during program comprehension. Reading a program entails tracing state changes through the execution sequence of a program, requiring rapid eye movements to quickly scan on-screen text and constructing coherent verbal representations from the incoming text. The operations that underlie reinstating verbal information in working memory over a period can be reduced by off-loading this process to an external representation. This off-loading effect moves essential processing from the auditory channel to the visual channel as students (1) map certain aspects of their mental representation to an external representation or (2) translate an external representation from one form to another (Schulte, 2008). For instance, students may rely on a tabular representation, writing the value of variables as each line of code is executed, rather than verbalizing them to maintain the verbal information in working memory. This mapping of information from the verbal representation in working memory to an external visual representation or on-screen text reduces the need to hold the information over an extended period, allowing students to allocate attentional resources more efficiently and preventing decay of memory over time. Students may also reason about how to solve a particular problem by decomposing it into smaller parts, each examined in more detail, which involves alternating between written comments, pseudocode, and code. This translating of visual representations to different forms or levels of abstraction reduces the amount of nonessential processing of information, ensuring that the material is better organized and can be readily assimilated to ease comprehension.

4.1 Case Examples from Intelligent Programming Tutors

Before proceeding to examine how different types of visual representations are implemented in the context of intelligent tutoring systems, it is important to clarify how the term is used in the discipline of computing education. Intelligent tutoring systems refer to any system that captures and analyzes student interactions to tailor instruction to the specific needs of different students (Shute & Zapata-Rivera, 2012). VanLehn (2006) draws a distinction between two functionalities to personalize instruction: an outer loop for the system to track student progress on task performance and an inner loop to deliver hints and feedback about steps taken by the student to solve a task. A step refers to any interaction that the student takes to achieve a goal or sub-goal during task performance. Meta-analyses of human and computer tutoring provide evidence that although the support offered by human tutors is more flexible and subtle, it is nonetheless comparable in many instances (VanLehn, 2011). This research has reported effect sizes that are nearly as effective as human tutoring and to significant, positive effect sizes in a variety of grade levels, subject domains, and instructional conditions (Kulik & Fletcher, 2016; Ma et al., 2014).

A few systems have been designed in computer science education to adapt instruction. In the domain of computing education, intelligent programming tutors diagnose the type of error made by students more often than the most common ones as in other domains, including errors regarding syntax, dependency, redundancy, typing, semantics, and so on (van der Bent et al., 2019). Much of the literature emphasizes techniques to generate automated feedback (Keuning et al., 2018) or hints (McBroom et al., 2019) on (partial) solutions generated by the student through the analysis of textual programming language, including pseudocode. Additional instructional features include assessments distinct from programming problems, pre-made plans of programs, program visualizations as teaching resources, lesson, and reference materials, as well as worked solutions as instructional resources (Crow et al., 2018). Meta-analyses focusing exclusively on intelligent programming tutors report comparable effects to those found in other disciplines, where these systems are shown to be more effective than a control condition regardless of whether they were the primary means of instruction or were an integrated component of learning activities that included other means of instruction (Nesbit et al., 2014).

4.1.1 Signaling in Problets

Problets refer to a class of overlay model tutors that rely on static program visualizations designed to represent statement elements in a structured manner, enabling students to interact with their properties and receive adaptive feedback (Kumar, 2015b, 2016, 2019). Problets deliver feedback through dialogue boxes where students are prompted to complete faded steps in the worked examples. Self-explanation prompts may focus on syntactic elements such as recognizing different types of elements, fixing bugs, or target semantic properties by tracing code execution and predicting the returned value (Kumar, 2015a). At each step, corrective feedback is provided on the practice opportunity along with instructional explanation of the correct answer. The program visualization illustrates the order of operations as well as the intermediate result at each step in order of evaluation of operators. The on-screen text for instructional content focused on information that was not explicitly alluded to in the visualization, for instance, alluding to concepts such as coercion that complement the order of evaluation of operators depicted in the illustration.

The term signaling is meant to refer in this context to the way the visualization provides cues for how to process the information, particularly in avoiding processing of nonessential information. This is particularly helpful in drawing student attention to a specific statement and breaking down the relevant elements into constituent parts that can be more readily understood. The signaled parts are now organized in a manner that is more amenable to be assimilated by students, organizing on-screen text in terms of the use of color, positioning, and shapes to guide them in how to mentally simulate the order of evaluation. It is typical of such approaches to place on-screen text near corresponding parts of the graphic to facilitate deduction of the order of operations (i.e., scanning from top to bottom of the graphic) by better organizing the material. One goal of the tutor is to make explicit standards for evaluating one's own understanding of program states and knowledge of features of the language, comparing the products of these operations to expected values to highlight discrepancies and correct misconceptions. According to the proposed model of self-regulation, students are expected to progressively internalize these standards, leading to increased efforts to trace program execution and reliance on debugging strategies to assess their own understanding of the program. Otherwise, students may fail to metacognitively monitor certain aspects of their understanding that leads to difficulties in later stages of learning and problem-solving.

4.1.2 Mapping in PLTutor

PLTutor is an intelligent programming tutor that attempts to simulate and make explicit program execution over time (Nelson, 2019; Nelson et al., 2017; Xie et al., 2018). PLTutor enables students to step forwards and back through program states to situate instruction that facilitates program tracing as well as understanding of syntax and program behavior. Each instruction of the program is executed one at a time, and the corresponding syntax element is highlighted, and instructional content delivered to the student along with a representation of the machine state. The later notion refers to mappings between features of the JavaScript language as well as the machine instructions that govern program execution, such as how instructions pop values from the stack, perform an operation with those values, and push the result onto the stack. These instructions are represented in the form of natural language explanations of the rationale for instructions, while namespace values come from the stack and are made explicit in a list menu. In doing so, students have opportunities to practice how to trace program execution at different steps of program execution, including (1) conceptual instructional content, (2) demonstration of execution step and machine instruction, and (3) prompt to fill in values for machine states. Students fill in these question prompts by hovering over any answer to show a textbox, type in the value, and receive feedback that addresses common misconceptions.

The primary of scaffolding program tracing through visual representations is what we call mapping representations. Tracing program execution is a skill that refers to students' efforts to examine code and infer state changes and outputs through the compilation and execution of a program (Lopez et al., 2008; Venables et al., 2009; Xie et al., 2019). Although on-screen code may be processed in the visual channel because of the manner of its representation, students mentally construct the corresponding program state while maintaining and reinstating verbal information in working memory that is reliant on the auditory channel. Because of the limited capacity of working memory, students may only hold a limited amount of information in auditory working memory, such as groupings of program statements of values assigned to a subset of variables. Students make decisions about which statements to pay attention to and the degree to which they should infer the relevant program states during execution by linking these statements to their own prior knowledge. For this reason, metacognitive processes inherent in monitoring and controlling auditory processing that involves encoding of distractor visual representations in working memory are critical to successful learning, and much attentional resources is allocated to remove distractors. Both PLTutor and tracing tables typically rely on prompting students to map information from their own verbal model in working memory to a visual medium, as on-screen text, to off-load the demands on working memory. In a similar manner to overlay model tutors reviewed above, the tutor provides external standards for students to judge their own understanding of program states by mentally simulating execution during runtime.

4.1.3 Translating in ProPL

ProPL is a dialogue-based tutor that engages students in natural language dialogue to plan a solution prior to implementing the solution by writing a program (Lane & VanLehn, 2004). ProPL relies on a four-step pattern to engage students in dialogue, asking them to (1) identify a programming goal, (2) describe a technique for attaining this goal, (3) suggest pseudocode steps that attain the goal, and (4) order the steps appropriately within the pseudocode. This pattern is repeated until each goal of the program has been attained, and the pseudocode is complete. Whereas the first two steps involve efforts by the students to decompose problems by identifying goals and corresponding algorithm statements, the later steps involve construction of the solution by implementing and integrating the correct plans as well as addressing errors or structural issues (Guzdial et al., 1998). Dialogue management in ProPL relies on anticipated responses recognized through certain phrases or semantic elements, questions to elicit student responses, as well as statements to address wrong answers or bottom-out utterances giving away the answer. Because ProPL monitors and evaluates the dialogue, students have the benefit of pseudocode that has been implicitly approved as well as edited by the tutor before tackling the implementation of the solution at a later stage of problem-solving. An effective plan is constructed by first asking students to simulate input and output operations to assess their understanding of the task. Then, repeated questioning is used to elicit and pump students to progressively refine programming goals that, once identified, are posted in the design notes pane. This is followed by explanatory questions that, once answered correctly, lead to the addition of comments beneath the relevant goals that specify the relevant techniques. Finally, students are asked to describe further the needed plan to update the pseudocode pane, where they may reorder and indent each pseudocode statement.

In translating visual representations form one form to another, students are supported in terms of assimilating information by reducing processing of extraneous material. Dialogue is quite effective in coaching students to translate on-screen text from one visual representation to another. For example, students alternate between conversing with the tutor, reviewing design notes (e.g., get initial value, read positive integer into a variable), and examining pseudocode statements (e.g., ask for initial value, read some variable) with ProPL. As Loksa and Ko (2016) mentioned in their study, novice programmers seldom engage in effective planning by relying on such strategies. However, much of the processing of on-screen text necessary to progressively refine a plan from the dialogue is no longer necessary given that the relevant products are represented in the form of design notes. At a later stage of the dialogue, the same visual representation of on-screen text is translated in the form of pseudocode statements, thereby lessening the need for further processing of design notes. At each step of translation, information that is interesting, albeit extraneous given the purpose of implementation at the later stage, is progressively eliminated to direct student attention to the most relevant information. The use of editing of on-screen text, indenting to support scanning pasts of graphic, and ordering of each statement by the tutor can also further structure the planning and reasoning processes inherent to the problem-solving task.

4.2 Role of Visualizations in Learning Analytic Dashboards

Whereas visualizations in intelligent programming tutors support students to gain skills through opportunities for practice and feedback, those implemented in learning dashboards serve to inform instructional decision-making by distilling actionable insights from student interaction data (Yigitbasioglu & Velcu, 2012). In other words, a contrast may be found in their respective roles, whether the system is designed to adapt rather than augment instruction, and systems often provide instructional features that serve these dual purposes. Learning analytics dashboards are designed to improve decision-making abilities by making explicit learning traces in context, listing potential instructional decisions, and what are the likely implications of those decisions (Klerkx et al., 2017). Feedback in these systems typically rely on performance indicators in the form of graphs, charts, or other diagrams that are either teacher or student-oriented (Bodily & Verbert, 2017; Dyckhoff et al., 2012; Hu et al., 2014; Mottus et al., 2015; Park & Jo, 2015). Existing research on the effectiveness of dashboards not only appraises their effectiveness in terms of learning gains (Kim et al., 2016) but also considers other factors such as visual appeal, usability, ease of understanding, perceived usefulness, and behavioral changes resulting from their adoption in instruction (Park & Jo, 2015; Verbert et al., 2013).

To mention only a few examples, Diana et al. (2017) describes their dashboard that facilitates introductory programming instructors to understand students' different patterns of help-seeking behaviors. The visualization facilitates external evaluation of student products by enabling them to review performance indicators and time on task and gain insights into the program states as well as difficulties faced during the task. Team Dashboard (Tarmazdi et al., 2015) visualizes the team mood, role distribution, and emotional climate so that teachers could diagnose group dynamics and generate feedback based on their diagnosis. Instructors have the benefit of visualizations that depict interactions between group members, which serve as a basis for recognizing different roles within a team. LAPLE provides a dashboard that exhibits learning difficulties students encounter while learning the C language (Fu et al., 2017). A heat map chart was used to indicate students' activities in learning, and a line-point chart manifests students' achievement. Hellings and Haelermans (2020) focused on learning progress by visually indicating students' behaviors and performance over time. In a similar manner, these authors designed pie charts to show students' grades and the average grade of a cohort.

5 Conclusion

In summary, students face significant challenges to gain understanding of programming while learning difficult programming topics. Visual representations may be useful to support students by making explicit aspects of program execution in the runtime environment or features of the programming language and development environment. In the process of assimilating information from visual representations, students regulate certain aspects of their own learning while building a mental representation of the program. This chapter has outlined an integrated model that distinguishes between modalities of representation of information as well as accounts for visual information processing within a cognitive architecture. The assumption is that this more nuanced account of domain-specific strategies that novice programmers rely on stands to inform the design of visual representations that lead to meaningful learning. These design principles include (1) signaling visual information with embedded cues; (2) mapping information from verbal representation to an external visual representation; and (3) translating information from one form of visual representation to another. Each design principle is exemplified in the context of visualizations embedded in intelligent programming tutors, namely, explaining and monitoring program comprehension with Problets (Kumar, 2016), tracing code execution with PLTutor (Nelson et al., 2017), as well as task understanding and planning with ProPL (Lane & VanLehn, 2003). These tutors are shown to support cognitive and metacognitive processes while automating the delivery of feedback through the system and serve a distinct function from learning analytic dashboards that support feedback delivered by instructors. Visual representations that are designed in accordance with these design principles are more likely to support program comprehension during self-regulated learning at each phase of task performance.

References

Altadmri, A., & Brown, N. C. (2015). 37 million compilations: Investigating novice programming mistakes in large-scale student data. In *Proceedings of the 46th ACM technical symposium on computer science education* (pp. 522–527). https://doi.org/10.1145/2676723.2677258

Azevedo, R. (2009). Theoretical, conceptual, methodological, and instructional issues in research on metacognition and self-regulated learning: A discussion. *Metacognition and Learning, 4*(1), 87–95. https://doi.org/10.1007/s11409-009-9035-7

Baddeley, A. (1998). Recent developments in working memory. *Current Opinion in Neurobiology, 8*(2), 234–238. https://doi.org/10.1016/S0959-4388(98)80145-1

Bau, D., Bau, D. A., Dawson, M., & Pickens, C. S. (2015). Pencil code: Block code for a text world. In *Proceedings of the 14th international conference on interaction design and children* (pp. 445–448). Association for Computing Machinery. https://doi.org/10.1145/2771839.2771875

Ben-Ari, M., Bednarik, R., Ben-Bassat Levy, R., Ebel, G., Moreno, A., Myller, N., & Sutinen, E. (2011). A decade of research and development on program animation: The Jeliot experience. *Journal of Visual Languages & Computing, 22*(5), 375–384. https://doi.org/10.1016/j.jvlc.2011.04.004

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418. https://doi.org/10.1109/TLT.2017.2740172

Bruce-Lockhart, M., Norvell, T. S., & Cotronis, Y. (2007). Program and algorithm visualization in engineering and physics. *Electronic Notes in Theoretical Computer Science, 178*, 111–119. https://doi.org/10.1016/j.entcs.2007.01.040

Bruce-Lockhart, M., Crescenzi, P., & Norvell, T. (2009). Integrating test generation functionality into the teaching machine environment. *Electronic Notes in Theoretical Computer Science, 224*, 115–124. https://doi.org/10.1016/j.entcs.2008.12.055

Brusilovsky, P., & Loboda, T. D. (2006). WADEIn II: A case for adaptive explanatory visualization. In *Proceedings of the 11th annual SIGCSE conference on innovation and technology in computer science education* (pp. 48–52). Association for Computing Machinery. https://doi.org/10.1145/1140124.1140140

Cross, J. H., Hendrix, T. D., & Barowski, L. A. (2011). Combining dynamic program viewing and testing in early computing courses. In *2011 IEEE 35th annual computer software and applications conference* (pp. 184–192). https://doi.org/10.1109/COMPSAC.2011.31

Crow, T., Luxton-Reilly, A., & Wuensche, B. (2018). Intelligent tutoring systems for programming education: A systematic review. In *Proceedings of the 20th Australasian computing education conference* (pp. 53–62). Association for Computing Machinery. https://doi.org/10.1145/3160489.3160492

Cunningham, K., Blanchard, S., Ericson, B., & Guzdial, M. (2017). Using tracing and sketching to solve programming problems: Replicating and extending an analysis of what students draw. In *Proceedings of the 2017 ACM Conference on international computing education research* (pp. 164–172). Association for Computing Machinery. https://doi.org/10.1145/3105726.3106190

de Souza, D. M., Kölling, M., & Barbosa, E. F. (2017). Most common fixes students use to improve the correctness of their programs. *IEEE Frontiers in Education Conference (FIE), 2017*, 1–9. https://doi.org/10.1109/FIE.2017.8190524

Diana, N., Eagle, M., Stamper, J., Grover, S., Bienkowski, M., & Basu, S. (2017). An instructor dashboard for real-time analytics in interactive programming assignments. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 272–279). Association for Computing Machinery. https://doi.org/10.1145/3027385.3027441

Dinsmore, D. L., Alexander, P. A., & Loughlin, S. M. (2008). Focusing the conceptual lens on metacognition, self-regulation, and self-regulated learning. *Educational Psychology Review, 20*(4), 391–409. https://doi.org/10.1007/s10648-008-9083-6

Dragon, T., & Dickson, P. E. (2016). Memory diagrams: A consistent approach across concepts and languages. In *Proceedings of the 47th ACM technical symposium on computing science education* (pp. 546–551). Association for Computing Machinery. https://doi.org/10.1145/2839509.2844607

Du Boulay, B. (1986). Some difficulties of learning to program. *Journal of Educational Computing Research, 2*(1), 57–73. https://doi.org/10.2190/3LFX-9RRF-67T8-UVK9

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Journal of Educational Technology & Society, 15*(3), 58–76.

Efklides, A. (2008). Metacognition: Defining its facets and levels of functioning in relation to self-regulation and co-regulation. *European Psychologist, 13*(4), 277–287. https://doi.org/10.1027/1016-9040.13.4.277

Fitzgerald, S., Lewandowski, G., McCauley, R., Murphy, L., Simon, B., Thomas, L., & Zander, C. (2008). Debugging: Finding, fixing and flailing, a multi-institutional study of novice debuggers. *Computer Science Education, 18*(2), 93–116. https://doi.org/10.1080/08993400802114508

Fraser, N. (2015). Ten things we've learned from Blockly. *IEEE Blocks and Beyond Workshop (Blocks and Beyond), 2015*, 49–50. https://doi.org/10.1109/BLOCKS.2015.7369000

Fu, X., Shimada, A., Ogata, H., Taniguchi, Y., & Suehiro, D. (2017). Real-time learning analytics for C programming language courses. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 280–288). Association for Computing Machinery. https://doi.org/10.1145/3027385.3027407

Gajraj, R. R., Bernard, M., Williams, M., & Singh, L. (2011). Transforming source code examples into programming tutorials. In *Proceedings of the 6th international multi-conference on computing in the global information technology (ICCGI'11)* (pp. 160–164).

Greene, J. A., & Azevedo, R. (2007). A theoretical review of Winne and Hadwin's model of self-regulated learning: New perspectives and directions. *Review of Educational Research, 77*(3), 334–372. https://doi.org/10.3102/003465430303953

Gries, D. (2008). A principled approach to teaching OO first. In *Proceedings of the 39th SIGCSE technical symposium on computer science education* (pp. 31–35). Association for Computing Machinery. https://doi.org/10.1145/1352135.1352149

Guo, P. J. (2013). Online python tutor: Embeddable web-based program visualization for cs education. In *Proceeding of the 44th ACM technical symposium on computer science education* (pp. 579–584). Association for Computing Machinery. https://doi.org/10.1145/2445196.2445368

Guzdial, M., Hohmann, L., Konneman, M., Walton, C., & Soloway, E. (1998). Supporting programming and learning-to-program with an integrated CAD and scaffolding workbench*. *Interactive Learning Environments, 6*(1–2), 143–179. https://doi.org/10.1076/ilee.6.1.143.3609

Harvey, B., & Mönig, J. (2010). Bringing "no ceiling" to scratch: Can one language serve kids and computer scientists. *Proc Constructionism*, 1–10.

Hellings, J., & Haelermans, C. (2020). The effect of providing learning analytics on student behaviour and performance in programming: A randomised controlled experiment. *Higher Education.* https://doi.org/10.1007/s10734-020-00560-z

Homer, M., & Noble, J. (2014). Combining tiled and textual views of code. *Second IEEE Working Conference on Software Visualization, 2014*, 1–10. https://doi.org/10.1109/VISSOFT.2014.11

Hu, Y.-H., Lo, C.-L., & Shih, S.-P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior, 36*, 469–478. https://doi.org/10.1016/j.chb.2014.04.002

Huizing, C., Kuiper, R., Luijten, C., & Vandalon, V. (2012). Visualization of object-oriented (Java) programs. In *Proceedings of the 4th international conference on computer supported education* (pp. 65–72). SciTePress-Science and and Technology Publications. https://doi.org/10.5220/0003924000650072

Hundhausen, C. D., Douglas, S. A., & Stasko, J. T. (2002). A meta-study of algorithm visualization effectiveness. *Journal of Visual Languages & Computing, 13*(3), 259–290. https://doi.org/10.1006/jvlc.2002.0237

Jimenez-Diaz, G., Gonzalez-Calero, P. A., & Gomez-Albarran, M. (2012). Role-play virtual worlds for teaching object-oriented design: The ViRPlay development experience. *Software: Practice and Experience, 42*(2), 235–253. https://doi.org/10.1002/spe.1071

Kaczmarczyk, L. C., Petrick, E. R., East, J. P., & Herman, G. L. (2010). Identifying student misconceptions of programming. , 107–111. : Association for Computing Machinery. doi:https://doi.org/10.1145/1734263.1734299.

Kelleher, C., & Pausch, R. (2005). Lowering the barriers to programming: A taxonomy of programming environments and languages for novice programmers. *ACM Computing Surveys, 37*(2), 83–137. https://doi.org/10.1145/1089733.1089734

Keuning, H., Jeuring, J., & Heeren, B. (2018). A systematic literature review of automated feedback generation for programming exercises. *ACM Transactions on Computing Education, 19*(1), 3:1–3:43. https://doi.org/10.1145/3231711

Kim, J., Jo, I.-H., & Park, Y. (2016). Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(1), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Klerkx, J., Verbert, K., & Duval, E. (2017). Learning analytics dashboards. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 143–150). Society for Learning Analytics Research. https://doi.org/10.18608/hla17.012

Kölling, M. (2008). Using BlueJ to introduce programming. In J. Bennedsen, M. E. Caspersen, & M. Kölling (Eds.), *Reflections on the teaching of programming: Methods and implementations* (pp. 98–115). Springer. https://doi.org/10.1007/978-3-540-77934-6_9

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research, 86*(1), 42–78. https://doi.org/10.3102/0034654315581420

Kumar, A. N. (2015a). Automated generation of self-explanation questions in worked examples in a model-based tutor. In C. Conati, N. Heffernan, A. Mitrovic, & M. F. Verdejo (Eds.), *Artificial intelligence in education* (pp. 682–685). Springer International Publishing. https://doi.org/10.1007/978-3-319-19773-9_91

Kumar, A. N. (2015b). The effectiveness of visualization for learning expression evaluation. In *Proceedings of the 46th ACM technical symposium on computer science education* (pp. 362–367). Association for Computing Machinery. https://doi.org/10.1145/2676723.2677301

Kumar, A. N. (2016). The effectiveness of visualization for learning expression evaluation: A reproducibility study. In *Proceedings of the 2016 ACM conference on innovation and tech-*

nology in computer science education (pp. 192–197). Association for Computing Machinery. https://doi.org/10.1145/2899415.2899427

Kumar, A. N. (2019). Does choosing the concept on which to solve each practice problem in an adaptive tutor affect learning? In S. Isotani, E. Millán, A. Ogan, P. Hastings, B. McLaren, & R. Luckin (Eds.), *Artificial intelligence in education* (pp. 143–147). Springer International Publishing. https://doi.org/10.1007/978-3-030-23207-8_27

Lajoie, S. P. (2008). Metacognition, self regulation, and self-regulated learning: A rose by any other name? *Educational Psychology Review, 20*(4), 469–475. https://doi.org/10.1007/s10648-008-9088-1

Lane, H. C., & VanLehn, K. (2003). Coached program planning: Dialogue-based support for novice program design. In *Proceedings of the 34th SIGCSE technical symposium on computer science education* (pp. 148–152). Association for Computing Machinery. https://doi.org/10.1145/611892.611955

Lane, H. C., & VanLehn, K. (2004, May). *A dialogue-based tutoring system for beginning programming*. In FLAIRS Conference (pp. 449–454).

Loksa, D., & Ko, A. J. (2016). The role of self-regulation in programming problem solving process and success. In *Proceedings of the 2016 ACM conference on international computing education research* (pp. 83–91). Association for Computing Machinery. https://doi.org/10.1145/2960310.2960334

Lopez, M., Whalley, J., Robbins, P., & Lister, R. (2008). Relationships between reading, tracing and writing skills in introductory programming. In *Proceedings of the fourth international workshop on computing education research* (pp. 101–112). Association for Computing Machinery. https://doi.org/10.1145/1404520.1404531

Ma, L. (2007). *Investigating and improving novice programmers' mental models of programming concepts* (Doctoral dissertation, University of Strathclyde). University of Strathclyde. Retrieved from https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.721.8479&rep=rep1&type=pdf

Ma, L., Ferguson, J., Roper, M., & Wood, M. (2011). Investigating and improving the models of programming concepts held by novice programmers. *Computer Science Education, 21*(1), 57–80. https://doi.org/10.1080/08993408.2011.554722

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901–918. https://doi.org/10.1037/a0037123

Maletic, J. I., Marcus, A., & Collard, M. L. (2002). A task oriented view of software visualization. In *Proceedings first international workshop on visualizing software for understanding and analysis* (pp. 32–40). https://doi.org/10.1109/VISSOF.2002.1019792

Malmi, L., Sheard, J., Kinnunen, P., Simon, & Sinclair, J. (2020). Theories and models of emotions, attitudes, and self-efficacy in the context of programming education. In *Proceedings of the 2020 ACM conference on international computing education research* (pp. 36–47). Association for Computing Machinery. https://doi.org/10.1145/3372782.3406279

Mayer, R. E. (2001). *Multimedia learning*. Cambridge University Press.

Mayer, R. E. (2005). *Cognitive theory of multimedia learning. In the Cambridge handbook of multimedia learning* (pp. 31–48). Cambridge University Press.

Mayer, R. E. (2008). Applying the science of learning: Evidence-based principles for the design of multimedia instruction. *American Psychologist, 63*(8), 760–769. https://doi.org/10.1037/0003-066X.63.8.760

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist, 38*(1), 43–52. https://doi.org/10.1207/S15326985EP3801_6

McBroom, J., Koprinska, I., & Yacef, K. (2019). A survey of automated programming hint generation—The HINTS framework. ArXiv:1908.11566 [Cs]. Retrieved from http://arxiv.org/abs/1908.11566

Miljanovic, M. A., & Bradbury, J. S. (2017). RoboBUG: A serious game for learning debugging techniques. In *Proceedings of the 2017 ACM conference on international comput-*

ing education research (pp. 93–100). Association for Computing Machinery. https://doi.org/10.1145/3105726.3106173

Moons, J., & De Backer, C. (2013). The design and pilot evaluation of an interactive learning environment for introductory programming influenced by cognitive load theory and constructivism. *Computers & Education, 60*(1), 368–384. https://doi.org/10.1016/j.compedu.2012.08.009

Mottus, A., Kinshuk, Graf, S., & Chen, N.-S. (2015). Use of dashboards and visualization techniques to support teacher decision making. In Kinshuk & R. Huang (Eds.), *Ubiquitous learning environments and technologies* (pp. 181–199). Springer. https://doi.org/10.1007/978-3-662-44659-1_10

Naps, T. L., & Stenglein, J. (1996). Tools for visual exploration of scope and parameter passing in a programming languages course. *SIGCSE Bulletin, 28*(1), 295–299.

Nelson, G. L. (2019). Personalized, adaptive tutorials for program tracing skills. In *Proceedings of the 19th koli calling international conference on computing education research* (pp. 1–2). Association for Computing Machinery. https://doi.org/10.1145/3364510.3366164

Nelson, G. L., Xie, B., & Ko, A. J. (2017). Comprehension first: Evaluating a novel pedagogy and tutoring system for program tracing in CS1. In *Proceedings of the 2017 ACM conference on international computing education research* (pp. 2–11). Association for Computing Machinery. https://doi.org/10.1145/3105726.3106178

Nesbit, J. C., Adesope, O. O., Liu, Q., & Ma, W. (2014). How effective are intelligent tutoring systems in computer science education? In *2014 IEEE 14th international conference on advanced learning technologies* (pp. 99–103). https://doi.org/10.1109/ICALT.2014.38

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

Park, Y., & Jo, I.-H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 24110–24133.

Park, K., Mott, B., Min, W., Wiebe, E., Boyer, K. E., & Lester, J. (2020). Generating game levels to develop computer science competencies in game-based learning environments. In I. I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial intelligence in education* (pp. 240–245). Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_44

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic. https://doi.org/10.1016/B978-012109890-2/50043-3

Prather, J., Becker, B. A., Craig, M., Denny, P., Loksa, D., & Margulieux, L. (2020). What do we think we think we are doing? Metacognition and self-regulation in programming. In *Proceedings of the 2020 ACM conference on international computing education research* (pp. 2–13). Association for Computing Machinery. https://doi.org/10.1145/3372782.3406263

Qian, Y., & Lehman, J. (2017). Students' misconceptions and other difficulties in introductory programming: A literature review. *ACM Transactions on Computing Education, 18*(1), 1–24. https://doi.org/10.1145/3077618

Quintana, C., Reiser, B. J., Davis, E. A., Krajcik, J., Fretz, E., Duncan, R. G., … Soloway, E. (2004). A scaffolding design framework for software to support science inquiry. *Journal of the Learning Sciences, 13*(3), 337–386. https://doi.org/10.1207/s15327809jls1303_4

Reiser, B. J. (2004). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *Journal of the Learning Sciences, 13*(3), 273–304. https://doi.org/10.1207/s15327809jls1303_2

Resnick, M., Maloney, J., Monroy-Hernández, A., Rusk, N., Eastmond, E., Brennan, K., … Kafai, Y. (2009). Scratch: Programming for all. *Communications of the ACM, 52*(11), 60–67. https://doi.org/10.1145/1592761.1592779

Rist, R. S. (1989). Schema creation in programming. *Cognitive Science, 13*(3), 389–414. https://doi.org/10.1016/0364-0213(89)90018-9

Rist, R. S. (1991). Knowledge creation and retrieval in program design: A comparison of novice and intermediate student programmers. *Human–Computer Interaction, 6*(1), 1–46. https://doi.org/10.1207/s15327051hci0601_1

Robins, A., Rountree, J., & Rountree, N. (2003). Learning and teaching programming: A review and discussion. *Computer Science Education, 13*(2), 137–172. https://doi.org/10.1076/csed.13.2.137.14200

Schraw, G. (2006). Knowledge: Structures and processes. In P. A. Alexander & P. H. Winne (Eds.), *Handbook of educational psychology* (pp. 245–263). Lawrence Erlbaum Associates Publishers.

Schulte, C. (2008). Block Model: An educational model of program comprehension as a tool for a scholarly approach to teaching. In *Proceedings of the fourth international workshop on computing education research* (pp. 149–160). Association for Computing Machinery. https://doi.org/10.1145/1404520.1404535

Schulte, C., Clear, T., Taherkhani, A., Busjahn, T., & Paterson, J. H. (2010). An introduction to program comprehension for computer science educators. In *Proceedings of the 2010 ITiCSE working group reports* (pp. 65–86). Association for Computing Machinery. https://doi.org/10.1145/1971681.1971687

Schunk, D. H., & Zimmerman, B. B. (Eds.). (2008). *Motivation and self-regulated learning: Theory, research, and applications*. Lawrence Erlbaum Associates Publishers.

Shute, V. J., & Zapata-Rivera, D. (2012). Adaptive educational systems. In P. J. Durlach & A. M. Lesgold (Eds.), *Adaptive technologies for training and education* (pp. 7–27). Cambridge University Press. https://doi.org/10.1017/CBO9781139049580.004

Sirkiä, T., & Sorva, J. (2012). Exploring programming misconceptions: An analysis of student mistakes in visual program simulation exercises. In *Proceedings of the 12th Koli calling international conference on computing education research* (pp. 19–28). Association for Computing Machinery. https://doi.org/10.1145/2401796.2401799

Sirkiä, T., & Sorva, J. (2015). How do students use program visualizations within an interactive ebook? In *Proceedings of the eleventh annual international conference on international computing education research* (pp. 179–188). Association for Computing Machinery. https://doi.org/10.1145/2787622.2787719

Sorva, J. (2012). *Visual program simulation in introductory programming education*. Aalto University School of Science.

Sorva, J., Karavirta, V., & Malmi, L. (2013). A review of generic program visualization systems for introductory programming education. *ACM Transactions on Computing Education (TOCE), 13*(4), 1–64.

Tarmazdi, H., Vivian, R., Szabo, C., Falkner, K., & Falkner, N. (2015). Using learning analytics to visualise computer science teamwork. In *Proceedings of the 2015 ACM conference on innovation and technology in computer science education* (pp. 165–170). https://doi.org/10.1145/2729094.2742613

Thomas, L., Ratcliffe, M., & Thomasson, B. (2004). Scaffolding with object diagrams in first year programming classes: Some unexpected results. *ACM SIGCSE Bulletin, 36*(1), 250–254. https://doi.org/10.1145/1028174.971390

Thuné, M., & Eckerdal, A. (2010). *Students' conceptions of computer programming* [Technical Report 2010–021]. Department of Information Technology, Uppsala University. Retrieved from Department of Information Technology, Uppsala University. website: http://uu.diva-portal.org/smash/get/diva2:347073/FULLTEXT01

Tillmann, N., Bishop, J., Horspool, N., Perelman, D., & Xie, T. (2014). Code hunt: Searching for secret code for fun. In *Proceedings of the 7th International workshop on search-based software testing* (pp. 23–26). Association for Computing Machinery. https://doi.org/10.1145/2593833.2593838

Vainio, V., & Sajaniemi, J. (2007). Factors in novice programmers' poor tracing skills. *ACM SIGCSE Bulletin, 39*(3), 236–240. https://doi.org/10.1145/1269900.1268853

van der Bent, R., Jeuring, J., & Heeren, B. (2019). The diagnosing behaviour of intelligent tutoring systems. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming learning with meaningful technologies* (pp. 112–126). Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_9

VanLehn, K. (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education, 16*(3), 227–265.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Veenman, M. V. J. (2007). The assessment and instruction of self-regulation in computer-based environments: A discussion. *Metacognition and Learning, 2*(2), 177–183. https://doi.org/10.1007/s11409-007-9017-6

Velázquez-Iturbide, J. Á., Pérez-Carrasco, A., & Urquiza-Fuentes, J. (2008). SRec: An animation system of recursion for algorithm courses. *ACM SIGCSE Bulletin, 40*(3), 225–229. https://doi.org/10.1145/1597849.1384332

Venables, A., Tan, G., & Lister, R. (2009). A closer look at tracing, explaining and code writing skills in the novice programmer. In *Proceedings of the fifth international workshop on computing education research workshop* (pp. 117–128). Association for Computing Machinery. https://doi.org/10.1145/1584322.1584336

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509. https://doi.org/10.1177/0002764213479363

Wang, P., Bednarik, R., & Moreno, A. (2012). During automatic program animation, explanations after animations have greater impact than before animations. In *Proceedings of the 12th Koli calling international conference on computing education research* (pp. 100–109). Association for Computing Machinery. https://doi.org/10.1145/2401796.2401808

Weintrop, D., & Wilensky, U. (2017). Comparing block-based and text-based programming in high school computer science classrooms. *ACM Transactions on Computing Education, 18*(1), 3:1–3:25. https://doi.org/10.1145/3089799

Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (pp. 153–189). Lawrence Erlbaum Associates Publishers.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *The educational psychology series. Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates Publishers.

Xie, B., Nelson, G. L., & Ko, A. J. (2018). An explicit strategy to scaffold novice program tracing. In *Proceedings of the 49th ACM technical symposium on computer science education* (pp. 344–349). Association for Computing Machinery. https://doi.org/10.1145/3159450.3159527

Xie, B., Loksa, D., Nelson, G. L., Davidson, M. J., Dong, D., Kwik, H., … Ko, A. J. (2019). A theory of instruction for introductory programming skills. *Computer Science Education, 29*(2–3), 205–253. https://doi.org/10.1080/08993408.2019.1565235

Yigitbasioglu, O. M., & Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems, 13*(1), 41–59. https://doi.org/10.1016/j.accinf.2011.08.002

Zimmerman, B. J. (2000). Attaining self-regulation. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183. https://doi.org/10.3102/0002831207312909

Chapter 5
Effectiveness of Dashboard and Intervention Design

Jeevan Pokhrel and Aruna Awasthi

1 Introduction

With the massive increase in user-generated content in educational institutions over the years, the need to incorporate relevant analytical techniques to process the wealth of data becomes more critical. The visualisation dashboards are a tool that provides meaningful and actionable insights at a glance, whereas the traditional reports based on statistics are not as easily interpreted by educators. The user-friendly visualisation techniques can be used to represent the data information in a clear and understandable format (Romero & Ventura, 2007). Hence, learning analytics (LA) uses data science methods to analyse data and report the analysis results with different visual and textual representations (Gašević et al., 2017) with LA dashboards.

A LA dashboard enables academics, students, and other stakeholders to communicate learning and teaching data. It allows academics to access students' learning behaviour and pattern in near real time and at scale. LA dashboards can help students to improve self-knowledge by monitoring learning status, history, and trends in their performance and reflect on their ability to achieve their learning goals (Verbert et al., 2013). Furthermore, LA dashboards aim to promote innovative learning environments by providing real-time personalised and automatically generated learning and teaching data (Papamitsiou & Economides, 2016). Due to technological advancements, dashboards can be automatically developed; however, it is challenging to develop one that fulfils most of the student requirements and influences their self-regulatory behaviour and learning outcomes.

J. Pokhrel (✉) · A. Awasthi
Senior Data Scientist, Data and Analytics, RMIT University, Melbourne, Australia
e-mail: jeevan.pokhrel@rmit.edu.au; aruna.awasthi@rmit.edu.au

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_5

Dashboard development is an iterative and continuous design process where recommendations and feedback from end-users are continuously evaluated, implemented, and tested to improve its effectiveness and usability. The LA dashboard design process must address areas such as the technical requirements needed to collect and visualise the information in real time, selecting the relevant and essential information and visualising it aesthetically. To support the continuous dashboard design usually requires conducting formative evaluations in an iterative way (Dick et al., 2005; Gustafson & Branch, 2002) and integrating the functionality as requested by academics and students in future updates.

An effective LA dashboard provides students with relevant insight, prompts user self-reflection, and potentially informs interventions that are aimed at optimising learning through visual reports (Grelle et al., 2012). These interventions can act as a catalyst to positively impact student outcomes. Well-designed interventions help students understand the data behind it and why they are receiving an intervention and provide adequate support and environment to help them achieve their learning outcomes (Wise, 2014). Moreover, interventions must be personalised, understandable, and transparent to the student's situation (Durall et al., 2014).

The rest of this chapter is structured as follows. Section 2 presents the current state of LA dashboards and their applications in the education sector. Section 3 illustrates how to build an effective dashboard design process. Further, sect. 4 describes various types of interventions and the intervention design principles. Section 5 presents two different use cases of visualisation/dashboard to demonstrate the effectiveness of dashboards and intervention design in the current LA community. These dashboards are operational within the Royal Melbourne Institute of Technology (RMIT) University and helping the learning and teaching community to understand student behaviour and learning outcomes. The summary of the chapter and future recommendations are discussed in sect. 6.

2 Related Work

The learning analytics area focuses on tracking student's learning activities and the context in which these activities occur through educational data mining and visualising them as LA dashboards. A considerable amount of literature has been published on developing dashboards to address the educational institutions' major concerns, such as improving the student learning experience, increasing retention rates, identifying at-risk students, and providing the students with supportive interventions. In addition, LA dashboards have also been studied to help students pick appropriate learning pathways in line with their academic goals and provide the relevant analytical reports to help them make strategic and informed decisions.

LA dashboards have been used in various educational institutions to optimise and enhance learning and teaching. Arnold (Arnold & Pistilli, 2012) presented Course Signals dashboard to identify students at risk of course failure. The research found that students who had access to the dashboard improved their grades and demonstrated better retention behaviour. SAM dashboard (Govaerts et al., 2012) provides visualisations of progress in the course for teachers and students. GLASS (Leony et al., 2012) and LOCO-Analyst (Ali et al., 2012) are similar dashboards that provide feedback to teachers on student activities and performance. SNAPP dashboard (Dawson et al., 2010) visualises the evolution of students' social interactions and online collaboration. Table 5.1 summarises some of the LA dashboard tools and their applications.

Most existing studies on dashboard designs assist teachers in exploring insights of student activities by analysing typical patterns in student's learning and performance; however, not as much attention had been given to study the effects of such tools on students (Jovanović et al., 2017).

There is now growing interest in student-focused LA dashboards as they provide students with personalised feedback (Bodily & Verbert, 2017). Some literature presents LA dashboards from different perspectives to support students' self-motivation, self-reflection, and social awareness. Sedrakyan (Sedrakyan et al., 2016) reported the gap between LA dashboard design for learners and educational concepts. According to Jivet (Jivet et al., 2017), the dashboard goals related to the development of learning dashboards foster awareness and reflection. They suggested that LA dashboards should aim to affect cognitive, behavioural, and emotional competencies alongside metacognitive competencies to support self-regulated learning. Sedrakyan (Sedrakyan et al., 2019) conceptualised a model by linking dashboard

Table 5.1 LA dashboard and applications

LA dashboard	Resource	Application
CourseViz	Mazza et al. (2007)	Monitor students' activities in distant courses using web log data (teacher-focused)
SNAPP	Dawson et al. (2010)	Network visualisation of learners' relationships within discussion forums (teacher-focused)
Course signals	Arnold and Pistilli (2012)	Improve retention and performance by effective interventions (student-focused)
Student activity meter (SAM)	Govaerts et al. (2012)	Self-monitor the students and awareness for teachers, providing an overview of activities and resource use in a virtual classroom over time (student-teacher focused)
Gradient's learning analytics system (GLASS)	Leony et al. (2012)	Visualise and compare learning performance by tracking the number and types of events (student-teacher focused)
LOCO-analyst	Ali et al. (2012)	Provide feedback on students' activities and performance (teacher-focused)
D2L BrightSpace insights	Jayaprakash et al. (2014)	Monitor students' activities in the LMS, real-time interventions (teacher-focused)
EduOpen	Dipace et al. (2019)	Monitor students' performances and trends over the medium to long term; provide instant feedback (student-teacher focused)
Stefla dashboard with DojoIBL platform	Jaakonmäki et al. (2020)	Aggregate data in a flexible way and can benefit teachers in student-driven learning (teacher-focused)

design concepts with the learning process and feedback concepts to improve the accuracy and effectiveness of the LA dashboard.

3 Effective Dashboard Design

Despite the widespread use of dashboards in learning analytics, many dashboards have failed to draw the necessary level of attention to its effectiveness and instead simply provide a display of readily available data to impress potential users (Janes et al., 2013; Jin & Yu, 2015; Matcha et al., 2019). In addition, careful attention should be given to address the adverse effects of LA dashboards on students' motivation (Krumm et al., 2014). It is challenging to find dashboard design guidelines grounded in foundational principles of learning analytics (Gašević et al., 2017). According to Few's dashboard design principles, an effective dashboard design should be based on understanding how we see and think (Few, 2006). A dashboard with effective design should visually display the essential information at a glance to achieve one or more objectives (Few, 2013). The essential characteristics of the dashboard are identified as follows: (a) dashboards are visual displays; (b) dashboards display the information needed to achieve specific goals; (c) a dashboard fits on a single computer screen; and (d) dashboards are used to monitor information instantly.

Effective dashboard design is related to several theoretical foundations such as situational awareness, human cognition and perception, and visualisation techniques (Yoo et al., 2015).

3.1 Situational Awareness

The information in an effective dashboard should support one's situated awareness and be deployed in a way that makes sense. Situational awareness is the general understanding of what a dashboard is and how it is used within different contexts, levels, and purposes, to simplify information and reach its target audience. The gap between user's knowledge and experience can be huge, and it is crucial to understand the user's problems and goals and anticipate their needs and expectations before moving ahead with the design part. A few general questions that can be asked when deciding about situational awareness include the following:

a) Who are the potential customers of the dashboard?
b) What specific information should be captured and displayed?
c) Which of this information is most important for achieving the goals?
d) What are valid comparisons that will allow us to see these items of information in a meaningful context?
e) What are data science methods appropriate for analysis?

This general understanding assists in formulating the general framework that will be applied to improve the efficiency of using a dashboard.

3.2 Human Cognition and Perception

Visual perception is another important concept that relates to the dashboard design. Few (2013) introduced three remarkable considerations:

- Human brains process visual information faster and more efficiently than text. Thus, to design a dashboard, visual elements such as graphs that fit on a single computer screen are better for rapid perception and memory retention.
- For efficient perception, appropriate pre-attentive attributes such as form, colour, spatial position, and motion should be properly utilised.
- According to Gestalt's six principles (Todorović, 2007) of perception, design elements such as proximity, similarity, enclosure, closure, continuity, and the connection should be considered in designing a dashboard.
  - *Proximity* describes how the mind perceives data as belonging to the same group when objects are positioned closely. If some space is included between them, the mind will perceive them as an independent.
  - *Similarity* is the brain's natural response to associate the elements that appear like one another, e.g. in shape, orientation, size, or colour.
  - *Enclosure* is when a border surrounds a series of objects, and they are considered a group.
  - *Closure* describes the tendency to try to give the object a complete form. When an object is incomplete and without any border, it is perceived as closed and incomplete.
  - *Continuity* is how we perceive several objects aligned closely as a continuous body.
  - *Connectedness* is related to simplifying objects connected by any uniform visual property, e.g. by a line. We will perceive them as a group instead of other elements being not connected.

3.3 Visualisation Techniques and Guidelines

The choice of the proper visualisation techniques is required to display the information that users want to know. When using a dashboard to visualise data, it is vital to have an effective design and demonstrate good design practices. The following dashboard design guidelines have been identified to communicate the data effectively:

- Target Audience – To keep the audience in mind and customise the dashboard accordingly. If the dashboard is not in line with what the users want and need, the dashboard will not be used optimally (Borden, 2015Few, 2013). Designers should base the design on user feedback and not assume that they understand something the same way. Designing dashboards is an iterative process; first, design the dashboard, put it out, get user feedback, and then improve it (Salesforce, 2013).
- Screen Boundaries – To fit visualisation in a single screen with all the displayed data visible simultaneously, with no scrolling required. Filling the visualisation dashboard with items outside the screen boundaries is only useless and confusing to users (Few, 2013; Lechner & Fruhling, 2014). It will not be easy to compare the visual data if the user needs to scroll between them.
- Choose Metrics That Matter – To select the data that is essential for analysis and decision-making. The concerns are reported in the predictive model when identified predictors are not relevant for teaching practice (Gašević et al., 2016), so, it is crucial to work together with the users to find the essential data.
- Data Needs Context – To provide context to the data, target values and comparison data can be shown to the users. Without proper context, the users will not understand if the data they are looking at is good or bad and if any action needs to be taken. Some ways to give context to the data is by showing the user target values or historical data (Kwapien, 2016; Lechner & Fruhling, 2014).
- Data Layout – To present the most important information at the top, the user usually starts to analyse the information on the dashboard. If some data needs to be compared, it must be grouped. The dashboard should be designed with the human visual perceptions in mind (Few, 2013).
- Choosing the Display Media – To include proper graphical/textual/map representations that best convey the data to the user. The graphs in a dashboard should appropriately represent the scales and units. For the presented data to be effective, it needs the relevant visualisation type, i.e. trends over time, line chart; comparison and ranking, bar chart; correlation, scatterplot; distribution, box plot; Likert scale, divergent bar chart; text; map; etc. (Few, 2013Kwapien, 2016).
- Display Media Design – To reduce clutter and have a good design for effectively conveying the data to the user by keeping the data-ink ratio in mind, which is meant to show the proportion of ink used for data compared to total ink used (Few, 2013). Levy (2017) suggested following the 5-second rule when designing the dashboard so that users should need no more than 5 seconds to find what they are looking for. Unnecessary 3D effects, gradient effects, shadows, and gridlines do not add value to the data (Few, 2013; Kwapien, 2016).
- Highlight the Valuable Information – To capture users' attention, make it easy for the audience to understand the important information. LA dashboard should display only information that students themselves think is useful.
- Colour Palette – To stick with few colours with their gradients and think about accessibility (e.g. colour blindness) when choosing colours. The bright colours are preferred for highlights as they draw the user's attention. The use of the organisation's brand colour should also be taken into account.

- Make the Dashboard Attractive – To keep the dashboard clean and neat looking. Choose the attractive dashboard designs which provide a snapshot of what is going on and prioritise information based on what the users need to see.
- Add Interactivity – To add interaction and encourage exploration by using drill-downs, filters, and styles, i.e. font type, colour choice, content layout, etc. (Few, 2013).
- Time and Updates – To display time so that the user knows when the data is updated. The frequency of the dashboard updates should be known to the user (Few, 2013).

It can be seen that many of the guidelines build upon each other. Figure 5.1 summarises the effective dashboard principles that will present the data in a meaningful way to the user, without cluttering and distractions in a dashboard.

Fig. 5.1 Effective dashboard design principles (EXCELINXL, 2020)

Recognising these dashboard principles, two in-house dashboards – early warning signs and constellation – are presented in Sect. 5.

4 Intervention Design

Learning analytics interventions have not yet been adequately explored. According to Wise (2014), a learning analytics intervention is defined as 'the surrounding frame of activity through which analytic tools, data, and reports are taken up and used'. These days most universities are inclined towards using data-heavy LA dashboards. The success of these dashboards mostly depends on the positive impact created on students through interventions. Learning analytics interventions are mostly either teacher or student focused. The timely interventions can help teachers update their curriculum, support at-risk students, and review their pedagogical approaches, whereas student-focused interventions help the at-risk students reflect and self-regulate and access adequate support and environment to achieve their learning outcomes.

4.1 Types of Intervention

The concept of intervention has a long history; however, in the context of learning analytics, it is still a topic of research and investigation. It is hard to find relevant literature that focuses on intervention types that are particularly designed for learning analytics. Therefore, we have considered the three types of intervention proposed by Geller (2005), which are close to the educational context, namely, instructional, supportive, and motivational.

4.1.1 Instructional

Instructional interventions aim to get the students' attention and instruct them in their journey to achieve their learning outcomes. It assumes that a person is motivated and ready to accept the challenge/change. This type of intervention consists of activators such as education sessions, training exercises, and directive feedback, mainly focusing on helping the students internalise the instructions. As each student's circumstance is unique, instructional interventions are more effective when they are specific and given one-on-one basis.

4.1.2 Supportive

The supportive intervention aims to help students to continue their positive behaviour and ensures continuity. It focuses on students' positive outcomes and provides feedback and recognition to encourage them to continue the same path.

4.1.3 Motivational

The motivational intervention aims to change the behaviour of students by providing some external encouragement. When students know what to do but knowingly deviate from their path, then motivational intervention can help. In this situation, an incentive or reward program can encourage learners to continue certain behaviour by assuring them of a positive consequence if they perform better.

The success of an intervention depends on how carefully and efficiently we design it. The effective intervention has the potential to create a significant impact on both learning and teaching experiences. In the following section, different principles of intervention design as proposed by Wise (2014).

4.2 Principles of Effective Intervention Design

Learning analytics intervention design principles must address questions such as why intervention is required, whom it should address, when is the right time, and how it should be executed. Considering the above questions, Wise (2014) has highlighted four principles of pedagogical learning analytics intervention design, namely, integration, agency, reference frame, and dialogue.

4.2.1 Integration

The intervention design should always be supported by data and analytics. Integrating analytics as a part of intervention helps students understand pedagogical intent and directs them towards their learning outcomes. The choice of metrics for intervention should be fit for purpose. Moreover, the instructor should identify beforehand what possible consequences of these metrics are expected. There are two additional elements, 'grounding' and 'goal setting and reflection', that form a part of the integration. Grounding helps students understand the logic of connections between analytics and intervention processes and make sense of analytics and how goals, action, and feedback are linked together. Meanwhile, goal setting and reflection provide the context and purpose of using the analytics into their learning processes, scale and set their goals, and self-reflect and self-regulate in the process.

4.2.2 Agency

The 'agency' principle endorses interventions as a positive agent to empower students to self-regulate and achieve their learning outcomes. Instructors should be mindful that the interventions do not cause distraction and stress on the students. In addition, the agency should promote goal setting and reflection to the students.

4.2.3 Reference Frame

The reference frame principle describes the comparison point to which students compare their current analytics. A good comparison point is essential, as the main motive of interventions is to guide students to self-regulate by reflecting on where they stand in terms of their goals or as compared to the same cohort of students. A reference point can be a productive activity set by an instructor. Student's prior activity can also be used as a reference point for comparison, or aggregate information of other students that belongs to the same cohort would be a good reference point for a student to evaluate their current position. Special care should be taken to ensure the student understands that the reference point is to improve their productivity rather than cause a detrimental competitive mentality.

4.2.4 Dialogue

Dialogue serves as a platform for negotiation for both instructors and students and discusses analytics. A dialogue backed by analytics focuses on students' self-reflection of their previous activities, empowering them to set their own goals and reference points and support and engage them in the process. This process helps instructors assess the individual student's circumstances, which they may not be aware of. It provides an opportunity to examine student's goal setting and analytics and provides support as deemed necessary. Moreover, the dialogic space provides a friendly environment for students to ask for help and the instructor to provide feedback and strategies. As the student-to-instructor ratio rises, the dialogue process becomes progressively more difficult; hence, the alternative approach to one-on-one (student-teacher) interaction should be adopted.

In conclusion, all these four principles are not independent and can impact the other if not carefully designed. For example, integration encapsulates all other principles, as analytics serves as the heart of intervention design. Simultaneously, the process of reflection links back to goals, utilises a reference frame for comparison, and is communicated with the instructor as part of a dialogue, etc. Hence, proper attention should be undertaken while designing an intervention to positively impact teaching and learning.

5 Case Studies

As described in Sects. 3 and 4, in the context of the effective dashboard and intervention design, data and analytics are the core, and they drive other principles; however, there are many challenges in modelling student data.

A significant effort must be applied when collating and consolidating the data sources. For example, student data within a university is managed by different units/departments and, in most cases, does not share the same databases for storage. The presence of various technologies (Oracle, SQL Server, Postgres) can potentially segment data sources. Additionally, it is also expected that a substantial proportion of valuable data resides in flat files (CSV, Excel, text), and as a result, significant effort must be applied when collating and consolidating the data sources.

Sensitive student data such as socioeconomic status (SES), non-English-speaking background (NESB), disability status, marital status, etc. can be crucial to the model. However, these sensitive data are confidential and are not readily available as students are reluctant to disclose this information. Additional care must be taken to ensure the confidentiality of the data sources when dealing with sensitive data.

In the case of a commencing student, previous historical academic data will naturally be absent, and therefore, only subsets of data/variables are available for analysis. Considering both commencing and returning students as a single entity can potentially mislead the analysis and impact its diagnostic performance.

In many programs, students can choose to withdraw from their program earlier than the originally allotted duration giving the option to receive the diploma equivalent of their respective program upon exiting. The reason for withdrawal captured in the database could cover many conditions, many of which are related to factors not captured in the institution's databases and do not qualify as a predictable classifier, e.g. illness. This introduces the problem of classifying the student as either a graduate or drop out. It is also expected that students transfer between programs, schools, and universities. When students transfer, they carry additional information with respect to the continuing students in the same cohorts. Hence, the integration of these student's attributes for analysis is complex.

Due to the diverse nature of courses and students in universities, quantifying variables is challenging. For example, course awards can be separated into two types – a competency module (i.e. pass or fail) and a relative scale (1 to 4) or percentile (1–100). Additionally, students can have varying enrolment statuses such as full time or part time and so on. Hence, quantifying and aggregating course and student variables to the program or university level can be very time-consuming in the initial development of creating usable datasets.

Considering all these data complexities, two use cases of a learning analytics dashboard are presented in the following section. 'Early warning signs' (EWS) is designed to act as catalyst or analytics for instructors and program managers for one-on-one intervention to support at-risk students, and 'constellation' helps program coordinators and curriculum designers to access program insights quickly and compare expected and observed behaviour of curriculum design. Authors do not claim that these use cases are the most ideal dashboard design practices; however, most of the recommendations proposed in the literature are incorporated in them. These use cases also reflect how the learning and teaching community is gradually progressing towards using the power of data, analytics, and visualisation to support students.

5.1 Early Warning Signs

Identifying students at risk of attrition as early as possible is desirable at several levels in a university, and doing so reduces the financial penalty for students and increases retention rates. Predicting student attrition is complex as it does depend not only on learning and teaching factors but also on social, behavioural, contextual, and economic factors. Student attrition prediction can be at a course level (i.e. course dropout), program/degree level, or university level. Predicting attrition at the course and program levels is more accurate and reliable as students share most of the teaching and learning resources. In contrast, due to the diverse nature of courses and programs across an institution, aggregating the data to the university level makes the prediction process challenging.

EWS is one of the effective dashboards at RMIT that identifies students at risk of attrition and triggers effective interventions to support these students and maximise the effectiveness of retention programs. It uses machine learning (ML) models to learn from historical student data and predict attrition on-demand at several points during the semester. Four different machine learning algorithms (logic regression classifier, random forest classifier, gradient boosting classifier, and AdaBoost classifier (Pedregosa et al., 2011)) are trained simultaneously, and their performance is measured using unseen (test) data. The best performing algorithm is then selected and used as a prediction algorithm for predicting future student attrition.

5.1.1 Prediction System

Figure 5.2 shows the attrition prediction system. The attrition prediction system building process consists of mainly three steps:

- Collecting and aggregating data from different sources
- Performing ETL (extract, transform, and load)
- Applying machine learning (i.e. feature selection, hyper-parameter tuning, and model training and selection)

The prediction system collects and aggregates data from the Student Information System (SIS), Learning Management System (LMS), and other sources (that includes equity and diversity, demographics, well-being, admissions and scholarships, etc.). The data come in different shapes and sizes, hence requires intensive data wrangling and pre-processing (ETL) to create a train and test dataset. Four

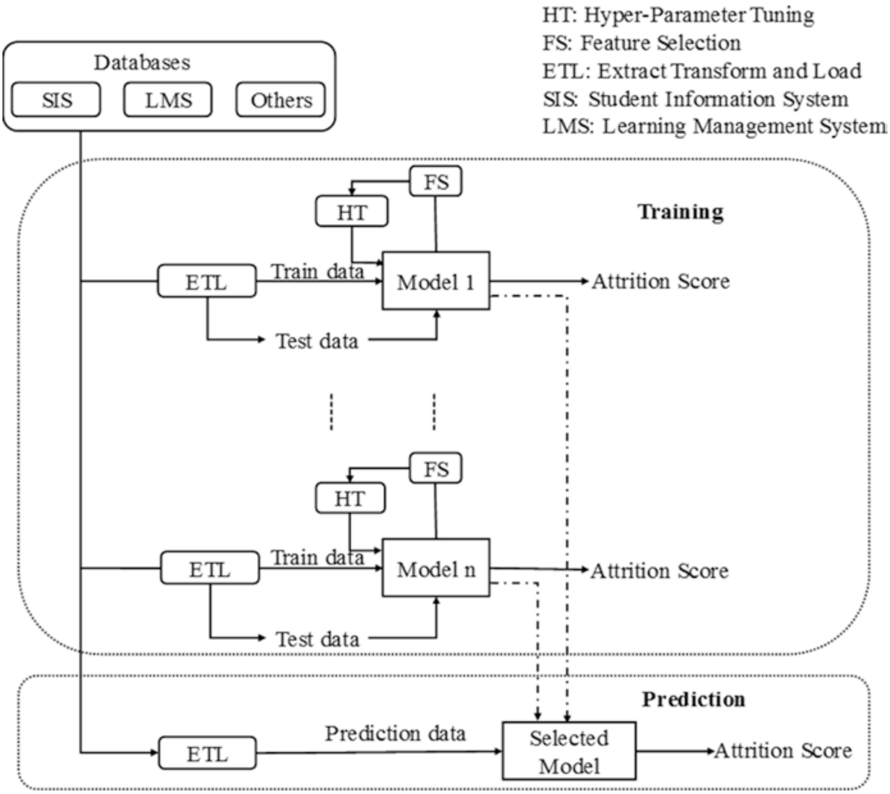


Fig. 5.2 Students' attrition prediction system

different machine learning algorithms were trained for our purpose which are logistic regression classifier, random forest classifier, gradient boosting classifier, and ada-boosting classifier that involved varying processes such as feature selection, hyper-parameter tuning, and model training and selection.

A brief description of these four machine learning algorithms (Cheng, 2019; Hilbe, 2015) used in EWS model is as follows:

a. Logistic regression classifier (LR): It is a regression technique used when the dependent variable is binary. It provides the relationship between a dependent binary variable and one or more independent variables.
b. Random forest classifier (RF): It is an ensemble learning method. It operates by creating multiple decision trees and merges them to produce more stable and accurate predictions.
c. Gradient boosting classifier (GB): It is an ensemble learning method. It also creates multiple trees like RF; however, RF creates each tree independently, whereas GB builds trees one at a time, and each new tree corrects errors made by the previously trained tree.

d. Ada-boosting classifier (AB): It is an ensemble learning method. It is similar to GB; however, it puts more weight on misclassified samples and less weight on correctly classified samples when creating new learners.

The system is modular enough to add new algorithms as required. Commencing and returning student cohorts were trained separately. The system is automated in such a way that the different models can be trained concurrently, and predictions can be produced on demand at different snapshot of time using the selected model (the one with highest performance).

Despite challenges in student data as previously discussed, 63 unique features for returning and 49 different features for commencing cohorts were selected, and after performing feature selection, 35 features were used to train the ML models. The best performing model was selected and used to predict the probability of attrition for each student, which was labelled into three groups: low, moderate, and high, as shown in the following Table 5.2.

If a student has a low score, there is no risk of attrition; if they have a high score, there is a high risk of attrition and a need for intervention and support, whereas a moderate score indicates they are not likely to attrite but requires monitoring and motivation.

F-measure is used for measuring model performance. F-measure is the weighted harmonic mean of precision and recall and is best suited for measuring model performance with imbalance classes (Estabrooks et al., 2001). Out of four different models, random forest classifier outperformed and was selected for further analysis, and the F-measure values of these four classifiers are listed in the Table 5.3.

Moreover, to assist the intervention process, the EWS dashboard was created that provides the necessary context, data, and analytics of students. The EWS dashboard dataset is updated daily to help instructors and program managers track their student's outcomes and act early as possible.

5.1.2 EWS Dashboard

EWS dashboard contains information at the program and student level. It is built using the Microsoft Power BI platform (Power BI Platform, 2021). Table 5.4 provides all the metrics used in the EWS dashboard along with their definitions.

(i) Program Level

The program-level information provides information aggregated at the program level. It provides information such as a total number of students at high risk,

Table 5.2 Attrition prediction probability classified into EWS score

Probability of attrition	EWS score
0–0.5	Low
0.5–0.75	Moderate
0.75–1	High

Table 5.3 Model accuracy using F-measure score

Classifiers	Commencing	Returning
Logistic regression	0.89	0.88
Random forest	0.93	0.94
Ada-boosting	0.90	0.90
Gradient-boosting	0.92	0.90

Table 5.4 Metrics used in the EWS dashboard along with their definitions

Metric	**Definition**
Academic load	Full time is 0.5 EFTSL or higher. N is an unknown enrolment type
Age	Age of student at the time of the data extract
Birth country	Country of birth as declared by the student
Disability	Self-declared disability identification
Employment status	Employment status self-declared by the student during the enrolment period
Enrolment count	Number of students with an active status enrolled in the program
EWS score	Program breakdown by early warning signs score, i.e. probability of attrition for each student, which is labelled into three groups: low, medium, and high
Indigenous	Students identifying as aboriginal or Torres Strait Islander
International/ domestic	Based on citizenship status, domestic and international students are classified
NESB	Self-declared non-English-speaking background status
Returning/ commencing	Commencing students are first-term enrolments for the program
SNAP	Students granted an offer via schools network access program
iExplorer	Link to student details (contains students' academic outcomes)
Canvas course lag	The number of courses student is lagging with respect to the mode of all other students in a program
Enrolled courses	Student number of course enrolments
Prev GPA	Students GPA in the previous semester
EFTSL	Effective full-time student load
Credit transfer	Student total number of credit transfer
Email	Link to the mail server to send email to individual student when necessary

enrolment count, indigenous student count, count of students that need support (disability), and count of students that enrolled through SNAP programs, along with distribution of students across EWS score, gender, age, birth country, course submission lag, academic load, returning and commencing status, and international/ domestic status at the program level. The following information helps program managers to get easy access to their program performance and demographics. The EWS dashboard program level data is shown in Fig. 5.3.

(ii) Student Level

The student-level information provides information of each student in a program. It provides information such as student identifier, first name, last name, EWS

Fig. 5.3 EWS dashboard with program-level information

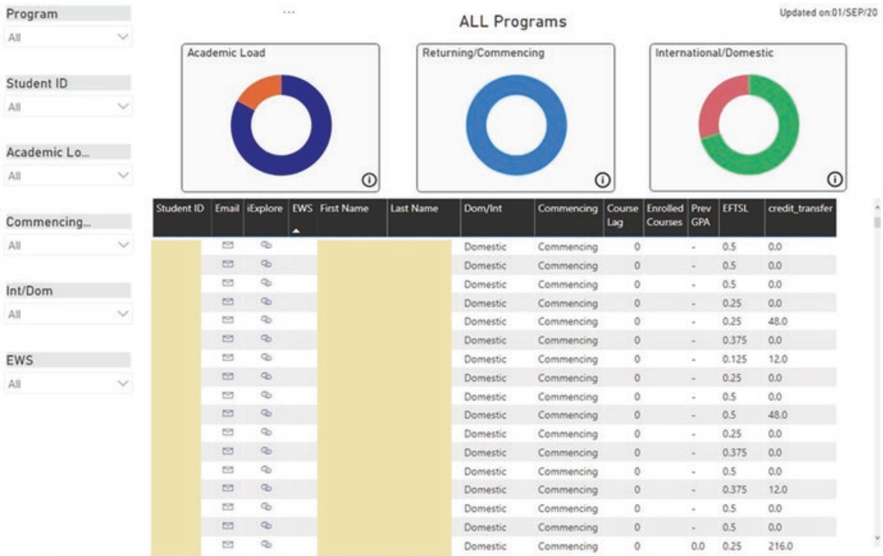


Fig. 5.4 EWS dashboard with student-level information

score, iExplorer link, domestic/international status, commencing/returning status, course lag, enrolled courses, previous semester GPA, EFTSL, and credit transfer. At this level, instructions can filter students at risk and track their academic performances to plan interventions one on one. The EWS dashboard student-level data is illustrated in Fig. 5.4.

The EWS dashboard information provides enough context and analytics about students that help program managers plan and act as required.

5.1.3 Interventions

As the EWS was built by the central learning analytics team, the primary challenge was to bring all program managers together and ensure that they buy-in. The program managers were assured that EWS was not yet another KPI-driven project accompanied by additional workload and scrutiny; moreover, it was designed solely to provide them with the most added value in assisting their existing activities to support students.

EWS dashboard is updated daily, and 'row-level security' (Power BI, 2021) was implemented so that a program manager can only view their corresponding cohort of students. In each update, student data changes so do the EWS model and the output. The early EWS prediction output, before the semester starts, allows program managers to act as early as possible to address potentially risk students, whether due to poor prior academic performance, return from LOA (leave of absence), or flagged enrolment activity. Later EWS output, after the class starts, includes student engagement metrics that help program managers target students who begin to struggle in the semester despite good historical academic outcomes. The feedback from program managers indicated that EWS scores alongside the student-level contextual information provided were very helpful and the dataset empowered them to quickly filter and identify at-risk students allowing them to target a smaller cohort. Some of the interventions include:

- One-on-one interaction between a program manager and a student
- Assisted a peer mentoring program where an academically sound senior or a friend will help the student at risk
- Initiated various hardship scholarship programs
- Initiated different support mechanisms to help different equity groups

Some of the limitations and recommendation for EWS include the following:

(a) Attrition is generally considered bad since both university and student lose time and money; however, not all attrition is bad. Suppose a student has health issues, difficulties balancing study and family, or is no longer interested in the degree, in that case, the best choice may be to leave; hence it is not always possible to differentiate between good or bad attrition.
(b) Predictive models are trained on normal human/student behaviour; however, when that normal behaviour is changed (e.g. due to COVID-19), some machine learning algorithms are no longer working as they should and requires retraining.
(c) Current attrition model lacks student assignment and attendance data, which will be incorporated in the future iterations.

5.2 Constellation

The program design is a challenging and iterative process. In an effective program design, the curriculum should be designed with the selection of core and elective courses so that it is aligned with student's acquirement of information and maturity developing with the required skillsets. It is also essential to quickly access the program insights and compare expected and observed behaviour of curriculum design. To address the challenge, a network graph-based visualisation tool is designed for visualising the live student traffic across courses associated with a program. It helps to understand course co-enrolment and the association between courses in a semester and among semesters and measures different student metrics to compare program design effectively. Hence, the constellation is designed keeping teacher-focused (program manager) intervention in mind, where teachers can analyse their program insights and improve its design and performance.

5.2.1 Fruchterman-Reingold (FR) Algorithm

The Fruchterman-Reingold (FR) algorithm (Fruchterman & Reingold, 1991) is based on a forced-directed algorithm. FR algorithm is inspired by the mechanical model proposed by Eades (Eades, 1984). A steel ring represents each node in the graph, and the edge (connection) between them is represented by a spring. Initially, the nodes are placed in a specific layout and let go, whereby the spring force between the nodes tends to bring them together, and the repulsive electric force separates them farther apart. The sum of these forces determines the direction of node movement. In each iteration, the system's energy is re-calculated by moving the nodes and changing the force between them unless the system reaches an equilibrium state. In the equilibrium state, the system's energy is minimum, and the nodes are in a stationary state.

The distance between the nodes is inversely proportional to the repulsive force; the repulsive force will gradually increase with the decrease in distance between the nodes that avoid the nodes' overlapping. On the other hand, the attractive force is proportional to the weight of the edge and square of the distance between nodes so that two nodes connected by the same edge will not be too far away from each other due to repulsion. In addition, the nodes connected with larger weights have a smaller distance between them than the nodes with smaller weights.

5.2.2 Constellation Visualisation

'Constellation' is a network graph-based visualisation tool that helps program coordinators and curriculum designers access program insights quickly and compare expected and observed behaviour of curriculum design. It captures the student co-enrolment in a program, as shown in Fig. 5.5. A Fruchterman-Reingold (FR)

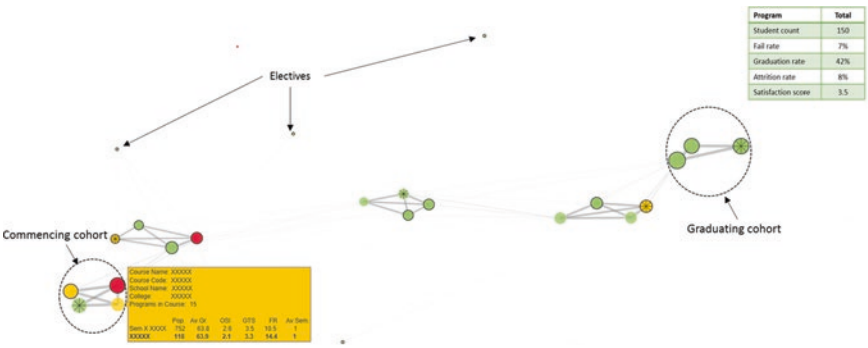


Fig. 5.5 Sample constellation of a program

Table 5.5 Course performance parameters

Performance parameters (course node)	Definition
Population (pop)	The total coursework population
Average grade (Av. gr.)	The average grade of all the coursework students
Overall satisfaction index (OSI)	The average OSI score of all the coursework students
Graduate teaching score (GTS)	The average GTS score of all the coursework students
Fail rate (FR)	The proportion of coursework students who failed
Average semester (av. sem.)	The average semester of all the coursework students
Programs in course	The distinct number of programs from where the coursework students belong

algorithm (Fruchterman & Reingold, 1991) is selected as a graph drawing algorithm. The student's course co-enrolment is represented using an undirected graph where the nodes are courses, and the edges between them represent the co-enrolment. Each node contains a course identifier and its performance parameters. A node is identified by the course name, course code, and school and college name, and the different performance parameters considered are population, average grade, mean overall satisfaction index (OSI), mean graduate teaching score (GTS), fail rate, and average semester. The size of the node represents the course population, and its colour represents the failure rate. The higher the student population, the bigger the node size. Similarly, the thickness of an edge represents a co-enrolment population. The higher the co-enrolment population, the thicker the edge.

The course performance parameters are categorised into two levels: program level and semester level, and this allows us to compare the course performance within a program and a semester as presented in Table 5.5. The program name is encrypted in the figure and represented by XXXXX, and the semester level information is represented by Sem X XXXXX. In addition to course performance parameters, the overall program performance parameter is also presented in Table 5.6.

Figure 5.5 presents the sample constellation of a structured program (structured program has a fixed set of core courses each year); hence there is a distinct pathway

Table 5.6 Program performance parameters

Performance parameters (overall program)	Definition
Student count	The total students in the population
Fail rate (FR)	The proportion of program students who failed in at least one coursework
Graduation rate	The proportion of final year students who graduated
Attrition rate	The proportion of students that left/drop from the program
Satisfaction score	The average OSI score of all the courses

of course selection each year, which is visible in the constellation as a distinct cluster of courses. Students' enrolment and co-enrolments between core courses are larger; hence the graph algorithm binds them together into distinct clusters (i.e. commencing, graduating with middle year student's cohort). In contrast, the enrolment and co-enrolment in elective courses are comparatively smaller; hence these courses are smaller in size and are scattered around the graph. In an unstructured program where there are no distinct core and elective courses, these clusters are not visible.

Each year the structure of a program might change due to students' enrolment, the number of courses offered, changes in core and elective courses, and many more. From a program manager's perspective, it is essential to understand the program's co-enrolments and performance in a given year and over different years. Hence, constellation offers them the possibility to view the snapshot of their overall program's performance at any given snapshot of a time.

5.2.3 Intervention

The response obtained from program managers is positive and has proved useful in identifying bottleneck courses, core and elective courses, and the overall performance of courses and a program. Some of the interventions through constellation include:

- Trigger to initiate discussions and reflection among program managers to review their program and its design.
- Yearly program review where constellation provides valuable insight.
- Identify the courses that are lacking behind and initiate action to support them.
- Course performance parameters such as GTS and OSI provided teachers the reflection of their overall teaching practices and take necessary action to improve their course material and teaching style.

Despite mostly positive comments from program managers, some of the recommendations/limitations highlighted include:

(a) Visualisations were presented in an html file using Plotly graphs (Plotly Technologies Inc., 2015); hence it lacked interactivity as other software tools provides (Power BI, Tableau).

(b) Constellations were generated at a given snapshot of time (i.e. temporal view); program managers were keen to see if longitudinal views of program journey (one semester to another) can be produced in a single constellation graph.
(c) Add soft and hard skill tags (certifications, internships, trainings) to understand where in the learning journey students are being up skilled.

6 Conclusion

The chapter recommends some of the best practices of dashboard and intervention design principles. It advocates how these dashboards can be crucial to trigger standard interventions. The dashboard should be designed considering the end users' perspective and should be clear, simple, and fit for purpose. Special care should be taken to ensure dashboards and visualisations do not inundate educators and students with data and introduce additional workloads. Dashboards and interventions should be the saviour for students and educators rather than a platform to critic their performance. It also recommends that dashboards should be driven by data and facts and highlights the challenges in collecting and modelling student data at a large scale.

The chapter also presents two use cases of LA dashboard/visualisation that are implemented at a large scale in one of the renowned universities in Australia (RMIT). Both of these use cases show the practical aspect of dashboard and intervention design and how they can support students and teachers.

Firstly, EWS focuses on supporting the students at risk and visualises EWS scores along with the program- and student-level information. EWS dashboard implementation highlights learning analytics processes by monitoring student activities, predicting students' behaviour, and intervening when necessary by providing intelligent feedback and support to improve the student experience and learning outcomes.

Secondly, constellation reviews program design, visualises courses and program relationships, and analyses the program's performance. Constellation visualisation can help educators identify key information about programs and courses with ease, fulfil their analytical gaps, and make intelligent decisions timely, which will accelerate the teaching and learning quality in practice.

Our future recommendation is to focus on improving these dashboards and to study the impact of the dashboards. There has been limited research on combining dashboard and intervention design in higher education. The use cases presented in this chapter monitor students' performance; however, it lacks monitoring intervention processes and tracking (or comparing) the students' performance, emotions, and behaviour before and after the intervention. Further research is needed on how to best integrate these dashboards and intervention design principles, for example, implementation of EWS dashboard into the classroom experience. Authors would consider integrating dashboard and intervention design and presenting it in a single dashboard that tracks the overall student journey.

References

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers and Education, 58*(1), 470–489.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In S. Dawson, C. Haythornthwaite, S. Buckingham Shum, D. Gasevic, & R. Ferguson (Eds.), *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270). ACM. https://doi.org/10.1145/2330601.2330666

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418. https://doi.org/10.1109/TLT.2017.2740172

Borden, P. (2015). *The 5 principles of great dashboard design*. Retrieved from http://blog.sumall.com/journal/Z-principles-great-dashboard-design.html.

Cheng, L., (2019). *Basic ensemble learning (Random Forest, AdaBoost, Gradient Boosting)- Step by step explained*, Retrieved from https://towardsdatascience.com/basic-ensemble-learning-random-forest-adaboost-gradient-boosting-step-by-step-explained-95d49d1e2725

Dawson, S., Bakharia, A., & Heathcote, E. (2010). SNAPP: Realising the affordances of real-time SNA within networked learning environments. In L. Dirckinck-Holmfeld, V. Hodgson, C. Jones, M. de Laat, D. McConnell, & T. Ryberg (Eds.), *Proceedings of the 7th international conference on networked learning* (pp. 125–133). University of Lancaster.

Dick, W., Carey, L., & Carey, J. O. (2005). *The systematic design of instruction* (6th ed.). Pearson/Allyn and Bacon.

Dipace, A., Fazlagic, B., & Minerva, T. (2019). The Design of a Learning Analytics Dashboard: EduOpen Mooc platform redefinition procedures. Journal of E-Learning and Knowledge Society, 15(3), 29–47. https://doi.org/10.20368/1971-8829/1135044.

Durall, E., Gros, B. (2014). Learning analytics as a metacognitive tool. *CSEDU: Sixth Annual Conference on Computer Supported Education, 1*, 380–384.

Eades, P. (1984). A heuristic for graph drawing. *Congressus Numerantium, 42*(11), 149–160.

Estabrooks, A. and Japkowicz, N. (2001). A mixture-of-experts framework for learning from imbalanced data sets. In International Symposium on Intelligent Data Analysis, Springer, Berlin, Heidelberg pp. 34–43.

EXCELINXL. (2020). *Effective dashboard design principles for best practices,* Retrieved from https://excelinexcel.in/ms-excel/articles/dashboard-design-principles/

Few, S. (2006). *Information dashboard design, The effective visual communication of data*. O'Reilly Media.

Few, S. (2013). *Information dashboard design: Displaying data for at-a-glance monitoring*. Analytics Press.

Fruchterman, T., & Reingold, E. (1991). Graph drawing by force-directed placement. *Software Practice and Experience, 21*, 1129–1164. https://doi.org/10.1002/spe.4380211102

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education, 28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice, 3*(1), 63–78.

Geller, E. S. (2005). Behavior-based safety and occupational risk management. *Behavior Modification, 29*(3), 539–561.

Grelle, W. and Drachsler, H. (2012). Translating Learning into Numbers: A Generic Framework for Learning Analytics, *Educational Technology & Society, 15*(3), 42–57.

Govaerts, S., Verbert, K., Duval, E., & Pardo, A. (2012). The student activity meter for aware- ness and self-reflection. In *Proceedings of the 2012 ACM annual conference on human factors in computing systems extended abstracts* (pp. 869–884). ACM.

Gustafson, K. L., & Branch, R. M. (2002). *Survey of instructional development models* (4th ed.). ERIC Clearinghouse on Information and Technology.

Hilbe, J. M. (2015). *Practical guide to logistic regression* (1st ed.). CRC Press LLC.

Jaakonmäki, R., et al. (2020). Understanding student-driven learning processes. In *Learning analytics cookbook* (SpringerBriefs in Business Process Management). Springer. https://doi.org/10.1007/978-3-030-43377-2_4

Janes, A., Sillitti, A., & Succi, G. (2013). Effective dashboard design. *Cutter IT Journal, 26*.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open-source analytics initiative. *Journal of Learning Analytics, 1*(1), 6–47. https://doi.org/10.18608/jla.2014.11.3

Jovanovic, J., Gasevic, D., Dawson, S., Pardo, A., and Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom, *Internet and Higher Education, 33*, 4–85.

Jin, S., & Yu, M. (2015). Analysis of trends in learning analytics-based dashboard research in e-learning environments. *Journal of Educational Information Media, 21*(2), 185–213.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, M. Pérez-Sanagustín (Eds.), Data Driven Approaches in Digital Education: Proceedings of the 12th European Conference on Technology Enhanced Learning (EC-TEL 2017), 12–15 September 2017, Tallinn, Estonia, pp. 82–96.

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). A learning management system-based early warning system for academic advising in undergraduate engineering. In J. A. Larusson & B. White (Eds.), *Learning analytics* (pp. 103–119). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4614-3305-7_6

Kwapien, A. (2016). *10 Dashboard design principles that will make your data analysis worth the effort*. Retrieved from http://www.datapine.com/blog/dashboard-design-principles- and-best-practices/.

Lechner, B., & Fruhling, A. (2014). *Towards public health dashboard design guidelines*. Paper presented at the HCI International 2014.

Leony, D., Pardo, A., de la Fuente Valentín, L., Sánchez de Castro, D., & Delgado Kloos, C. (2012). GLASS: A learning analytics visualisation tool. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), *Proceedings of the 2nd international conference on learning analytics and knowledge LAK '12* (pp. 162–163). ACM.

Levy, E. (2017). *4 Design principles for creating better dashboards*. Retrieved from https://www.sisense.com/blog/V-design-principles-creating-better-dashboards/.

Matcha, W., Ahmad, U. N., Gasevic, D., Pardo, A. (2019). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective, In: *IEEE Transactions on Learning Technologies*, pp ?

Mazza, R., & Dimitrova, V. (2007). CourseVis: a graphical student monitoring tool for supporting instructors in webbased distance courses. *International Journal of Human-Computer Studies*, *65*(2), 125–139.

Papamitsiou, Z., & Economides, A. A. (2016). Learning analytics for smart learning environments: A metaanalysis of empirical research results from 2009 to 2015. *Learning, Design, and Technology.* https://doi.org/10.1007/978-3-319-17727-4_15-1

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … others. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*(Oct), 2825–2830.

Plotly Technologies Inc. (2015). Collaborative data science. . https://plot.ly.

Power BI. (2021). *Row-level security (RLS) with Power BI*, Retrieved from https://docs.microsoft.com/en-us/power-bi/admin/service-admin-rls

Power BI Platform. (2021). Retrieved from https://powerbi.microsoft.com/en-us/

Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications, 33*(1), 135–146.

Salesforce. (2013, December 18). *The nine principles of killer dashboards*. Retrieved from http://www.slideshare.net/Salesforce/the-nine-principles-of-killer-dashboards/

Sedrakyan, G, Järvelä, S, Kirschner, P. (2016). Conceptual framework for feedback automation and personalisation for designing LADs. In: *Proceedings of the conference on online measures of learning processes*, EARLI SIG 27, 2016.

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualisations: Linking dashboard design and data visualisation concepts. *Journal of Computer Languages, 50*, 19–38.

Todorović, D. (2007). W. Metzger: Laws of seeing. *Gestalt Theory, 28*, 176–180.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509.

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In *Proceedings of LAK 2014* (pp. 203–211). Association of Computer Machinery.

Yoo, Y., Lee, H., Jo, I.-H., Park, Y. (2015) Educational dashboards for smart learning: Review of case studies. In: Chen, G., Kumar, V., Kinshuk, Huang, R., Kong, S.C., et al. (eds.) *Emerging Issues in Smart Learning*. LNET, pp. 145–155. Springer, . doi: https://doi.org/10.1007/978-3-662-44188-6_21.

Chapter 6
What Do MOOC Dashboards Present to Learners?

An Analysis from a Community of Inquiry Perspective

Wenting Sun, Clara Schumacher, Li Chen, and Niels Pinkwart

1 Introduction

The development of Massive Open Online Courses (MOOCs) enabled the possibility for offering teaching and learning resources of educational institutions to learners at large-scale online. As MOOCs are facilitated through digital learning environments, learners' digital traces can be tracked and logged. These methods are associated with learning analytics as they use static and dynamic information about learners and learning environments, assessing, eliciting, and analyzing them for real-time modeling, prediction, and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). However, to support learners, learning analytics need to offer feedback on learning processes and outcomes as well as meaningful recommendations (Schumacher, 2020). Learning analytics feedback is predominantly offered via learning dashboards (Vieira et al., 2018). Dashboards that report the interactions between learners and their online learning environment in a meaningful way are considered to enhance self-regulated learning (Bodily et al., 2018), as they help learners to get an overview and reflect on their activities, which means that learners are provided more support to change their learning behavior accordingly (Jivet et al., 2018).

W. Sun (✉) · C. Schumacher · N. Pinkwart
Humboldt-Universität zu Berlin, Berlin, Germany
e-mail: sunwenti@informatik.hu-berlin.de; clara.schumacher@hu-berlin.de; niels.pinkwart@hu-berlin.de

L. Chen
University of Mannheim, Mannheim, Germany
e-mail: lcheb@mail.uni-mannheim.de

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_6

However, learning analytics feedback (and thus dashboards) still faces the issue of providing feedback on outcomes (instead of on learning processes) that enable learners to derive actionable knowledge for optimizing their learning (Sedrakyan et al., 2020). In addition, the design and evaluation of learning dashboards call for more guidance from learning sciences (Jivet et al., 2018; Verbert et al., 2020). As a well-known model in online education, the Community of Inquiry (CoI) model aims at supporting deep and meaningful learning experiences through the design of learning environments referring to a collaborative constructivist approach (Akyol & Garrison, 2011b). Considering reflective communication as the essential of learning experience, CoI has the potential to provide guidance for online course design and pedagogy (Kaul et al., 2018).

Technological pedagogical content knowledge (TPCK) and self-regulation learning theories have also been considered for analyzing dashboards in MOOCs. But considering the recording and presentation of learners' personal learning processes and a large number of interactions between learners, the CoI model (teaching presence, cognitive presence, and social presence) seems more suitable for analyzing MOOC dashboards. This chapter is structured as follows: the theoretical background on MOOCs, learning dashboards, and the CoI model are introduced, and research questions are derived in Sect. 2. The selected MOOCs, the coding scheme, and the analysis procedure are described in Sect. 3. Results for each research question are presented in Sect. 4, and finally discussion and conclusion are offered in Sect. 5.

2 Background

2.1 Massive Open Online Courses

It is generally assumed that the term MOOCs originated in 2008 and became a buzzword in 2012 (Daniel, 2013; Liyanagunawardena et al., 2013). At the time of writing, the COVID-19 pandemic led to the unprecedented online learning and teaching, which has increased educators' and learners' experience in distance education (Muhazir et al., 2020). Regarding MOOCs, two types are distinguished (Kesim & Altinpulluk, 2015): (1) cMOOCs which are related to Siemens' (2009) theoretical approach of connectivism, emphasizing social learning in a network to create knowledge as well as participants' own responsibility for learning instead of formal assessments, and (2) xMOOCs which are content-driven courses combining videos, assignments, and related supporting materials that learners can work with in their own pace. Although cMOOCs appeared earlier, most MOOCs that were offered in the recent years are xMOOC provided via platforms such as Coursera or EdX (Kesim & Altinpulluk, 2015). Video lectures, reading materials, quizzes, assignments, exams, and discussion forums are commonly included in xMOOC courses, thus resembling university courses (Nkuyubwatsi, 2013). The fundamental characteristics of MOOCs are being free and open to anyone with internet access, participatory, and distributed over social learning environments (Baturay, 2015). MOOC platforms are associated to elite higher education institutions, for instance, Coursera was founded by professors from Stanford University, EdX is the platform of Harvard and the MIT, and FutureLearn is owned by the Open University UK (Baturay, 2015). The two main platforms for MOOCs in China are iCourse owned by the publisher Higher Education Press of the Chinese Educational Ministry and an internet company, plus XuetangX, which are organized by Tsinghua University.

Based on previous reviews on MOOCs, Deng et al. (2019) identified that related research focused on the identification of trends, participants' characteristics, understanding of learning behavior and outcomes, teaching activities, and experiences of the users while relationships between teaching and learning factors need to be investigated further. Due to being implemented fully online, MOOCs require the mutual interaction among learners, instructors, and peers online. However, compared with traditional face-to-face classes, online learning environments are less structured, and learners need more support for learning processes, whether in mastering content or in enhancing motivation (Bekele, 2010; Bodily et al., 2018). Less structured online learning environments are associated with difficulties in self-regulating learning (Broadbent & Poon, 2015), while self-regulated learning is a positive factor influencing learners' behavior in MOOCs (Kizilcec et al., 2017; Lee et al., 2019; Littlejohn et al., 2016). Further, the low completion rates of MOOCs are partly related to low level of self-regulated learning (Gütl et al., 2014; Kizilcec & Halawa, 2015; Yu et al., 2019). Thus, to improve completion rates of courses, Web 2.0 and serious games for course success (Aparicio et al., 2019), big data for dropout prediction (Liang et al., 2016), machine learning, and other technologies are introduced. Fostering participants' self-regulation is considered to be beneficial for accomplishing a MOOC (Jansen et al., 2020). Self-regulated learners set learning goals, plan, organize, perform, self-regulate, self-monitor, and self-evaluate their learning processes to achieve their learning goals (Pintrich, 2000). Providing personal feedback and visualization of learning behaviors, learning dashboards are considered to increase learners' engagement in terms of assignment submission and learners' success in terms of final grade (Davis et al., 2016). Also, dashboards in MOOCs are considered to support self-regulated learning (Lee et al., 2019).

Moreover, culture and subject might impact the design of MOOCs. For instance, cultural factors influence the development strategies of MOOCs (Schuwer et al., 2015). Social environmental factors, tradition, and social norms have an impact on learners' motivation to enroll in (de Barba et al., 2016) and the institutions' drivers for adopting MOOCs (Ma & Lee, 2018). Furthermore, subject features, learning, and teaching activities impact the design of MOOCs (Pilli & Admiraal, 2017). Thus, in this chapter culture and subject were regarded as factors influencing the design of dashboards.

2.2 Learning Dashboards

"A learning dashboard is a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann et al., 2017, p. 37). The predominant visualizations of learning dashboard include bar graphs, pie charts, table matrices, tag clouds, line charts, risk quadrants, scatter plots, win-loss charts, sociograms, timelines, signal lights, and wattle trees (Yoo et al., 2015). Data used for visualizations include learning artifacts produced by learners (e.g., posts, documents), social interaction (e.g., ratings, comments, messages), usage of learning resources (e.g., videos, texts), time spent on activities, performance in (self-)assessments (Verbert et al., 2014), and self-report data (Klerkx et al., 2017). By visualizing the results of educational data mining in a meaningful way, learning dashboards enable instructors and learners to reflect and regulate their behavior in online courses (Yoo et al., 2015). Thus, these visualizations of relevant data should have the capacity to support stakeholders in their decision-making processes (Broos et al., 2020) by augmenting human capabilities (Klerkx et al., 2017). However, such visualizations used to enhance learners' and teachers' understanding of the analyses are considered to be difficult to understand (Aguilar, 2018). And the focus of these visualizations is often limited to instructors instead of learners and use simple representations of resource usage instead of learning processes (Vieira et al., 2018). Actually, as Broos et al. (2020) emphasized, the focus should be on offering actionable feedback to learners through the dashboards instead of offering all visualizations that learning analytics can provide.

Research on learning dashboards is mostly undertaken in the context of higher education (Schwendimann et al., 2017). Research interests include investigating students' sense-making of the visualizations. For example, using a qualitative approach, Alabi and Hatala (2017) found that students did not follow the instructions on how to interpret the visualizations while resulting in incorrect assumptions and misunderstanding. Furthermore, they found that even having limited understanding of the visualizations, participants request further information about visualizations and the underlying algorithms (Alabi & Hatala, 2017). Similarly, Rohloff et al. (2019) found that participants in a MOOC were asking for additional explanations of the visualizations on the dashboard. In addition, the question of the impact of learning dashboards on learning processes and outcomes is of interest. In a quantitative study, Broos et al. (2020) found that the use of a learning dashboard (showing learners' study strategies and tips) was positively related to first-year students' average grade. Kim et al. (2016) found that students receiving a learning dashboard had higher final scores, whereas the frequency of dashboards usage had no significant effect. Moreover, Bodily et al. (2018) found that learning dashboards were seldomly used and thus have little impact on learning processes and outcomes. Due to contrasting findings, a literature review concluded that further research on the impact learning dashboards have on learning outcomes and behavior is required (Bodily & Verbert, 2017).

The scale of content and activity increases the possibility of large numbers of learners attending MOOCs and decreases the chance that instructors engage with individual learners (Kovanović et al., 2018; Ng & Widom, 2014). Self-determination in the beginning of the learning and indirect contact with instructors and peers during the learning process require learners' autonomy and self-regulation in MOOCs learning activities (Park et al., 2016). Self-regulated learning can be strengthened by creating a learning environment that guide learners' actions towards learning, which makes the underlying cognitive process recognizable and encourages improvement (Panadero, 2017). The visualization of learning activities displayed on learning dashboards can support the development of such an online learning environment within MOOCs. Moreover, such dashboards do not only aim at supporting learners but also instructors and learning designers by offering insights into students' activities and progress as well as usage of specific course materials (Dipace et al., 2019).

Research and reviews about learning analytics within MOOCs have already been conducted (Moissa et al., 2015) but are limited regarding analyzing learning dashboards. Rohloff et al. (2019) evaluated a redesigned MOOC dashboard for students and found high agreement on usability and usefulness of the dashboard. In addition, their participants considered that the dashboard supported their self-regulation through monitoring, reflection, and changing of learning behavior plus increasing their motivation for planning (Rohloff et al., 2019). For developing a new dashboard for EduOpen, Dipace et al. (2019) analyzed the student and instructor dashboards of three major platforms and found that learning dashboards visualized students' courses, their progress (Coursera, EdX) or achievements (FutureLearn), messages (Coursera), or discussions (EdX) (Dipace et al., 2019).

As depicted above, learning dashboards are associated with high hopes of supporting learning but are criticized for not sufficiently considering learning theory and not offering actionable feedback. Furthermore, implemented learning dashboards are lacking empirical evaluation (Schwendimann et al., 2017). Thus, to improve dashboards' support for online learning experience, this chapter uses the CoI model (teaching presence, cognitive presence, and social presence) to systematically analyze MOOCs and their related learning dashboards.

2.3 Community of Inquiry (CoI) Model

The Community of Inquiry (CoI) model aims at describing and evaluating the factors of collaborative and meaningful learning experience through inquiry-based learning process (Garrison et al., 2010; Kovanović et al., 2018). In this regard, the CoI model assumes that knowledge is constructed via discourse establishing a shared understanding in a community and recognizes the influence of the environment (Garrison, 2009). Generally, an online learning environment can be regarded as a community of inquiry if it contains three elements, cognitive presence, social presence, and teaching presence (Garrison et al., 1999), which are interdependent of each other and considering deep and meaningful learning as the core of the model (Akyol & Garrison, 2011b). Cognitive presence describes the process of inquiry with resolution as a summary of one cycle, and social presence refers to the interpersonal relationship in the learning community, while teaching presence leads the whole course process (Akyol & Garrison, 2011b). Those elements consist of different categories. (1) Cognitive presence consists of four phases, the triggering event for recognizing and defining the problem, the exploration of the problem via information and other perspectives, through integration in the discourse sense-making is achieved, and resolution includes the choice of the best ideas and to initiate another inquiry circle (Garrison et al., 2001). The essence of cognitive presence is purposeful reflection and discussion, while the understanding of learning goals facilitates the inquiry process (Garrison, 2009). (2) This requires social presence which develops gradually from open communication and group cohesion to affective affiliations (Garrison, 2009). (3) Teaching presence is shared by all participants of the course community, connecting with metacognition, and facilitates the completion of the inquiry process (Akyol & Garrison, 2011a). Teaching presence consists of design and organization (e.g., curriculum, tasks, timelines), facilitation of learning activities and appropriate guidance, as well as direct instruction (Damm, 2016).

As the CoI model has been developed for understanding the dynamics of online learning (Arbaugh et al., 2008), it serves as a foundation for conducting research in the area of MOOCs. The feasibility of the CoI model in MOOCs has been verified by empirical researchers. Damm (2016) verified the ability of the CoI model to measure the efficacy of MOOCs design and implementation through the engagement of learners in MOOCs. Kovanović et al. (2018) reported the reliability and validity of the CoI survey instrument in MOOCs. More importantly, the presence of the elements of the CoI model is related to successful MOOCs. Holstein and Cohen (2016) analyzed large numbers of student perceptions of MOOCs and found that the design of successful MOOCs is considering cognitive presence, social presence, and teaching presence. However, though the CoI model could describe some features of MOOCs, more efforts are needed to interpret elements of the online learning communities (Kaul et al., 2018).

As introduced above, learning dashboards are considered to help learners focusing on their individual learning process, especially self-regulated learning. Learning dashboards in MOOCs are rare (Rohloff et al., 2019), research analyzing learning dashboards using a theoretical framework is scarce (Jivet et al., 2018; Verbert et al., 2020), and MOOCs also call for learning theory foundation for further development (Schuwer et al., 2015). The more effectively learners identify the auxiliary effects of MOOCs' participants (including peer, instructors, platform designers, and learners' past learning trajectory), the more possibly learners improve their own learning paths appropriately. Thus, this chapter used the CoI model as theoretical foundation to explore the current situation of MOOCs and their learning dashboards.

2.4 Research Questions

Besides the theoretical foundation about MOOCs, learning dashboards, and the CoI model, two factors guided the research questions of this chapter, culture and course subject. Considering the availability of MOOCs and the background of the authors, two subjects (computer science and education) on English and Chinese MOOC platforms were selected. Thus, the following four research questions guided our research:

1. Which elements of the CoI model are included in the selected MOOCs?
2. Which elements of the CoI model are represented on the learning dashboards of the selected MOOCs?
3. Are there differences between MOOCs related to computer sciences and those in the domain of educational science?
4. Are there differences between MOOCs related to English MOOC platforms and those in Chinese MOOC platforms?

3 Methods

3.1 Description of the Selected MOOCs

The data for this qualitative analysis was collected from five different MOOC platforms, Coursera (English), FutureLearn (English), EdX (English), iCourse (Chinese), and XuetangX (Chinese). The focus was on courses of two subjects: education and computer science. From each subject, 2 courses were chosen on each platform, resulting in a total of 20 courses analyzed (see Table 6.1 for course details). The selection criteria for choosing the courses include high numbers of enrollment, no fees for registration and attention, high number of reviews, and a self-paced design. Numbers of enrollment of the chosen courses ranged from 5901 to 810,585 ($M = 175{,}211.2$; SD = 188,392.104). For education courses, numbers of enrollment ranged between 5901 and 266,452 ($M = 95{,}849.7$; SD = 91,561.645), and for computer science courses, enrollment rates were between 46,776 and 784,905 ($M = 254{,}572.7$; SD = 235,709.838).

3.2 Analysis Procedure and Coding Scheme

The transcript analysis method used in this chapter is called negotiated coding approach (Garrison et al., 2006). To analyze the current state of MOOC courses and learning dashboards from a Community of Inquiry perspective, the CoI model and

Table 6.1 Selected MOOC courses

Platform	Topic of course	Course code	Institution	Numbers of enrollment	Length of course	Effort	Level
Coursera (English)	Teach online	CE1	UNSW Sydney (Australia)	126,380	5 weeks	18 h/w	Introductory
	e-Learning ecologies: Innovative approaches to teaching and learning for the digital age	CE2	University of Illinois at Urbana-Champaign	28,097	4 weeks	19 h/w	Introductory
	Build a modern computer from first principles: from Nand to Tetris (project-centered course)	CC1	Hebrew University of Jerusalem	118,930	6 weeks	44 h/w	Introductory
	Algorithms, Part I	CC2	Princeton University	784,905	6 weeks	54 h/w	Intermediate
FutureLearn (English)	How to teach online: providing continuity for students	FE1	FutureLearn	91,753	4 weeks	2 h/w	Introductory
	Teach English online	FE2	Cambridge Assessment English	266,452	4 weeks	5 h/w	Introductory
	Computer programming for everyone	FC1	University of Leeds	72,891	2 weeks	2 h/w	Introductory
	Digital skills: artificial intelligence	FC2	Accenture	68,591	3 weeks	2 h/w	Introductory
EdX (English)	Introduction to data wise: a collaborative process to improve learning and teaching	EE1	Harvard University	119,674	10 weeks	1–2 h/w	Intermediate
	EdX101: overview of creating an EdX course	EE2	EdX	23,041	1 week	1–2 h/w	Introductory
	CS50's web programming with Python and JavaScript	EC1	Harvard University	810,585	7 weeks	10–30 h/w	Introductory
	Python basics for data science	EC2	IBM	272,526	5 weeks	2–5 h/w	Introductory

Platform	Topic of course	Course code	Institution	Numbers of enrollment	Length of course	Effort	Level
iCourse (Chinese)	Flipped classroom teaching method 1.5 (翻转课堂教学法1.5)	IE1	Peking University	251,630	8 weeks	3–8 h/w	Introductory
	Gamification teaching methods (游戏化教学法)	IE2	iCourse	10,808	8 weeks	3–5 h/w	Introductory
	Advanced C language programming (C语言程序设计进阶)	IC1	Zhejiang University	46,776	13 weeks	3–5 h/w	Intermediate
	University computer: introduction to computational thinking (大学计算机—计算思维导论)	IC2	Harbin Institute of Technology	383,420	17 weeks	3–5 h/w	Introductory
XuetangX (Chinese)	New classroom in the e-era: an introduction to online education(e时代的新课堂-在线教育概论)	XE1	Tsinghua University	34,761	1 semester	80 units total	Introductory
	Online teaching examples and analysis (在线教学课例与解析)	XE2	Tsinghua University	5901	Self-paced	61 units total	Introductory
	C++ language programming foundation(C++语言程序设计基础)	XC1	Tsinghua University	433,322	1 semester	253 units total	Introductory
	Design and analysis of algorithms (算法设计与分析)	XC2	Tsinghua University	59,203	1 semester	85 units total	Introductory

indicators needed to be adapted. Therefore, three experts in the field of education developed the first version of the CoI coding scheme based on the theory of the CoI model and instruments used in previous research. Besides the CoI framework survey instrument (Akyol & Garrison, 2008; Arbaugh et al., 2008; Damm, 2016), the codes for teaching presence were referring to research of Anderson et al. (2001). Research of Akyol and Garrison (2011b) served as the basis for developing the coding scheme for cognitive presence, and the codes related to social presence referred to research of Garrison et al. (1999). After the initial development of the coding scheme, the educational researchers used several MOOC courses and learning dashboard data to discuss and modify the coding scheme. Finally, a coding scheme suitable for MOOC courses and learning dashboards was achieved (see Table 6.2). Next, the researchers coded the 20 courses and related dashboards individually according to the coding scheme and later actively discussed the coding results to achieve the final coding results.

4 Results

In the following subsections, the findings related to each of the four research questions are presented. As every indicator has been found in the course design of the MOOCs in Sect. 4.1, detailed descriptions were given only for those 18 indicators with particular high or low occurrence (for further details on the results, see Appendix). Regarding the findings on learning dashboards (Sect. 4.2), all six indicators that were available on the analyzed dashboards were explained in detail. The results do not cover indicators that were marked as "UA" which means that the content was not accessible without paying a course fee or due to not being in the certificate application period. Furthermore, if platforms did not provide specific functionalities related to the indicators but participants showed related behavior, those indicators were coded as "P," which will also not be reported in the results section. For analyzing the difference between the two subjects of courses, only results will be described in detail (Sect. 4.3) where the indicators differ at least for three courses. Regarding the results on differences between English and Chinese MOOCs (Sect. 4.4), the ratio was used due to imbalanced number of courses, and only differences greater than 20% are reported.

4.1 Elements of the Community of Inquiry Model Represented in MOOC Courses

All indicators of the coding scheme were present in the sample of courses. However, some of the indicators (TP2e, TP3a, CP1b, CP4a, CP4b, CP4c, SP1a, SP3b) were only present in less than half of the courses, whereas other indicators could be found

Table 6.2 CoI coding scheme

Elements	Categories	Codes	Indicators
Teaching presence (TP)	Design and organization (TP1)	TP1a	Important course topics are shown
		TP1b	Important course goals are visualized
		TP1c	How to participate in course is introduced
		TP1d	Important deadlines are communicated (e.g., submissions; live sessions)
		TP1e	Netiquette is established
	Facilitation (TP2)	TP2a	Area of agreement and disagreement in course discussion is identified
		TP2b	Prompts for participating in course activities are shown
		TP2c	Related topics to encourage to explore new concepts are shown
		TP2d	Explanations of topics facilitate learning
		TP2e	Lessons/materials are designed in an encouraging way
		TP2f	Sequences of contents are sound
	Direct instruction (TP3)	TP3a	Feedback about learners' strength and weaknesses related to course goals is offered
		TP3b	Timely feedback is provided
		TP3c	Responding to technical concerns
		TP3d	The instructor is present (e.g., interaction, sufficient guidance of discussion to focus on course-relevant topics)
		TP3e	Learners' activities in platform can be overviewed by themselves
Cognitive presence (CP)	Triggering event (CP1)	CP1a	New course topics are shown
		CP1b	Problems are recognized by learners
		CP1c	Real-world problems or case studies related to course topics are offered
		CP1d	Assessments or exercises are offered to participants
	Exploration (CP2)	CP2a	Related external links are offered (e.g., current news)
		CP2b	Next learning activities or learning strategies are recommended (discussions and forum posts related to current topics or learner's knowledge are displayed)
		CP2c	Headlines of new discussions/forum posts
	Integration (CP3)	CP3a	Recommendations of materials or solution strategies to help understand new concepts or answering questions
		CP3b	Participants can and do exchange their perspectives on problems
		CP3c	Reflection on course topics and tasks is encouraged
	Resolution (CP4)	CP4a	Solutions to assessments can be displayed (e.g., participants are offered possibilities to apply their new knowledge)
		CP4b	Learners give feedback to peer assignment work and argue for the results
		CP4c	Discussions about solutions are offered

(continued)

Table 6.2 (continued)

Elements	Categories	Codes	Indicators
Social presence (SP)	Personal/ affective expressions (SP1)	SP1a	A self-introduction thread is prompted
		SP1b	Some course participants are distinct from others (e.g., some posts can be followed by learners)
		SP1c	Personal or affective expressions are visible in the discussions/are promoted
	Open communication (SP2)	SP2a	Learners can post
		SP2b	Others' contributions are recognized (e.g., add reviews to others' posts)
		SP2c	The forum/discussion board is used frequently, and interaction takes place (e.g., answering questions)
	Group cohesion (SP3)	SP3a	Tools for collaboration are offered
		SP3b	Connections to other participants are suggested (e.g., study buddies, learning groups)

in the majority of the courses (TP1a, TP1c, TP2f, TP3c, TP3e, CP1d, CP3b, SP1b, SP2a, SP2b) (see Table 6.3 for details).

Out of the 16 indicators relating to TP, 2 (TP2e, TP3a) occurred only seldomly, while 5 (TP1a, TP1c, TP2f, TP3c, TP3e) indicators had a high occurrence.

For design and organization (TP1), all courses have displayed important course topics (TP1a), which appeared in the form of syllabi that were displayed in the introduction before enrollment and in the weekly overview of learning content. Only the courses on XuetangX did not provide a detailed overview about the course topics before enrollment. Except FE2 (FutureLearn), almost all of courses explained that how to participate in the course (TP1c), usually including how to finish courses and what should be paid attention to when learning.

For facilitation (TP2), almost all courses have a sound sequence of contents (TP2f). In the courses an overview about each week's topics was given, then either related learning materials were provided, or participants were asked to state their experiences related to the topic. CE1 used an introductory questionnaire about learners' preferences and characteristics (e.g., self-efficacy to teach online, subjects taught, time of teaching online) to offer a more personalized learning experience by showing relevant materials related to subjects taught, forum entries, and general recommendations as well as an overview about the relevant course modules (TP2c). But only 7 out of 20 courses used an encouraging course design (TP2e). For example, in FE2 (Coursera), participants were included by being asked to comment their expectations about that course. To cover the needs of different learners of self-working or employed English teachers, short interviews, texts, and discussions were included. When learners complete a self-defined weekly learning plan, such as studying for 2 h per week, a prompt containing an encouraging sentence appears in the Coursera platform. When enrolling in a course on iCourse and setting a time for studying for the first time, learners were given a course coupon worth nearly 1€.

Table 6.3 CoI indicators coding results

Indicator codes	Courses showing indicators	Dashboards showing indicators
TP1a	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
TP1b	CE1, CE2, CC1, CC2, FE1, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IC1, IC2, XE1, XC1	CE1, CC1, CC2, IE1, IC1
TP1c	CE1, CE2, CC1, CC2, FE1, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
TP1d	CE1, CE2, CC1, CC2, FC2, EE1, EC1, EC2, IE1, IC1, XE1, XC1	CE1, CC1, EC1, IC1
TP1e	CE1, CE2, CC1, CC2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XC1	
TP2a	CE1, CE2, CC1, CC2, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IC1, XC2	
TP2b	CE1, CE2, CC1, CC2, FE1, FE2, FC1, EE1, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XC1, XC2	
TP2c	CE1, CE2, CC2, FE1, FE2, FC1, FC2, EE2, EC2, IE1, IC1, XC1	
TP2d	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, XE1, XC1	
TP2e	CE1, CC1, FE2, FC2, IE1, IC1, IC2	
TP2f	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
TP3a	CE1, EE1, EE2, EC2, IE2, IC2, XC2	
TP3b	CE1, FC1, EE1, EE2, EC2, IE1, IC1, IC2, XE1, XC1	EE1
TP3c	CE1, CE2, CC1, CC2, FE1, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XC1, XC2	
TP3d	CE1, CE2, CC1, CC2, FE1, FE2, FC2, EE2, EC2, IE1, IC1, IC2, XE1, XC1, XC2	
TP3e	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2
CP1a	CE2, CC2, FC2, EE2, EC2, IE1, IE2, IC1, IC2, XE2, XC2	
CP1b	CE1, CC1, FE1, FE2, FC2, EE2, IE1, IC1	
CP1c	CE1, FE1, FE2, FC1, EE1, EE2, EC1, EC2, IE1, IE2, IC1, XE1	

(continued)

Table 6.3 (continued)

Indicator codes	Courses showing indicators	Dashboards showing indicators
CP1d	CE1, CE2, CC1, CC2, FE2, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	CE1, CE2, CC1, CC2, FC1, FC2, EE1, EE2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2
CP2a	CE1, CE2, CC2, FE1, FE2, FC1, FC2, EE1, EE2, IE1, IC1	
CP2b	CE1, CE2, CC1, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2, XE1, XC1, XC2	
CP2c	CE1, CE2, CC1, CC2, FC1, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XC1	
CP3a	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC1, EC2, IE1, IE2, IC1, IC2	
CP3b	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
CP3c	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE2, XC2	
CP4a	CE1, CC2, EE2, EC2, IE1, IE2, IC2, XE1, XC1	
CP4b	CE1, CE2, CC2, IE1, IE2	CE1
CP4c	CE1, CE2, CC2, FC2, EC2, IE1, IE2, IC2	
SP1a	CE1, CE2, FE1, FE2, FC1, FC2, EE1, IE2	
SP1b	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
SP1c	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE2, EC2, IE1, IE2, IC1, IC2, XE2, XC2	
SP2a	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
SP2b	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE1, XE2, XC1, XC2	
SP2c	CE1, CE2, CC1, CC2, FE1, FE2, FC1, FC2, EE1, EE2, EC2, IE1, IE2, IC1, IC2, XE2, XC2	
SP3a	CE1, CC1, FC1, EE1, EC1, IC2	
SP3b	CE1, FC1, EE1, EC1, IE1, IC1	

Regarding direct instruction (TP3), in all courses except EC1, learners have received an overview about their learning activities (TP3e). For example, learners received an overview about their activities related to course units or resource types (e.g., assessments, videos) either regarding percentage of materials accessed or their performance. The abovementioned (under TP2f) overview about the relevant course modules for participants based on the entry questionnaire in CE1 also refers to indicator TP3e as it represents learner's activities by displaying assessment attempts and scorings plus maximum points possible (see Fig. 6.1 for details). Regarding the response to technical concerns (TP3c), the platforms also offered some Q&A tips, or learners could contact the help center to ask technical questions. The courses provided feedback only in form of assessment scores related to the course topics, while some gave more elaborated feedback on why a question is correct or incorrect. Thus, the platforms did not directly provide learners with feedback about their strengths and weaknesses related to course goals (TP3a). For instance, in EE1 (EdX), learners received detailed information about the explanations why an answer is correct or incorrect.

Out of the 13 indicators of CP, 4 (CP1b, CP4a, CP4b, CP4c) were found seldomly, while 2 (CP1d, CP3b) occurred frequently.

Regarding the category trigging event (CP1), except the course FE1 (FutureLearn) having an assignment at the end of the last study week and XE2 (XuetangX) having no assignments, all other courses have assignments or exercises (CP1d) every study week or unit. In eight of the analyzed courses, it was found that problems can be recognized by learners (CP1b). For example, in FE2, participants were frequently guided to reflect on the challenges of teaching process and potential problems in online settings and then reported in the comments. With regard to course design supporting this indicator, Coursera provided a "note" function in which learners can use to take screenshots of the lecture videos and note down their questions or thoughts.

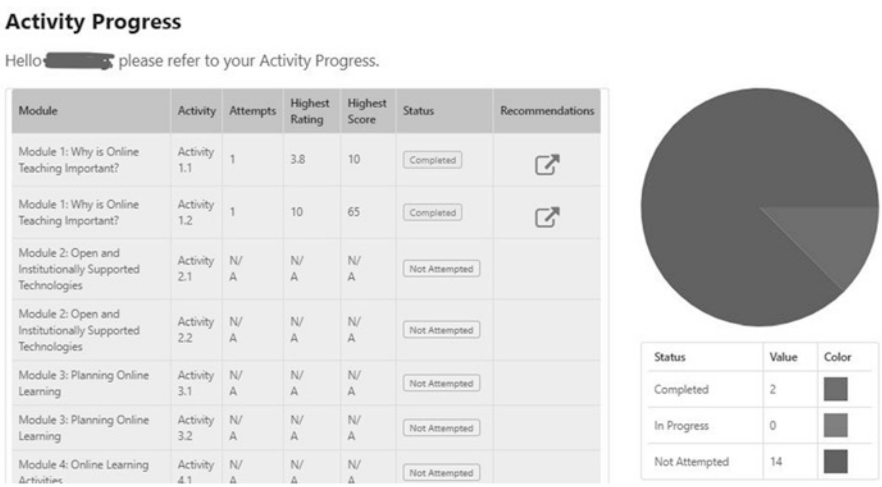


Fig. 6.1 Adaptive learning modules recommended dashboard in CE1 (Coursera)

For the category integration (CP3), discussion forums have played a big role in participants' exchanging their perspectives on problems (CP3b). In the recommendation of materials or solution strategies to help understand new concepts or answering questions (CP3a), the course CE1 (Coursera) displayed examples to explain questions in peer assignments are offered, like what tools can be used and how to do next steps. In EE1 (EdX) explanations about the correct or incorrect answers to multiple choice questions were provided to learners after the final try. Regarding CP3c (encourage refection on course topics and tasks), in FE1 (FutureLearn) participants were asked to reflect on course topics at the end of a week learning, while in IE1 (iCourse), participants were asked to publish a post, like self-reflection about what they have learned, what touched them, and what they plan to learn next.

All three indicators of the category resolution (CP4) have a low occurrence. Five courses used peer feedback. For instance, in CE1, after submitting a peer assignment, learners have the possibility to receive feedback from peers following recommended rubrics (CP4b) (see Fig. 6.2 for details). If received, learners' submission and the peer feedback were displayed in juxtaposition facilitating that learners could relate the received feedback to their solutions. Furthermore, learners could express their opinions about the feedback received and use the feedback for revision of their

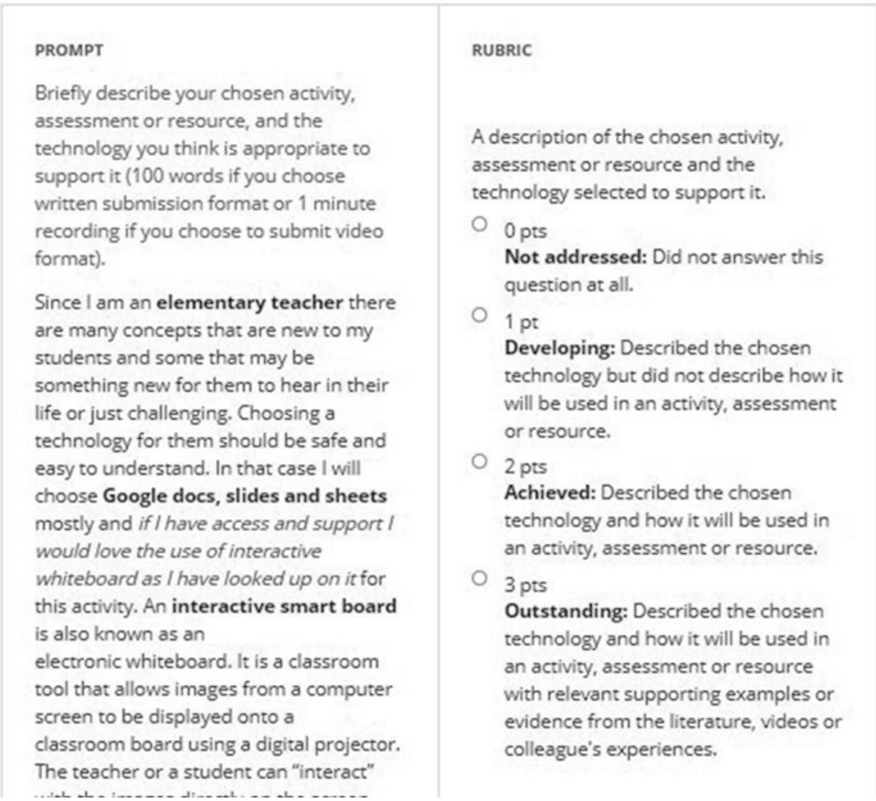


Fig. 6.2 Assignment rubrics dashboard in CE1 (Coursera)

assignment. In IE1, subsections in the discussion forum were implemented which includes a test and homework discussion area (CP4c). In those subsections, solutions to assessment could be displayed (CP4a), and learners could give feedback to each other about assignments (CP4b) and discussions about solutions (CP4c).

Out of the eight indicators of SP, two (SP1a, SP3b) have a low occurrence, and three (SP1b, SP2a, SP2b) have a high occurrence. For the category personal and affective expression (SP1), self-introduction threads (SP1a) were found less frequently (in eight courses) than the indicator that some participants are distinct from others (SP1b), both of which usually appeared in discussion forums. Learners could up vote, reply to, or follow other learners and/or posts of interest to them, which provides operational convenience for learners to distinguish other course participants. In terms of open communication (SP2), except one course (EC1), all courses provided posting functionalities in discussion forums or comment sections (SP2a) and a reply function enabling learners to give feedback or recognizing posts of others (SP2b). For the category group cohesion (SP3), only in six courses, related study buddies or learning groups were recommended (SP3b). Many courses (e.g., CE1, EE1, or IC1) recommended external social platforms such as Facebook, Twitter, or WeChat.

4.2 Elements of the Community of Inquiry Model Represented on MOOC Dashboards

Regarding the MOOC dashboards, the coding revealed the presence of the following indicators: TP1b, TP1d, TP3b, TP3e, CP1d, and CP4b.

With regard to teaching presence, 4 (TP1b, TP1d, TP3b, TP3e) out of 16 possible indicators were found on the dashboards. Referring to design and organization (TP1), two indicators were found. For example, the visualization of important course goals (TP1b) was implemented as a calendar or a mini weekly calendar. On Coursera, participants could define their days and time for studying and received a simple related visualization (see Fig. 6.3 for details). On iCourse, learners could define study time and days and received an overview about the time (e.g., 15 out of 30 min) and the days (e.g., 1 out of 3) they have already studied per week and the relevant study tasks for each day (see Fig. 6.4 for details).

To communicate important course deadlines (TP1d) such as submissions (e.g., assignments and peer review due time) or live sessions, visualizations on dashboards were included in four courses. On iCourse, learners received a weekly schedule displaying assignment (see Fig. 6.4 for details). On Coursera, the dashboard showed the study time for each learning material and due dates for assignments and peer reviews (see Fig. 6.5 for details). During examinations in IC1 (iCourse), a mini digital watch is displayed to help learners complete the test within the specific timeframe.

Referring to direct instruction (TP3), two indicators were found. With regard to the course topic (using data for educational purposes) in EE1 (EdX), participants answer questions about their individual situation. Then through a stoplight

Fig. 6.3 Simple learning plan dashboard in CE1 (Coursera)

Fig. 6.4 Simple learning plan dashboard in IC1 (iCourse)

dashboard, participants received immediate feedback (TP3b) about how often activities related to the suggested process of collaboratively using educational data were performed (see Fig. 6.6 for details). Furthermore, in EE1 (EdX), participants received a bar chart indicating how many tasks learners have passed and failed. In all courses except EC1, participants could receive an overview about their learning activities on a dashboard (TP3e). In CE1, participants see a pie chart as an overview about completed, not attempted, and tasks that are currently in progress (see Fig. 6.1 for details). On iCourse, participants received an overview about all their courses

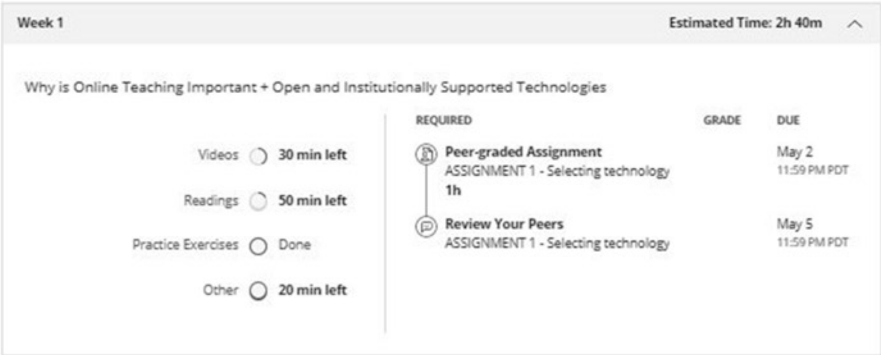


Fig. 6.5 Deadline dashboard in CE1 (Coursera)

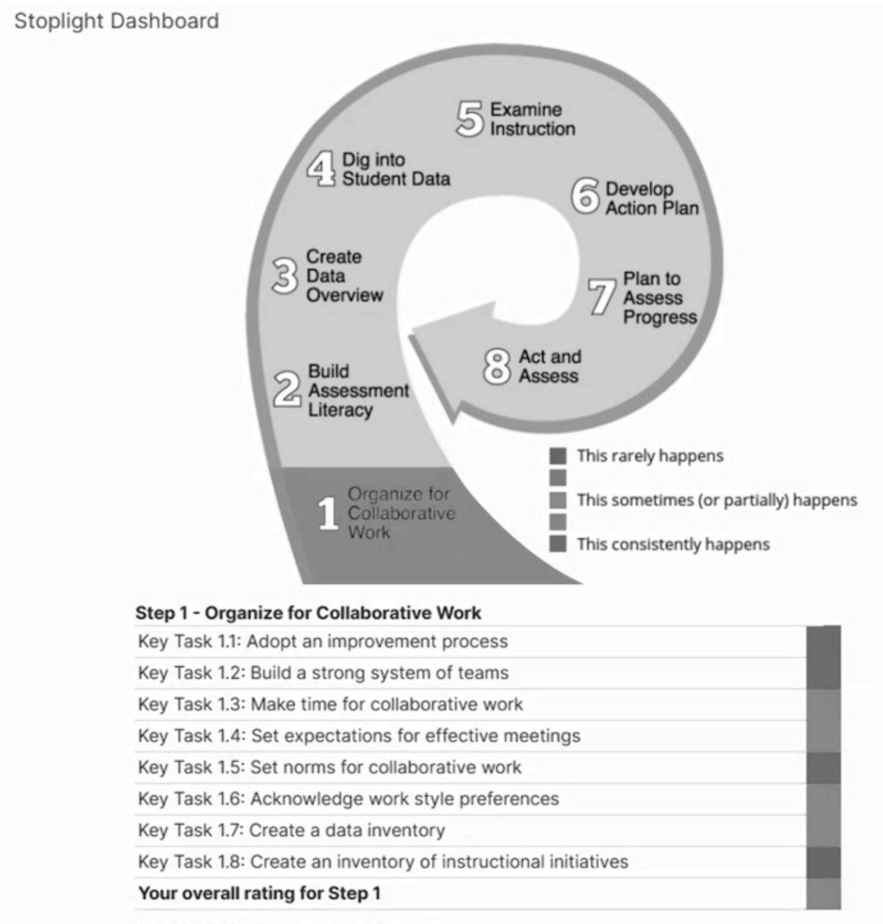


Fig. 6.6 Spotlight dashboard in EE1 (EdX)

enrolled with bar chart showing their progress (e.g., 4 out of 40 units). On XuetangX, participants were shown a list of the assessments related to course topics indicating the percentage of completion and the result (see Fig. 6.7 for details). On Coursera, a timeline combined with doughnut charts were presented to learners indicating their progress in each week and the whole course.

Regarding CP, 2 out of 13 indicators have been identified on the dashboards. For the category trigging event (CP1), except four courses, all courses displayed assignments (CP1d) on progress dashboards with links to related assessments if available. Related to the resolution (CP4) regarding peer-reviewed assignments, learners receive an overview of their assignment activity with peers (CP4b); CE1 (Coursera) was the only course using a dashboard to express this indicator. On this dashboard like interface, learners could compare their resolution of assignments with the feedback given by peers and could express their own opinions on the responses of peers and resubmit a resolution.

4.3 Differences of Represented Community of Inquiry Elements Between the Domains of Education and Computer Sciences

When analyzing the two course subjects, education and computer science in the sample, only two indicators have difference for at least three courses, both in CP: CP1c and CP2a.

In computer science, four out of ten courses worked with real-world problems or case studies (CP1c), whereas eight out of ten courses on education used them. For example, in CE1 (Coursera), IE1 (iCourse) and XE1 (XuetangX) case studies were

Fig. 6.7 Assignment overview dashboard in XC1 (XuetangX)

presented in the lecture videos. In EE1 (EdX), case studies were presented in videos, and participants could test their understanding afterwards. For instance, in CE1 (Coursera), external learning materials and resources with samples related to the course topic were offered. In the computer science courses, common computer games were used for programming exercises in FC1 (FutureLearn) or mimicking commercial web design in EC1 (EdX) as case studies.

In seven out of ten education courses, related links were offered (CP2a), while this was only the case for four out of ten computer science courses. For example, external links in CE1 (Coursera) referred to a comprehensive description of the online teaching process from learning outcome, technology tool matrix to technology learning tips. EE1 (EdX) recommended their Twitter and Facebook webpage for following updates on course topics. IE1 (iCourse) provided related materials as expanded resources for interested participants to read. In computer science courses, FC1 (FutureLearn) recommended LinkedIn to help learners realize which computer programming skills are essential in current relevant jobs. In IC1 (iCourse), external links were given to a related programming platform for participants to download code.

4.4 Differences of Represented Community of Inquiry Elements Between English and Chinese MOOCs

As the analyzed sample contained two Chinese MOOC platforms and three English MOOC platforms, the ratio of the number of displayed indicators to the total number of courses was compared. Indicators with a ratio difference greater than 20% are TP1b, TP2a, TP2c, TP2d, TP3b, CP1a, CP2a, and CP3a.

In terms of TP, English MOOC courses provided participants with more detailed course goals (TP1b). In facilitation (TP2), related topics to explore new concepts (TP2c) were used in 75% of the English MOOCs but only in 37.5% of the Chinese MOOCs. Also, explanations of topics (TP2d) were displayed in all English MOOC courses but only in 62.5% of the Chinese courses. Furthermore, participants in English MOOCs published more posts in the discussion forum that are related to agreement or disagreement (TP2a). Though feedback in most Chinese MOOCs was timely (TP3b), the feedback given was always simple on whether the answer is right or wrong.

Regarding CP, in Chinese MOOCs, new course topics (CP1a) were explicitly mentioned which was less in English MOOCs. In contrast, in 75% of the English MOOCs, related external links about new topics (CP2a) were posted, whereas this was only the case for 25% of the Chinese MOOCs. Recommendations on materials or solution strategies (CP3a) were given in all English MOOCs to help learners answering questions, whereas this was only true for 50% of the Chinese courses.

Regarding differences of indicators on the dashboards for English and Chinese MOOCs, differences were less than 20%. Overall, six indicators (TP1b, TP1d, TP3b, TP3e, CP1d, CP4b) found on dashboards were present in all English MOOCs, whereas two (TP3b, CP4b) out of the six indicators were not present on Chinese dashboards.

5 Discussion and Conclusion

Summary of Findings The findings revealed that all elements, categories, and related indicators related to the CoI model were present in the courses on the five MOOC platforms selected. Through learners' reviews, Holstein and Cohen (2016) also found the presence of TP, CP, and SP, which was related to successful MOOCs. In our sample, one course (EC1) was rather separated from the MOOC platform linking to external teaching tools. In EC1, the discussion forum and overview of learners' activities plus the completion and submission of assignments were facilitated via other platforms, which means that nearly half of the TP indicators and almost all the CP and SP indicators could not be identified on the MOOC platform.

However, the current state of development of the dashboards is limited, and representation of the indicators was very low. When comparing the MOOC platforms, Coursera, EdX, and iCourse provided more elaborated dashboard functionalities such as important deadlines and timely feedback, whereas FutureLearn provided only simple representations of learning activities.

Regarding the elements of the CoI model found in the MOOC courses, indicators related to TP appeared more frequently than CP and SP. Through a diagnostic MOOC evaluation method, Nie et al. (2020) also found that most MOOCs are content- or lecture-based courses and offer only limited support for self-regulated learning. This might be due to the fact that all five selected MOOC platforms offer xMOOC which are associated with behaviorist learning approaches related to transfer of information (Kesim & Altinpulluk, 2015). However, this kind of design may be not suitable for the development of high-level cognitive skills among participants, like self-regulation (Terras & Ramsay, 2015).

With regard to students setting their own learning goals (TP1b), the offered functionalities were too simple and mostly only referred to setting a period of study time. Learners should have the possibility to define individual learning goals resulting in adaptive study paths, making use of the advantages of digital learning environments and receiving scaffolds for appropriate learning strategies. Also, with regard to monitoring learning activities, the related overviews in the analyzed MOOCs were too simple without offering comparisons to learners' own goals or peer performance or activities.

In terms of helping learners with the course content, Chinese MOOCs make use of newer approaches of intelligent tutoring systems. Although needs further improvement, the intelligent teaching assistant in XC1 (XuetangX) used chatbot functionalities to help learners with questions on course resources, basic course concepts, and common platform operation problems. For displaying related topics to encourage learners exploring new concepts (TP2c), in XC1 (XuetangX), simple concept maps for explaining the relationship among the concepts were used, and when clicking on one course concept, learners received short descriptions and the places of related course videos within this course, through which learners could find other knowledge points related to the new concept in video or seek help from other information sources.

In addition, instructors' presence (TP3d) in MOOCs needs to be improved. Interaction with instructors was mostly facilitated via the discussion forum or feedback on assignments. However, depending on the technical implementation and due to the large number of posts written by other participants, instructors' comments are not only small in quantity but also difficult to find in platform operation. Only in CE1 (Coursera), instructor's profile picture was placed on the side of the discussion forum, and learners could click on it to directly navigate to all posts of the instructors. Thus, Ross et al. (2014) emphasized that the complexity of instructors' role in MOOCs should be adequately addressed to help MOOC learners, instructors, and designers better realize what teaching and learning at scale mean. In this regard, findings revealed some differences referring to the design of courses between Chinese MOOCs and English MOOCs. Compared to English MOOCs, Chinese MOOCs had more specific sections in the discussion forum, such as an instructors' Q&A area or a classroom discussion-exchange area in the discussion forum. In the courses CC1 (Coursera), learners could easily find all posts of the instructors by clicking on the instructors' profile picture in the discussion forum. But in other English MOOCs, learners had to check posts one by one to find those of the instructors (highlighted with an icon). In Chinese MOOCs, participants could post new comments in the discussion forum and received feedback from the instructor only during the certificate application period; otherwise discussions can only be read. On the one hand, this approach limits communication but also reduces the workload of instructors. On the other hand, participants know that during this time they will get feedback. In contrast, in English MOOCs, discussion forums could be used always, but most of the feedback might only be provided by peers.

Regarding CP, the platforms do not provide sufficient functionalities to enable learners applying the knowledge they have learned (CP1d, CP3b, CP3c). For instance, the usage of assignments and exercises was not sufficient or only focused on basic declarative tests which are easy to be analyzed. Furthermore, very few specific functionalities were found fostering learners' joint reflection on topics or critical discussions about resolutions. Hence, it is argued that assessments in MOOCs should go beyond being sole indicators of learning performance by offering learners formative feedback (Admiraal et al., 2014, 2015). Moreover, how to better use the pedagogical function of peer assignment is a big issue in MOOCs research (Alcarria et al., 2018; Garcia-Loro et al., 2020). Through surveying and interviewing MOOC learners and coordinators, García Espinosa et al. (2015) found that due to the lack of thorough feedback and monitoring of learning activities as a result of the large size of MOOCs, engagement of learners is deficient. Thus, it is important to enhance both the assessment practices and related feedback processes in MOOCs. Related to this, findings indicated difference between the two subjects. In the education courses, in particular, those on online teacher training more frequently use case studies and peer assignment and have sounder syllabi. For example, in CE1 (Coursera), learners could actively discuss peer assignments and the feedback received. Peer assignment and feedback were not specifically embedded in the analyzed computer science courses. Besides this, self-reflection and analysis of the own situation were used in education courses but not in computer science courses. For example, the dashboard used in EE1 (EdX) offered participants an evaluation about their current situation with regard to using educational data. These results might be due to the higher pedagogical knowledge and characteristics of both instructors and learners in education courses. Prior knowledge is an important predictor of MOOC participants to revisit their previous works (Kennedy et al., 2015). The designers and learners of the education course might be better at presenting and reflecting on teaching activities, which improves the practicality of curriculum activities and learning activities.

Regarding SP, learning buddies or learning groups were recommended (SP3b) seldomly, and social processes were often directed to social media platforms not specifically aiming at learning and training functions. Furthermore, the discussion forums in the analyzed course did not have a specific structure for supporting SP (SP1b, SP2b, SP2c), while TP and CP also frequently appeared in the discussion forums, which might result in navigation difficulties for participants. Actually, Chiu and Hew (2018) suggested to integrate the use of the discussion forum in the course requirements and to encourage learners to read and comment discussions, which influences learning in MOOCs. Furthermore, it is suggested to particularly highlight important posts or summaries to increase their purview and peer learning (Chiu & Hew, 2018). But Yousef et al. (2014) also found that the meaningful usage of social tools and instructional design in MOOCs is a highly challenging task.

Implications of the Findings Based on the findings of this study, dashboards seem to be scarcely used for supporting self-regulated learning. As dashboards are closely related to the domain of learning analytics, it needs to be scrutinized if MOOCs and platforms currently make sufficient use of the possibilities learning analytics offer. In particular, dashboards for learners seem to be scarce (Rohloff et al., 2019), and even with regard to the dashboards presented to educators or developers, it remains questionable whether the data and visualizations presented offer relevant insights for the different stakeholders (Chitsaz et al., 2016). As MOOCs are characterized by high numbers of participants and only few instructors, the use of learning analytics would facilitate course design as well as support for participants planning and monitoring their learning processes.

In the CoI model, TP is shared by all participants in learning communities (Akyol & Garrison, 2011b). Due to different prerequisites and demands, it is suggested to provide individual learners with different dashboards and enable learners to design and organize their own dashboards. To facilitate direct instruction, dashboards might contain feedback provided by the instructors or peers. Findings of this study reveal that even though all indicators of TP are present in current MOOCs, their content and forms are too simple. To offer learners guidance throughout the course even with few instructors available, goal-oriented dashboards are required. For example, in CE1 through questionnaires about course modules and personal profile, dashboards recommended adaptive learning modules to help learners find their topics of interest quickly. To guide purposeful dialogues in discussion forums, more specific areas are needed. For instance, those areas could be task 1, solution discussion area; task 1, related materials recommended by peers; or task 1, case studies recommended by peers, not just topic 1 and topic 2. Also, learners' contribution to platform can be regarded as one indicator to course completion.

The core of CP is the meaningful learning experience from a collaborative constructivist perspective (Akyol & Garrison, 2011b), which refers to both individual and collaborative learning processes. A dashboard showing the comparison between individual learning goals and course tasks would offer learners to reflect their learning progress. With focus on supporting individual learners, MOOCs might offer adaptive learning paths based on individual learning goals including a dashboard for supporting monitoring, reflection, and feedback for adjusting learning processes. As individual goals guide learners' activities, Stracke (2017) states that completion of individual goals and intentions maybe is a suitable indicator of MOOC completion. Thus, learners should be actively involved in the development of learning analytics to include their needs and increase their willingness to share personal data (Dollinger & Lodge, 2019; Ifenthaler & Schumacher, 2016).

SP influences the interpersonal relationship in learning communities (Akyol & Garrison, 2011b). SP cannot be formed automatically and requires additional guidance to stimulate sharing of experiences and to promote the construction of personal meaning. However, findings on SP indicate needs for improvement in MOOCs such as that discussion forums require more specific guidance and structure. Therefore, Atapattu et al. (2016) suggest analyzing discussions for informing instructors about topics participants have difficulties with and that might require additional attention or instruction. Furthermore, as many participants with different prerequisites are enrolled in MOOCs, peer learning should be supported via recommendations of suitable learning buddies or groups through profile match (automatically or chosen by learners themselves).

Limitations and Further Research Needs This study faces several limitations. The selected sample is limited as it only included courses from two subjects, three English and two Chinese MOOC platforms. Thus, no other national MOOC platforms such as openHPI in Germany, EduOpen in Italy, Open2Stuy in Australia, or Schoo in Japan were investigated. Hence, the generalizability of the results and conclusion is limited. Moreover, the study only investigated what was accessible in the courses but did not investigate the course participants' perceptions of the presence of the CoI model elements. Thus, upcoming studies might enhance Holstein and Cohens' (2016) study using qualitative interviews or questionnaires. In addition, analysis of posts in the discussion forums using data mining might enhance the findings. Also, the pedagogical value and design of MOOC discussions require further research (Onah et al., 2014). Besides the CoI model, no other specific educational theory guided the analysis of the MOOCs or dashboards. As the indicators were scarcely present on dashboards, it needs to be investigated further how suitable the CoI model is for investigating and designing learning dashboards. Learning dashboards in MOOCs seem to be still emerging and should be researched further, by including the needs of all relevant stakeholders. Also, the possibilities for supporting participants of MOOCs using learning analytics and how to better combine learning analytics, MOOCs, and learning theories still require further interdisciplinary efforts.

Appendix: Overview About Coded CoI Elements for Each MOOC and Related Dashboard

	CE1		CE2		CC1		CC2		FE1		FE2		FC1		FC2		EE1		EE2		EC1		EC2		IE1		IE2		IC1		IC2		XE1		XE2		XC1		XC2	
Indicators	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D
TP1a	+	–	+	–	+	–	+	–	+	P	+	P	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
TP1b	+	+	+	–	+	+	+	+	+	–	P	–	+	–	+	–	+	–	+	–	+	–	+	–	+	+	–	–	+	+	+	–	+	–	–	–	+	–	–	–
TP1c	+	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
TP1d	+	+	+	–	+	+	+	–	–	–	–	–	–	–	+	–	+	–	UA	–	+	+	+	–	+	–	–	–	+	+	–	–	+	–	–	–	+	–	–	–
TP1e	+	–	+	–	+	–	+	–	–	–	–	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	–	–	–	–	+	–	–	–
TP2a	+	–	+	–	+	–	+	–	P	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–	–	–	+	–	–	–	P	–	–	–	P	–	+	–
TP2b	+	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–
TP2c	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	P	–	+	–	–	–	+	–	+	–	–	–	+	–	P	–	–	–	–	–	+	–	P	–
TP2d	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	P	–	+	–	–	–	+	–	P	–
TP2e	+	–	P	–	+	–	P	–	P	–	+	–	P	–	+	–	P	–	P	–	–	–	P	–	+	–	P	–	+	–	+	–	–	–	–	–	–	–	P	–
TP2f	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
TP3a	+	–	–	–	–	–	–	–	–	–	–	–	P	–	–	–	+	–	+	–	–	–	+	–	P	–	+	–	P	–	+	–	–	–	–	–	–	–	+	–
TP3b	+	–	P	–	–	–	P	–	–	–	P	–	+	–	P	–	+	+	+	–	–	–	+	–	+	–	UA	UA	+	–	+	UA	+	–	–	–	+	–	P	–
TP3c	+	–	+	–	+	–	+	–	+	–	P	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–
TP3d	+	–	+	–	+	P	+	–	+	–	+	–	–	–	+	–	–	–	+	–	–	–	+	–	+	–	UA	UA	+	–	+	UA	+	–	–	–	+	–	+	–
TP3e	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	–	–	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
CP1a	–	–	+	–	–	–	+	–	–	–	P	–	P	–	+	–	–	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	–	–	+	–
CP1b	+	–	–	–	+	–	–	–	+	–	+	–	P	–	+	–	P	–	+	–	–	–	–	–	+	–	–	–	+	–	P	–	P	–	–	–	P	–	P	–
CP1c	+	–	–	–	–	–	–	–	+	–	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	P	–	+	–	–	–	–	–	P	–
CP1d	+	+	+	+	+	+	+	+	P	P	+	P	+	+	+	+	+	+	+	+	+	–	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
CP2a	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	–	–	+	–	–	–	+	–	–	–	–	–	–	–	–	–	–	–
CP2b	+	–	+	–	+	–	–	–	P	P	P	P	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	+	–
CP2c	+	–	+	–	+	–	+	–	P	P	P	P	+	–	–	–	+	–	+	–	–	–	+	–	+	–	+	–	+	–	+	–	+	–	–	–	+	–	–	–

	CE1		CE2		CC1		CC2		FE1		FE2		FC1		FC2		EE1		EE2		EC1		EC2		IE1		IE2		IC1		IC2		XE1		XE2		XC1		XC2	
Indicators	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D
CP3a	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	−	−	P	−	P	−
CP3b	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	+	−	+	−	+	−	+	−
CP3c	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	−	−	+	−	−	−	+	−
CP4a	+	−	P	−	UA	−	+	−	P	−	P	−	P	−	−	−	P	−	+	−	−	−	+	−	+	−	+	−	P	−	+	−	+	−	−	−	+	−	P	−
CP4b	+	+	+	−	P	−	+	−	P	−	P	−	P	−	−	−	−	−	−	−	−	−	−	−	+	−	+	−	P	−	−	−	−	−	−	−	−	−	−	−
CP4c	+	−	+	−	P	−	+	−	P	−	P	−	P	−	+	−	P	−	UA	UA	−	−	+	−	+	−	+	UA	P	−	+	UA	−	−	−	−	−	−	−	−
SP1a	+	−	+	−	−	−	−	−	+	−	+	−	+	−	+	−	+	−	−	−	−	−	−	−	P	−	+	UA	P	−	−	−	P	−	−	−	−	−	−	−
SP1b	+	−	+	−	+	−	+	−	+	P	+	P	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	+	−	+	−	+	−	+	−
SP1c	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	−	−	+	−	+	+	+	UA	+	−	+	UA	−	−	+	−	−	−	+	−
SP2a	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	+	−	+	−	+	−	+	−
SP2b	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	+	−	+	−	+	−	+	−
SP2c	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	−	−	+	−	+	−	+	UA	+	−	+	UA	P	−	+	−	P	−	+	−
SP3a	+	−	−	−	+	−	−	−	−	−	P	−	+	−	−	−	+	−	−	−	+	−	−	−	−	−	−	−	−	−	+	−	−	−	−	−	−	−	−	−
SP3b	+	−	−	−	−	−	−	−	P	−	−	−	+	−	−	−	+	−	−	−	+	−	−	−	+	−	−	−	+	−	−	−	P	−	−	−	−	−	−	−

Note. *C* course, *D* dashboard, + indicator was found, − indicator was not found, *UA* information cannot be accessed without fees, *P* indicators were partly found, meaning that platform does not provide the functionality, but those indicators can be found in discussion forum's posts; for course names and indicator descriptions, see Table 6.1

References

Admiraal, W., Huisman, B., & Pilli, O. (2015). Assessment in massive open online courses. *The Electronic Journal of e-Learning, 13*(4), 207–216.

Admiraal, W., Huisman, B., & van de Ven, M. (2014). Self- and peer assessment in massive open online courses. *International Journal of Higher Education, 3*(3), 119–128. https://doi.org/10.5430/ijhe.v3n3p119

Aguilar, S. J. (2018). Learning analytics: At the nexus of big data, digital innovation, and social justice in education. *TechTrends, 62*, 37–45. https://doi.org/10.1007/s11528-017-0226-9

Akyol, Z., & Garrison, D. R. (2008). The development of a Community of Inquiry over time in an online course: Understanding the progression and integration of social, cognitive and teaching presence. *Journal of Asynchronous Learning Networks, 12*(3), 2–33.

Akyol, Z., & Garrison, D. R. (2011a). Assessing metacognition in an online community of inquiry. *Internet and Higher Education, 14*(3), 183–190. https://doi.org/10.1016/j.iheduc.2011.01.005

Akyol, Z., & Garrison, D. R. (2011b). Understanding cognitive presence in an online and blended community of inquiry: Assessing outcomes and processes for deep approaches to learning. *British Journal of Educational Technology, 42*(2), 233–250. https://doi.org/10.1111/j.1467-8535.2009.01029.x

Alabi, H., & Hatala, M. (2017). Best intentions: Learner feedback on learning analytics visualization design. In *LAK '17: Proceedings of the 7th international learning analytics and knowledge conference*. The Association for Computing Machinery.

Alcarria, R., Bordel, B., de Andrés, D. M., & Robles, T. (2018). Enhanced peer assessment in MOOC evaluation through assignment and review analysis. *International Journal of Emerging Technologies in Learning, 13*(1), 206–219. https://doi.org/10.3991/ijet.v13i01.7461

Anderson, T., Rourke, L., Garrison, D. R., & Archer, W. (2001). Assessing teaching presence in a computer conferencing context. *Journal of Asynchronous Learning Networks, 5*(2), 1–17.

Aparicio, M., Oliveira, T., Bacao, F., & Painho, M. (2019). Gamification: A key determinant of massive open online course (MOOC) success. *Information & Management, 56*(1), 30–54. https://doi.org/10.1016/j.im.2018.06.003

Arbaugh, J. B., Cleveland-Innes, M., Diaz, S. R., Garrison, D. R., Ice, P., Richardson, J. C., & Swan, K. P. (2008). Developing a community of inquiry instrument: Testing a measure of the Community of Inquiry framework using a multi-institutional sample. *Internet and Higher Education, 11*, 133–136. https://doi.org/10.1016/j.iheduc.2008.06.003

Atapattu, T., Falkner, K., & Tarmazdi, H. (2016). Topic-wise classification of MOOC discussions: A visual analytics approach. In *Proceedings of the 9th international conference on educational data mining (EDM)*.

Baturay, M. H. (2015). An overview of the world of MOOCs. *Procedia - Social and Behavioral Sciences, 174*, 427–433. https://doi.org/10.1016/j.sbspro.2015.01.685

Bekele, E. A. (2010). Motivation and satisfaction in internet-supported learning environments: A review. *Educational Technology & Society, 13*(2), 116–127. https://doi.org/10.2307/jeductechsoci.13.2.116

Bodily, R., Ikahififo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598.

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418. https://doi.org/10.1109/TLT.2017.2740172

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *Internet and Higher Education, 27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Broos, T., Pinxten, M., Delporte, M., Verbert, K., & De Laet, T. (2020). Learning dashboards at scale: Early warning and overall first year experience. *Assessment and Evaluation in Higher Education, 45*(6), 855–874. https://doi.org/10.1080/02602938.2019.1689546

Chitsaz, M., Vigentini, L., & Clayphan, A. (2016). Toward the development of a dynamic dashboard for FutureLearn MOOCs: Insights and directions. In *Show me the learning. Proceedings ASCILITE* (pp. 116–121). ASCILITE.

Chiu, T. K. F., & Hew, T. K. F. (2018). Factors influencing peer learning and performance in MOOC asynchronous online discussion forum. *Australasian Journal for Educational Technology, 34*(4), 16–28. https://doi.org/10.14742/ajet.3240

Damm, C. A. V. (2016). Applying a community of inquiry instrument to measure student engagement in large online courses. *Current Issues in Emerging eLearning, 3*(1), 20160428.

Daniel, J. (2013). Making sense of MOOCs: Musings in a maze of myth, paradox and possibility. *Journal of Interactive Media in Education, 2012*(2). https://doi.org/10.5334/2012-18

Davis, D., Chen, G., Jivet, I., Hauff, C., & Houben, G.-J. (2016). Encouraging metacognition & self-regulation in MOOCs through increased learner feedback. In S. Bull, B. M. Ginon, J. Kay, M. D. Kickmeier-Rust, & M. D. Johnson (Eds.), *Proceedings of the LAK 2016 workshop on learning analytics for learners*. Association for Computing Machinery.

de Barba, P. G., Kennedy, G. E., & Ainley, M. D. (2016). The role of students' motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning, 33*(3), 218–231. https://doi.org/10.1111/jcal.12130

Deng, R., Benckendorff, P., & Gannaway, D. (2019). Progress and new directions for teaching and learning in MOOCs. *Computers and Education, 129*, 48–60. https://doi.org/10.1016/j.compedu.2018.10.019

Dipace, A., Fazlagic, B., & Minerva, T. (2019). The design of a learning analytics dashboard: EduOpen MOOC platform redefinition procedures. *Journal of e-Learning and Knowledge Society, 15*(3), 29–47. https://doi.org/10.20368/1971-8829/1135044

Dollinger, M., & Lodge, J. (2019). What learning analytics can learn from students as partners. *Educational Media International, 56*(3), 218–232. https://doi.org/10.1080/09523987.2019.1669883

García Espinosa, B. J., Tenorio Sepúlveda, G. C., & Ramírez Montoya, M. S. (2015). Self-motivation challenges for student involvement in the open educational movement with MOOC. *International Journal of Educational Technology in Higher Education, 12*, 91–103.

Garcia-Loro, F., Martin, S., Ruiérez-Valiente, J., Sancristobal, & Castro, M. (2020). Reviewing and analyzing peer review inter-rater reliability in a MOOC platform. *Computers and Education, 154*. https://doi.org/10.1016/j.compedu.2020.103894

Garrison, D. R. (2009). Communities of inquiry in online learning. In P. L. Rogers, G. A. Berg, J. V. Boettcher, C. Howard, L. Justice, & K. D. Schenk (Eds.), *Encyclopedia of distance learning* (pp. 352–355). IGI Global.

Garrison, D. R., Anderson, T., & Archer, W. (1999). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education, 2*(2–3), 87–105. https://doi.org/10.1016/S1096-7516(00)00016-6

Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education, 15*(1), 7–23. https://doi.org/10.1080/08923640109527071

Garrison, D. R., Anderson, T., & Archer, W. (2010). The first decade of the community of inquiry framework: A retrospective. *The Internet and Higher Education, 13*(1–2), 5–9. https://doi.org/10.1016/j.iheduc.2009.10.003

Garrison, D. R., Cleveland-Innes, M., Koole, M., & Kappelman, J. (2006). Revisiting methodological issues in transcript analysis: Negotiated coding and reliability. *The Internet and Higher Education, 9*(1), 1–8. https://doi.org/10.1016/j.iheduc.2005.11.001

Gütl, C., Rizzardini, R. H., Chang, V., & Morales, M. (2014). Attrition in MOOC: Lessons learned from drop-out students. In L. Uden, J. Sinclair, Y. Tao, & L. D. (Eds.), *Learning technology for education in cloud. MOOC and Big Data*. https://doi.org/10.1007/978-3-319-10671-7_4

Holstein, S., & Cohen, A. (2016). The characteristics of successful MOOCs in the fields of software, science, and management, according to students' perception. *Interdisciplinary Journal of e-Skills and Lifelong Learning, 12*(2016), 247–266. https://doi.org/10.28945/3614

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The Sage encyclopedia of educational technology* (Vol. 2, pp. 447–451). Sage.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. https://doi.org/10.1007/s11423-016-9477-y

Jansen, R. S., van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2020). Supporting learners' self-regulated learning in massive open online courses. *Computers and Education, 146*. https://doi.org/10.1016/j.compedu.2019.103771

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *LAK 18: Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40). The Association for Computing Machinery.

Kaul, M., Aksela, M., & Wu, X. (2018). Dynamics of the community of inquiry (CoI) within a massive open online course (MOOC) for in-service teachers in environmental education. *Education Sciences, 8*(2). https://doi.org/10.3390/educsci8020040

Kennedy, G., Coffrin, C., de Barba, P., & Corrin, L. (2015). Predicting success: How learners' prior knowledge, skills and activities predict MOOC performance. In *LAK ´15: Proceedings of the fifth international conference on learning analytics and knowledge* (pp. 136–140). Association for Computing Machinery.

Kesim, M., & Altinpulluk, H. (2015). A theoretical analysis of MOOCs types from a perspective of learning theories. *Procedia - Social and Behavioral Sciences, 186*, 15–19. https://doi.org/10.1016/j.sbspro.2015.04.056

Kim, J., Jo, I.-H., & Park, Y. (2016). Effects of learning dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(13), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Kizilcec, R. F., & Halawa, S. (2015). Attrition and achievement gaps in online learning. In *L@S ´15: Proceedings of the second (2015) ACM conference on learning @ Scale* (pp. 57–66). Association for Computing Machinery.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. *Computers and Education, 104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Klerkx, J., Verbert, K., & Duval, E. (2017). Learning analytics dashboards. In C. Lang, G. Siemens, A. F. Wise, & D. Gašević (Eds.), *The handbook of learning analytics* (pp. 143–150). Society for Learning Analytics Research (SoLAR).

Kovanović, V., Joksimović, S., Poquet, O., Hennis, T., Čukić, I., de Vries, P., Hatala, M., Dawson, S., Siemens, G., & Gašević, D. (2018). Exploring communities of inquiry in massive open online courses. *Computers and Education, 119*, 44–58. https://doi.org/10.1016/j.compedu.2017.11.010

Lee, D., Watson, S. L., & Watson, W. R. (2019). Systematic literature review on self-regulated learning in massive open online courses. *Australasian Journal of Educational Technology, 35*(1), 28–41. https://doi.org/10.14742/ajet.3749

Liang, J., Yang, J., Wu, Y., Li, C., & Zheng, L. (2016). Big data application in education: Dropout prediction in EdX MOOCs. In *Proceedings of the IEEE second international conference on multimedia big data (BigMM)* (pp. 440–443). IEEE.

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *Internet and Higher Education, 29*, 40–48. https://doi.org/10.1016/j.iheduc.2015.12.003

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008–2012. *The International Review of Research in Open and Distributed Learning, 14*(3), 202–227. https://doi.org/10.19173/irrodl.v14i3.1455

Ma, L., & Lee, C. S. (2018). Investigating the adoption of MOOCs: A technology–user–environment perspective. *Journal of Computer Assisted Learning, 35*(1), 89–98. https://doi.org/10.1111/jcal.12314

Moissa, B., Gaparini, I., & Kemczinski, A. (2015). A systematic mapping on the learning analytics field and its analysis in the massive open online courses context. *International Journal of Distance Education Technologies, 13*(3), 1–24. https://doi.org/10.4018/IJDET.2015070101

Muhazir, A., Sugianto, S., Simarmata, J., & Sudarminto, P. (2020). The utilization of massive open online course concept during corona pandemic outbreak. In *Proceedings of the international conference on social, sciences and information technology* (pp. 169–176). Springer, Kisaran.

Ng, A., & Widom, J. (2014). Origins of the modern MOOC (xMOOC). In F. M. Hollands & D. Tirthali (Eds.), *MOOCs: Expectations and reality. Full report* (pp. 34–47). Columbia University.

Nie, Y., Luo, H., & Sun, D. (2020). Design and validation of a diagnostic MOOC evaluation method combining AHP and text mining algorithms. *Interactive Learning Environments*, 1–14. https://doi.org/10.1080/10494820.2020.1802298

Nkuyubwatsi, B. (2013). Evaluation of massive open online courses (MOOCs) from the learner's perspective. In *12th European Conference on e-Learning*. Sophia Antipolis, France.

Onah, D. F. O., Sinclair, J., & Russel, B. (2014). Exploring the use of MOOC discussion forums. In *London international conference on education (LICE-2014)* (pp. 1–4). LICE.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00422

Park, T., Cha, H., & Lee, G. (2016). A study on design guidelines of learning analytics to facilitate self-regulated learning in MOOCs. *Educational Technology International, 17*(1), 117–150.

Pilli, O., & Admiraal, W. F. (2017). Students' learning outcomes in massive open online courses (MOOCs): Some suggestions for course design. *Journal of Higher Education, 7*(1), 46–71.

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press.

Rohloff, T., Sauer, D., & Meinel, C. (2019). Student perception of a learner dashboard in MOOCs to encourage self-regulated learning. In *2019 IEEE international conference on engineering, technology and education (TALE)* (pp. 1–8). IEEE.

Ross, J., Sinclar, C., Knox, J., Bayne, S., & Macleod, H. (2014). Teacher experiences and academic identity: The missing components of MOOC pedagogy. *MERLOT Journal of Online Learning and Teaching, 10*(1), 57–69.

Schumacher, C. (2020). Linking assessment and learning analytics to support learning processes in higher education. In J. M. Spector, B. B. Lockee, & M. D. Childress (Eds.), *Learning, design, and technology*. Springer.

Schuwer, R., Jaurena, I. G., Aydin, C. H., Costello, E., Dalsgaard, C., Brown, M., Jansen, D., & Teixeira, A. (2015). Opportunities and threats of the MOOC movement for higher education: The European perspective. *The International Review of Research in Open and Distributed Learning, 16*(6), 20–38. https://doi.org/10.19173/irrodl.v16i6.2153

Schwendimann, B. A., Rodríguez-Triana, M. Í. J., Vozniuk, A., Priet, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*. https://doi.org/10.1016/j.chb.2018.05.004

Siemens, G. (2009). *What is connectivism?* Retrieved from https://docs.google.com/document/d/14pKVP0_ILdPty6MGMJW8eQVEY1zibZ0RpQ2C0cePIgc/preview?pli=1

Stracke, C. M. (2017). The quality of MOOCs: How to improve the design of open education and online courses for learners? In P. Zaphiris & A. Ioannou (Eds.), *Learning and collaboration technologies. Novel learning ecosystems. LCT 2017* (pp. 285–293). Springer.

Terras, M. M., & Ramsay, J. (2015). Massive open online courses (MOOCs): Insights and challenges from a psychological perspective. *British Journal of Educational Technology, 46*(3), 472–487. https://doi.org/10.1111/bjet.12274

Verbert, K., Fovaerts, S., Duval, E., Santos, J. L., van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal Ubiquitous Computing, 18*(6), 1499–1514. https://doi.org/10.1007/s00779-013-0751-2

Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A., & De Laet, T. (2020). Learning analytics dashboards: The past, the present and the future. In *LAK ´20: Proceedings of the 10th international conference on learning analytics & knowledge* (pp. 35–40). The Association for Computing Machinery.

Vieira, C., Parsons, P., & Vyrd, V. (2018). Visual learning analytics of educational data: A systematic literature review and research agenda. *Computers and Education, 122*, 119–135. https://doi.org/10.1016/j.compedu.2018.03.018

Yoo, Y., Lee, H., Jo, I.-H., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In G. Chen, V. Kumar, R. H. Kinshuk, & S. Kong (Eds.), *Emerging issues in smart learning. Lecture notes in educational technology* (pp. 145–155). Springer.

Yousef, A. M. F., Chatti, M. A., Schroeder, U., & Wosnitza, M. (2014). What drives a successful MOOC? An empirical examination of criteria to assure design quality of MOOCs. In *IEEE 14th international conference on advanced learning technologies*. Athens, Greece.

Yu, C.-H., Wu, J., & Liu, A.-C. (2019). Predicting learning outcomes with MOOC clickstreams. *Education Sciences, 9*(2). https://doi.org/10.3390/educsci9020104

Chapter 7
Powerful Student-Facing Dashboard Design Through Effective Feedback, Visualization, and Gamification

Fatma Bayrak, Pınar Nuhoğlu Kibar, and Selay Arkün Kocadere

1 Introduction

Students interact with learning systems and with each other within these learning systems, leaving their digital footprints behind in the process (Pardo et al., 2019; Ryan et al., 2019). These can be rapidly analyzed through machine learning and predictive modeling techniques (Pardo et al., 2019). In this way, patterns emerge from learner behaviors, and it becomes possible to support learning through these patterns – a process known as learning analytics (LA), which starts with data and continues with supporting learning (Gašević et al., 2015).

The main functions of LA are predicting student learning success and providing proactive and personalized feedback (Dawson et al., 2014; Lim et al., 2019b). Furthermore, as system users may not be able to interpret data tables and statistics, it becomes necessary to present results obtained through LA in a user-friendly visual form (Chatti et al., 2012). LA dashboards (LADs) provide such graphical representations of the collected data and analytics performed to support teachers and students (Pardo & Dawson, 2015). In the early stages of LA, dashboards for teachers were studied most intensively (Teasley, 2017). At the time, dashboards were used to identify at-risk students, sift out ineffective content, support traditional face-to-face lectures, assist teachers in staying aware of the subtle interactions in their courses, and support online or blended learning (Klerkx et al., 2017). While student-facing dashboards for learners who have control over their learning process were less studied at that time (Chatti et al., 2012; Kitto et al., 2017), as mentioned in the Horizon 2020 report, it is now more common practice to give learners access to their own learning analytics dashboard (Brown et al., 2020).

F. Bayrak (✉) · P. Nuhoğlu Kibar · S. A. Kocadere
Hacettepe University, Ankara, Turkey
e-mail: fbayrak@hacettepe.edu.tr; pnuhoglu@hacettepe.edu.tr; selaya@hacettepe.edu.tr

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_7

Many researchers have acknowledged the effect of feedback on learning and now have honed in on interaction data-based feedback with an upward trend toward student-facing dashboards. Related to this, Pardo et al. (2017) state that there is a need to investigate the relationship between LAD interventions and feedback types and to review feedback through comprehensive data sets derived through technology. For learners to perceive data-enriched feedback quickly and clearly, determining how to visualize the information becomes prominent.

Beyond examining the relationship between feedback types and LAD, it seems critical to consider LAD design from a feedback loop perspective to increase the effectiveness of LAD. Sadler (1989) mentions that the feedback loop closes when the learners take the appropriate actions to close the gap after being presented with the feedback. On the contrary, if the learner does not take action and does not show improvement, it means that the feedback loop is not closed and does not have an effect. It can be stated that the purpose of student-facing dashboards is for learners to monitor their own processes, to make decisions based on provided data, and to act in line with it. Although the feedback via dashboard is effectively presented, learners may still fall short of their full potential, such as when the learner chooses not to interpret and act on the feedback presented to them. In this manner, the learner's lack of action does not benefit his/her progress (Ryan et al., 2019; Teasley & Whitmer, 2017). One solution may be to use gamification to motivate learners to take action. Embedding gamification components and mechanics into the learning environment can enable learners to visit dashboards more frequently for monitoring purposes and to take action following the provided feedback, resulting in improvement. The feedback and gamification design regarding the feedback loop determines the content and functioning of the dashboard. Designing feedback and gamification for students to close the loop seems more possible by visualizing them in a holistic perspective in LAD.

In this section, first, the feedback literature is examined, and then design suggestions for LAD are presented, with emphasis on feedback. The dashboard design is scrutinized in terms of information design for maximum visualization effect of feedback. In order to close the feedback loop and increase the learner's interaction, dashboard design is handled here from the perspective of gamification.

2 Student-Facing Dashboards from the Perspective of Feedback

The crucial role of feedback in improving learners' learning is seen in multiple meta-analysis studies (Hattie & Timperley, 2007; Wisniewski et al., 2020). However, different terms of feedback are encountered in the literature. When these terms and definitions are examined, it is noteworthy that some terms are used interchangeably. This situation could be confusing. Therefore, in Table 7.1 these terms and definitions are presented, and the intersecting points are shown.

Table 7.1 Level and terms of feedback

Level	Definition	Terms used in the literature
Task	Information about whether the learner's answers are correct or incorrect	Verification (Butler & Winne, 1995; Kulhavy & Stock, 1989) Knowledge of result (Butler & Winne, 1995) Outcome feedback (Butler & Winne, 1995) Summative feedback (Butler & Winne, 1995)
Process	Hints, directing the student to the content, thoroughly explaining the answer, examining errors, and providing working examples and guidance	Elaborated (Butler & Winne, 1995; Kulhavy & Stock, 1989) Process-oriented feedback (Sedrakyan et al., 2019, 2020; Rakoczy et al., 2013)
Self-regulated	Showing the student a way to monitor, manage, and regulate their behavior for learning	

Hattie and Timperley (2007) classified the feedback at four levels: task, process, self-regulation, and self. Feedback given at the task is about whether the learner's performance is correct or not. This is also referred to as outcome feedback, knowledge of results, or summative feedback (Butler & Winne, 1995). Process level feedback is specific to the processes underlying the tasks. Examples at this level include giving links between ideas, examining mistakes, and giving hints (Hattie & Gan, 2011; Shute, 2008). When the literature is examined in further depth, it is seen that elaborated, cognitive, or process-oriented feedback terms are used for process feedback (Butler & Winne, 1995; Rakoczy et al., 2013). That the term process or process-oriented feedback is used more widely in LAD studies recently is of noteworthy interest (Sedrakyan et al., 2019, 2020). In some studies, this term is used for both process and self-regulated level. Self-regulation level feedback shows the student a way to monitor, manage, and regulate their behavior for learning. Feedback encourages autonomy, self-control, self-management, and self-discipline (Hattie & Timperley, 2007). Self-level feedback includes expressions of praise (Hattie & Timperley, 2007). Recently, self-feedback is being studied as affective feedback within the scope of Intelligent Tutoring Systems, but affective processes are not covered in this section.

Pardo et al. (2017) stated that LADs usually contain task-level feedback, from which it is more difficult to extract information about learning or self-regulation processes. Recent interest in providing automatic, scaled, and real-time feedback to learners at these levels has also been expressed by LA researchers, such as in Sedrakyan et al. (2020) and Pardo et al. (2019). Through these studies, it is observed that the types of data and procedures collected to give feedback at the self-regulation level differ.

Another classification is about feedback time: immediate and delayed (Shute, 2008). However, these classifications are made for assessment feedback. In other words, they are given according to the assessment task's current status of completion. With recent advances in technology, students' behavior in the system has become much more rapidly observable. Within the scope of LA, data can be collected and analyzed immediately, and feedback accessed in real time (Winnie, 2017), which is one of LA's strengths. However, some analytics require data over a longer period, and feedback can only be given after that time has elapsed. For example, in time, it can be predicted whether the student will drop out or not. In addition to data collected from the volume of words and timing in which learners contribute in forums or reports, studies continue in the field of machine learning on automatic scoring of learners' messages (Sychev et al., 2020; Zhang et al., 2019). In this way, it will soon be possible to provide such feedback prepared by teachers automatically and in real time.

In order for the learner to make sense of his/her performance, he/she needs references that they can compare themselves to. Nicol (2020) has emphasized that students generate internal feedback by comparing their current knowledge against some reference information. Correspondingly, a classification is made according to the reference to which performance is compared, and these are called criterion-, self-, and norm-referenced feedback (Hattie & Gan, 2011). In criterion-referenced feedback, standards and existing situations are compared (Brookhart, 2008, p. 22). While self-referenced feedback is based on the learner's previous performances, norm-referenced feedback includes information based on the learner's performance compared with that of other learners (Brookhart, 2008, p. 23). It is seen that in LA studies comparisons are handled as reference frame principles (Lim et al., 2019a; Wise, 2014; Jivet et al., 2020).

Hattie and Timperley (2007) also emphasized that feedback should answer all of the following three questions:

1. Where am I going (what are the goals)? – Feed up
2. How am I going (what progress is being made toward the goal)? – Feedback
3. Where to next (what activities need to be undertaken to make better progress)? – Feedforward

Based on these questions, the next step in the process should be clear to the learner within the feedback. This way, the learner receiving the feedback can also see what he/she must do to close the gap and take action. As mentioned before, Sadler (1989) stated that the feedback loop closes when the learners take appropriate actions to close the gap after being presented the feedback. If the learner does not take action and does not show improvement, it means that the feedback loop is not closed and it does not have an effect. In the light of social constructivism, the description of feedback transformed from presenting information (Black & Wiliam, 1998; Hattie & Timperley, 2007; Kulhavy & Stock, 1989; Mory, 2004; Ramaprasad, 1983; Shute, 2008) to a process (Boud & Molloy, 2013; Carless & Boud, 2018; Henderson et al., 2018; Winstone, 2019), which involves taking action in light of the feedback.

In summary, two characteristics of feedback can be identified from those mentioned earlier. The first of these is the level of feedback. While it is seen that different names are used for feedback, it is agreed that feedback should include the current situation and recommendations. The second feature of feedback is that it contains a comparison reference in order to make sense of the feedback. Learners have different preferences regarding comparisons made with criteria, norm, and self. Accordingly, it is widely thought a wide variety of comparisons is useful. In terms of these features, the implications for LADs include the concept that dashboards should include suggestions and different types of comparisons.

With the developments in technology, types of data such as which videos the learners watch, how long they spend in a question, the number of words or characters in the answer, etc. can also be obtained. These types of data can be very diverse. In their systematic reviewing study, Schwendimann et al. (2016) classified indicators collected during the e-learning process as action, result, social, content, context, and learner related. Furthermore, Pardo (2018) presents a model to reconceptualize feedback in data-rich learning experiences. He stated that to analyze and predict learner behavior, algorithms should be considered a part of the feedback process. Based on this, it is seen that there is a need to talk about analytics.

Cambridge Dictionary defines analytics as a process in which a computer examines information using mathematical methods to find useful patterns (Fleckenstein & Fellows, 2018; Ndukwe & Daniel, 2020). Accordingly, four analytics are mentioned in data science: descriptive, diagnostic, predictive, and prescriptive analytics. Descriptive analytics is the examination of data to answer the question "What happened?". Diagnostic analytics search for an answer to the question "Why did it happen?". Predictive analytics provides insight on "What will happen?". At this point, Pardo and Dawson (2015) have stated that if we can predict how students will behave while participating in a learning experience, perhaps we can anticipate failure, complications, and anomalies and promptly deploy the appropriate remediation actions or intervention. The learner must find an answer to why he/she is in the risky group and what they have to do to remove themselves from it. Prescriptive analytics contains more information in this sense (Ryan et al., 2019) and is a combination of descriptive analytics and predictive analytics that answers the question "What should we do?". From this point of view, analytical levels mentioned within the LA and feedback examples are presented in Table 7.2.

In summary, in terms of feedback, we can state that dashboards presented to learners should include current state and recommendations. From this point on, prescriptive analytics, which is the most complex level, strengthens feedforward further with data-based recommendations. Recommendations should be presented at other analytics levels by instructors, the system, or both, as these will help learners decide on their next steps. The system developed by Pardo et al. (2019) is an example of supporting teachers to write recommendations based on learning analytics.

Students can be encouraged to get in contact with their teacher or with peers, especially if they fail even after following the recommendation. The system's message as "study with a friend or teaching assistant because the videos were not helping you succeed" is an example for this case (Bodily et al., 2018). Pardo et al. (2019) indicated that the definition of feedback has turned into a more dialogic form. Winstone et al. (2017) found all forms of dialogue on feedback, including that of peers, are vital to improvement, too. A mechanism in order to encourage not only taking but also providing peer feedback could be integrated into the system. As a matter of fact, giving peer feedback is itself a gain (Nicol, 2013).

Table 7.2 Feedback examples at different analytics levels

Data analytics	Analytics that answers ...	How am I going? (What progress is being made toward the goal?)	Where to next? (What activities need to be undertaken to make better progress?)
Descriptive analytics	What happened?	Example: Test 1 has ten questions and you answered one of them incorrectly	Example: You can go to the X second of the video. In this way, you can find the correct answer
		Example: You have completed 2 tests The time you spend on the content is 35 min and the total number of your entries to the system is 15	Example: The tests you have not answered: Test 3, Test 4 ... The content you have not reviewed are: Video 1, Video 2, discussion ...
Diagnostic analytics	Why did it happen?	Example: The time you spent in the content is 20 minutes In previous years, it was found there is a relationship between the time spent on the content and achievement Last year, in the first 2 weeks, those who watched Video 1, Video 2 and Video 3 were successful	Example: It would help if you spared time for content The videos that you haven't finished watching are listed below: ...
Predictive analytics	What will happen?	Example: You have completed 2 tests. The time you spent in the content is 40 minutes, and your entries to the system were 10 In previous years, learners who continued in this way failed the course	Example: It would help if you changed some of your study habits Note: The learner must find an answer to why he/she is in the risky group and what he/she has to do to remove themselves from it. Prescriptive level contains more information in this sense (Ryan et al., 2019)
Prescriptive analytics	What should we do?	Example: You have completed two tests. The time you spent in the content is 40 min and your total number of questions in the forum was 10 In previous years, learners who continued in this way failed the course Note: Prescriptive analytics is a combination of descriptive analytics and predictive analytics	Example: In the course, 70 percent of those whose grade is at least 65 in Test 1, whose grade is at least 70 in Test 2, and the people who wrote the most questions in the forum were successful 60% of those whose grade is at least 50 in Test 1, whose grade is at least 80 in Test 2, and the people who wrote the most questions in the forum were successful You can try any path you want It can be expressed more simply as follows: To achieve this course, you should increase your scores in Test 1 and Test 2. To manage this, we recommend you to repeat video X and be more active in the forum

Within the scope of this section, the feedback literature has been summarized and recommendations presented. However, when appropriate visualization is not done, perceptibility of feedback can be difficult or cause wrong decision-making. Accordingly, visualization processes will be discussed in the next section.

3 Learning Dashboards from the Gamification Perspective

Gamification is defined as using game elements and design techniques in non-game contexts (Werbach & Hunter, 2012) and has become a frequently used instructional method. Kocadere and Çağlar (2018) defined instructional gamification as an approach using game design principles in the learning environment to interest and motivate learners. While the most commonly used elements are points, badges, and leaderboards (Subhash & Cudney, 2018), levels, charts, rewards, and stories are some of the other game elements used in gamification. Depending on the gamification design, these items trigger mechanics like competition, collaboration, resource acquisition, and transaction (Kocadere & Çağlar, 2018). By each element integrated into the learning environment, feedback is provided to the students. Feedback, the core constituent of dashboards, can also be considered as the main structure in gamification. Gamification technologies have the groundwork to use LA for empowering feedback. It can even be said that without LA, gamification does not reach its full potential and does not have the desired effect on learning (Spector et al., 2016). It can be said that feedback presented via dashboards like showing badges, progress, or a comparative status is a complementary part of gamification. From a similar point of view, Freitas et al. (2017) listed advantages of gamified dashboards as positive effects of visualization, competition-collaboration opportunities, and increased engagement. The combination of analytics and gamification has been interpreted as a powerful tool by Goethe (2019) to motivate users to engage. In line with Goethe (2019), Mah (2016) suggested using LA to produce badges as personalized feedback to improve learning and enhance the retention of the students. Gamification studies show positive effects such as increased motivation, engagement, and consequently enhanced performance (Özhan & Kocadere, 2020). This blended structure indicates two emphases, in which the second one is the focus of this study.

1. Designing effective dashboards that take into account both LA-based feedback and visualization principles can be considered a way to improve the effects of gamification.
2. With its effects, gamification can be seen as a method of serving the effectiveness of dashboards by increasing participation and motivation for taking action.

No matter what purpose and how well student-faced dashboards are designed, students need to learn to examine, interpret, and make decisions based on the information presented to them (Teasley & Whitmer, 2017). According to Carless and Boud (2018), feedback literacy consists of four steps: appreciating feedback; making judgments; managing effect; and taking action as a result of the other three steps.

These steps basically indicate the interaction of students with feedback. Nicol (2010) highlighted the importance of students' interactions with feedback and stated it might be even more important than the quality of their teachers' comments. He also mentioned students' need to change their future actions based on the feedback they get. Ryan et al. (2019) indicated while dashboards ease teachers into providing feedback, especially in crowded classes, it does not guarantee motivation for learners to act accordingly. Han and Xu (2019) expressed how students under-engaged with feedback despite their teachers' efforts to provide it. Both Bodily et al. (2018) and Sansom et al. (2020) mentioned the need for further studies to motivate students to engage with dashboard feedback. Based on all of these, two points attract attention:

1. The need to motivate learners to increase their interaction with dashboards
2. To encourage them to take action after considering the provided feedback

As mentioned before, with its capacity for motivation and engagement, gamification has the potential to be the solution for this lack. Winstone (2019) wanted to integrate operating logic from fitness apps into feedback loops to engage students with the feedback and direct them to track their own results. Even though she did not use the term gamification, what she is describing is basically gamifying to increase students' engagement with feedback. In this part of the chapter, a series of suggestions about gamifying the feedback loop to motivate learners to monitor their progress through dashboards and take action will be listed below. The key concepts will be seen as bold to facilitate to follow.

Visualizing the learners' path is one of the main points highlighted by Charleer et al. (2016) in their study about creating effective LA dashboards. An equivalent of a game board, and pawns/avatars, which will be included in the dashboard, allows students to see their goals, their position relative to their goals, and their next task. The digitized visual representation of a game board answers the "What are the goals?", "What progress is being made toward the goal?", and "What activities need to be undertaken to make better progress?" questions of Hattie and Timperley (2007). Visible progress is one of the main requirements in gamification. Signs for completed/unlocked levels, three stars to be filled up, or a simple progress bar could be used to show the learner's progression on the path. This big picture may also be an encouraging factor when students falter. As a matter of fact, Winstone et al. (2017) indicate that encouraging students to monitor their overall performance may prevent demotivation.

The last question from above, "Where to next?", can only be replied in a limited way on the path. For example, the table of contents or the next week's quiz can be seen as one further step toward the learner's goal. However, the answer should be more specific in relation to the action to be taken by the learner to close the gap between their current performance and ideal performance (Sadler, 1989). For encouraging students to take action, recommendation paths based on LA as part of the feedback can be developed. From a game point of view, creating a nonlinear path is favorable; it could also be said from the learning field, the more the students have control over their learning, in other words have a chance to pick from their options, the better they learn. Recommendation in one part of the dashboard should lead learners to action. Additionally, learners that follow the recommendations should be rewarded. One barrier to engaging feedback is not seeing efforts "paid off" (Winstone et al., 2017). Therefore, the positive consequences of actions learners take based on the feedback should be visible to them. At this point, the advantage of learning analytics that work based on real-time data and the instant feedback produced based on it can easily be seen. The capacity to provide instant feedback on the learning strategies they have determined can also be an element that will support students' self-regulation skills. In other words, encouraging learners to use dashboards in this way can improve their ability to control their learning processes.

Points are one of the main elements that can be used, as they easily combine with assessment results from assignments and exams. On the one hand, learners' general interaction with the system, such as the frequency of logins and/or the interest in educational resources, can be demonstrated in points. On the other hand, in a gamification design that focuses on the usage of feedback, points produced from time spent in the dashboard monitoring feedback, taking action from suggestions in the feedback, and accuracy of the action can be generated. The "points" can either be formed by assessment results directly or can include various units of measurement like frequency of logging in.

Graphs and iconic visuals, especially when grounded on LA, are powerful tools for the visualization of game elements. For instance, through them, students can evaluate their own progress, by time, and make a comparison of their performance against that of their classmates. Although competition is not every player's favorite game mechanic (Kocadere & Çağlar, 2018), dashboard components that provide comparison chances are still found useful by students (Park & Jo, 2015). Furthermore, Nicol (2020) emphasized the importance of comparing oneself with others for learning. Leaderboards are one of the most popular comparison methods used in gamification. Leaderboards don't necessarily rank by points. For example, students/teams can be listed according to the number/variety of their badges. Another example might be lining up learners considering their quickness in taking actions in line with the system recommendations or considering the amount of time spent in the system.

Tenório et al.'s (2020) study is an example from a similar perspective. In this study, the teacher defined goals as interacting at least 60% with the resources. Students have a dashboard that involves visuals about points, levels, progress over time with regard to defined interaction, and interaction with each educational resource. When the teacher determines any situation under expectation, he sends a new assignment to this specific group/student via email. With this notification, the teacher gives information about the task, task deadline, potential reward, and related resources at hand to utilize in order to achieve the mission. Following this, the impact of this intervention can also be visualized. The results of this study indicate improvement in students' engagement, motivation, and learning outcomes.

As is always the case in both games and gamification, the user's next step should be given in clear and small chunks (Rouse, 2004). In particular, recommendations should be provided in that fashion. Winstone et al. (2017) found students were inactive in using feedback that gave unrealistic expectations and did not provide them enough time for action. A certain amount of time must be given to students for them to act in response to how the feedback has directed them. Still, it would also be wise to provide notifications that will cover the distance in the learner's engagement loop (Zichermann & Cunningham, 2011). Sansom et al. (2020) also mentioned that reminder systems might increase dashboard usage as well.

In conclusion, the iterative process from the gamification perspective can be clarified as follows:

1. Define challenges by combining determined game mechanics and goals.
2. Present challenges in doable pieces and link to rewards (virtual goods, badges, stars, etc.).
3. Diversify challenges and branch out the path as much as possible.
4. Give enough time for each challenge and recall to the dashboard via notifications.
5. Give feedback, including rewards, on actions they took through the dashboards.
6. Make learners' progress and status visible and provide opportunities for comparison.
7. When they achieve goals, re-engage them with new challenges.

In games, driving players into corners is not acceptable (Rouse, 2004), and it is not a preferred method in learning environments either. Since the main purpose is to improve learning, we should avoid herding students into dead ends. Providing different paths and giving clear instructions regardless of diversifying paths can be a solution in this situation. Winstone et al. (2017) mentioned that students need to understand the feedback and find a way to act after considering it. Likewise, Aguilar (2018) calls attention to always giving a way for students to improve. Some potential moves in line with these suggestions are (a) planning bonus tasks that provide opportunities for gaining points through extra assignments, (b) diversification of recommendations in order to give students different ways to enhance learning, or (c) "replay" chances such as retaking tests or revision of homework.

Gamification should prioritize learning and be integrated into the course in a meaningful way. Clicking the dashboard should not be a discrete requirement, but rather a natural extension for how students follow the course. In like manner, both Sansom et al. (2020) and Charleer et al. (2016) have made similar suggestions, such as integrating the dashboard into students' workflow for the adoption of dashboards as part of the learning process.

Up to this point, the interaction of LA and feedback with gamification and visualization of the path, progress, and ranking has often been discussed, but it should be noted that visualization's connection with gamification is not limited to game elements. For example, adding a back story like fighting with pirates, running from zombies, and designing badges in line with the story might motivate learners more. Gamification is based on games that take their power from visuality. Games can even be described as information design artifacts with high information density (O'Grady & O'Grady, 2008, p. 25). Gamified applications that have gone through an effective information design process seem more remarkable than others. Gamified or not, this concept also applies for dashboards. Freitas et al. (2017) mentioned a similar point that visualization principles enrich gamified dashboards and support learners to explore dashboards.

4 Visualization of Learning Dashboards

Placing the dashboard between the words of information design term, Few (2006) drew attention to the visual design of dashboards, which has a great impact on their effectiveness. With the phrase "information dashboard design," he qualified dashboards as information design output and defined the dashboard as a "visual display of the most important information needed to achieve one or more objectives, which fits entirely on a single computer screen so it can be monitored at a glance." The International Institute for Information Design (IIID) defines information design as "the defining, planning, and shaping of the contents of a message and the environments in which it is presented, with the intention of satisfying the information needs of the intended recipients" (idX, 2007). There is an emphasis on message transmission in information design, and when it comes to learning dashboards to be used for learning-teaching processes, the information design process becomes more specialized due to its target audience and purpose. The message to be designed in the information design of learning dashboards appears as feedback aiming to improve learning by covering information based on the learning process.

Schwendimann et al. (2017) treat the dashboards used in the learning-teaching process as learning dashboards and defines them as "single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations," which draws attention to what educational dashboards should contain. Beyond the content of learning dashboards, Schwendimann et al. (2017) remarked that visualizations in educational dashboards are very similar to those created for other fields and that they should be customized and designed with field-specific visual metaphors to be used in learning processes. In fact, they point to the question of how these learning indicators should be visualized, which is closely related to information design.

While dashboards aim at effective transmission of information reached through the intensive data visualization process, the result can be complex interfaces filled with incomprehensible data graphs when the information design process is not implemented efficiently. Data visualization enables the communication of complex and unorganized dense data effectively through the visual representation of its graphical or pictorial format (Pettersson, 2021) which forms the basis of the graph-intense content to be visualized in the learning dashboards through the LA process. The types of data included in graph-intense representations and the relationships established between them are determinant in the complexity of the graph, which in turn determines the level of learner benefit from the representation. Shneiderman (2003) draws attention to this relation and proposes Visual Information-Seeking Mantra for graphical user interfaces as learning dashboards, which covers seven tasks as overview, zoom, filter, details-on-demand, relate, history, and extracts over seven main data types as one/two/three/multidimensional, temporal, tree, and network. The information-seeking task classification seems to be extended for specialized and sophisticated graphs which can be developed with various combinations of determined data types. Ware (2013) points out the depth of the classification of data types with a similar approach and divides data into two forms: entities and relations. Entities are objects intended to be visualized; relations are structures between objects and patterns formed by these objects. Determining or exploring the attributes of the entities and relations constitutes an important stage of data visualization. For student-facing learning dashboards, this process takes place in the form of deciding what types of metrics related to learning will be addressed, how these metrics will be examined in combination, and what kind of indicator will be presented to learners as feedback.

Although the data visualization process is the basis for developing an effective learning dashboard, the main step is how to convey this message to the learners. Learning analytics dashboards consisting of data-intensive graphs created in line with the data visualization process that has not been combined with information design are often described as complicated by the target audiences who are low graph literate or unfamiliar with the specialized graphs. At this point, it should be taken into consideration that the knowledge base of the target group (specific group or broad audience) and information density is decisive in the form and function of the information design product to be developed (O'Grady & O'Grady, 2008, p. 24).

4.1 Graph Literacy Effect on Learning Dashboard Visualization

Graph literacy, which covers the skills of reading and drawing graphs (Fry, 1981), is closely related to the level of benefit from dashboards (Park & Jo, 2015). The effectiveness of a graph is related to the prior knowledge and experience of the learner in reading the type of presented graph (Clark & Lyons, 2011). In terms of the effectiveness of dashboards, the literacy levels of the students regarding the dashboard to be presented should be considered in the context of learning (Sansom et al., 2020). At this point, it is critical to produce design solutions by considering the varying levels of graph literacy among learners for increasing the level of the learners' benefit from the dashboard.

Regarding the solution of problems arising from graph literacy, adding components to the learning process that aim to increase the graph literacy of learners is one of the first design solutions that comes to mind. Placing a help menu explaining how to read graphs can support students in reading the graphs used on the dashboard (Park & Jo, 2015). Similarly, adding just-in-time training to dashboards that require reading complex graphs can also support learners in how to interpret complex graphs (Mautone & Mayer, 2007).

Another suggested design solution to address different literacy levels is to offer dashboards with options such as simple and advanced, which vary according to the complexity level of data graphs it contains (Park & Jo, 2015). The simple option enables low-literate learners to read the graph, while advanced options allow highly literate learners to make more detailed inferences over the data. Presenting different options of graphics according to the complexity level on a single dashboard provides an advantage for students with different literacy levels; but on the other hand, adding view options may result in overcomplexity and clutter in the dashboard design (Bodily et al., 2018).

Simpler viewing options are generally structured with more commonly recognized graphs in dashboards, which overlap with an instructional graphic design approach. In any graphics used in a learning environment, where the data-intensive relationship is visualized, it is recommended to choose graph types familiar to the learners as often as possible (Clark & Lyons, 2011, p. 121). Familiarity with the graphic format may differ even in different uses of the same graph type. The vertical use of bar charts, which is more familiar, is interpreted faster than its horizontal use (Fischer et al., 2005). When examining the chart types used in studies on dashboard design, it was seen that bar charts, line graphs, pie charts, network graphs, etc. are used extensively and do not differ according to the learning context or the learner groups (Schwendimann et al., 2016). Although the authors did not examine the distribution of the graphs used in research by years, examining the change may also affect the design decisions to be taken related to graph familiarity usage.

The development of data visualization tools has changed and improved the design of interfaces to cover different graph types (Rendgen, 2012). Newly developed interfaces introduce different graphic types and visualization styles to the target audience. Accordingly, the required literacies change, and from this continual change emerges the question of how to design more digestible visual messages where data-intensive, extraordinary graphics are used extensively. Without a doubt, these changes in required literacies have caused infographics to become more visible in digital media than ever before.

4.2 Visualization of Learning Dashboards from the Information Design Perspective

Infographics, which are outputs of the information design process, are an effective visualization form that enables the transfer of important points and relationships within the information to be conveyed through a holistic graphic with complementary text and iconic visuals (Nuhoğlu-Kibar & Pettersson, 2021). According to the requirements of information design, infographics can be developed statically, semi-dynamically, and dynamically, according to the variability of information and interaction level (Lankow et al., 2012, p. 74). They can cover one or more types of comparison, data, flow chart, image based, timeline, process, metaphor, and narrative type of infographics (Dyjur & Li, 2015). Although it is not actually mentioned in the literature, the infographic design approach contains answers to the question of how data-intensive dashboards can be designed effectively, as they enable information to be transferred interactively through a story by converging text and iconic visuals.

The effectiveness of an infographic depends on the quality of the information that the infographic content wants to convey and the visual quality of the design applied to transfer this information, which correspond to the content generation and visual design generation dimensions (Nuhoğlu Kibar & Akkoyunlu, 2017). The content generation dimension focuses on how content is structured and organized. This dimension draws attention to the design principles of using headings and subheadings, grouping information into sub-information groups, ensuring systematic and continuity between sub-information groups and within the group, highlighting important information, and providing visual information with clear and concise explanations. The visual design generation dimension examines the visual features of text (font and text line features) and visuals (color effect on visibility, harmony, redirection, and used reality level and tags) that make up the infographic separately and additionally examines the big picture (visual hierarchy, redirection, rhythm, emphasis, consistency, balance, and integrity) formed by the combination of text and other visuals.

In particular, when the purpose of visualization is pedagogical (as in learning dashboards), and the aim is not reaching detailed data analysis, using pictorial icons, symbols, or words directly on charts can help provide cognitive efficiency. Such design solutions will reduce a step in the learner's cognitive process as they attempt to figure out the category of data they have encountered as part of their graph reading (Ware, 2013, pp. 316, 320). Similarly, when it comes to the learning dashboard, adding scaffolding texts help students to interpret graph-intense information on the dashboard and enable them to make forward-looking inferences (Park & Jo, 2015). With the aforementioned information visualization approach, Ware (2013) points to infographics, where rapid understanding is the main purpose and the scope of content and data visualization is limited for that purpose. Thus, more blank space can be opened on the design plane to other visualization elements (symbols, icons, images, and words) that can be applied to graphic-intensive presentations.

The design structure of static multi-block infographics contains clues about the basic principles for the visual design of learning dashboards. Organizing complex data or ideas in a multipart visual representation structure and presenting them in a single display (Sommer & Polman, 2018), creating a story by combining image and text with a flow of information (Lu et al., 2020), and structuring the flow of information with the feature that makes the relationships visible (Albers, 2015) draw attention to three interrelated points regarding the improvement of visual designs in learning dashboards: (1) text and visual integration, (2) flow of information, and (3) whole-part relationship. These three points draw attention to three aspects of graph-intense learning dashboards that could be improved through an effective spatial placement by considering the relation between the all kinds of items that make up the content. In the simplest terms, this is possible by determining the proximity of the elements and placing them according to the strength of the relationship between them. In the design process, it is performed as follows: (1) placing the associated visuals and texts that constitute the smallest unit in the content; (2) the placement of these units according to the relationship between the parts, which will form the flow; and (3) creating the perception that each unit is a part of the whole.

The tendency to present data on the status of the learner on the dashboard without creating connections between the pieces overlooks the necessity to reflect on the learning context and processes. Decisions taken in the context of the content and visual type of the parts to be included are followed by the decision to bring these parts together. This points to another common dashboard design mistake – placement – where many problems encountered in dashboard design can be solved based on the principle of proximity (Few, 2006). The ability to view recommendations in conjunction with an interactive scatter plot that displays the learner's knowledge, instead of presenting the learner's situation data and their associated recommendation on separate pages, is an example of how proximity can be a design solution (Bodily et al., 2018). Defining the relationship between the parts, placing them according to the principle of proximity, and ensuring continuity between the parts will create the information flow in the dashboard. The reflection of the information flow on the dashboard makes the learning process/context visible and traceable on the dashboard.

Excessive and incorrect use of colors, use of different graphic types serving the same purpose for diversity reasons, and excessive decoration of the interface are common mistakes (Few, 2006). Color is one of the most important design elements used in directing attention. How it is used in design is critical because it supports coding in terms of learning. It can have important design functions such as highlighting important information in the interface, defining sub-information groups, and ensuring integrity in the interface. As an interface where the learning process is monitored, it is recommended to use color in learning dashboards to support learning and include decoration in a way that will increase the attractiveness without shading the content.

Moreover, as they convey messages quickly by combining graphs with text within a limited space, dashboards motivate audiences into taking action by bringing their attention to essential information (Few, 2006). In order to achieve this, it is vital to incorporate visual attention elements into the dashboard design. In addition to highlighting important information, recommendations aimed at galvanizing students into action can be made more recognizable by differentiating them from other items on the dashboard in terms of visual features. Placing the recommendations close to the status of the learners (without using scrolls or nested menus on the same screen) increases the visibility of the recommendations (Bodily et al., 2018). Interactive radar graphs and associated displays are also methods used to effectively display multidimensional status recommendations.

5 Discussion and Conclusion

This study proposes a perspective for student-facing dashboards that combines (1) feedback design to show students their status and the further actions to be taken, (2) gamification design to urge students to act in the direction of feedback, and (3) information design to visualize feedback and gamification design effectively. Feedback design for deciding which information to be presented to students constituted the initial step of dashboard design. In order to motivate students to monitor their learning process and close feedback loop, the dashboard was strengthened with gamification. The feedback and gamification design was visualized in a cohesive and holistic manner with the information design perspective. Although it looks like a sequential structure, these three components require an interwoven design process according to the purpose and design approach of the dashboard. Design suggestions for student-facing LADs according to feedback loop can be summarized as follows:

- Present the learner's current status, gap between desired and current state with a comparison point, and give recommendations on how to fill the learning gap.
- Give recommendations based on challenges to fill the gap by linking goals with game elements, give feedback including rewards on the action they took through the dashboards, provide enough time, and recall to the dashboard via notifications to re-engage learners with new challenges.
- Visualize the learner's current status, recommendations, position in the learning process, and game elements, which forms the functioning of the process, while considering the relationship between all. Visualize by integrating different visual elements (symbols, icons, images, scaffolding texts, titles, etc.) and consider the differing literacy levels of learners when providing visual design solutions (such as adding different graphs forms when imparting information).

In order to put theory to practice, a snapshot of a hypothetical learning dashboard was provided in Figs. 7.1, 7.2, and 7.3. The left side of the dashboard is visualized in Fig. 7.1 and the right side in Fig. 7.2. From top to bottom, the left side covers the general situation of the learner, detailed information on learning activities, activities done in the system over time, and forward-looking predictions. The right side visualizes respectively from top to bottom the radar chart created for certain variables, related recommendations, test, and assignment details. Figure 7.3 presents the information that can be displayed by hovering over the icons on the left side of the dashboard.

When designing the dashboard, it was assumed that the system it belongs to has some features. Providing automatic recommendations based on LA was one of these assumptions. Either sending automatically (Bodily et al., 2018) or manually (Pardo et al., 2019), the recommendation or support for action stands out in most of the LA studies (Jivet et al., 2020; Bodily et al., 2018). Our preference on being automatic was for supporting learners for them to close their feedback loop. A

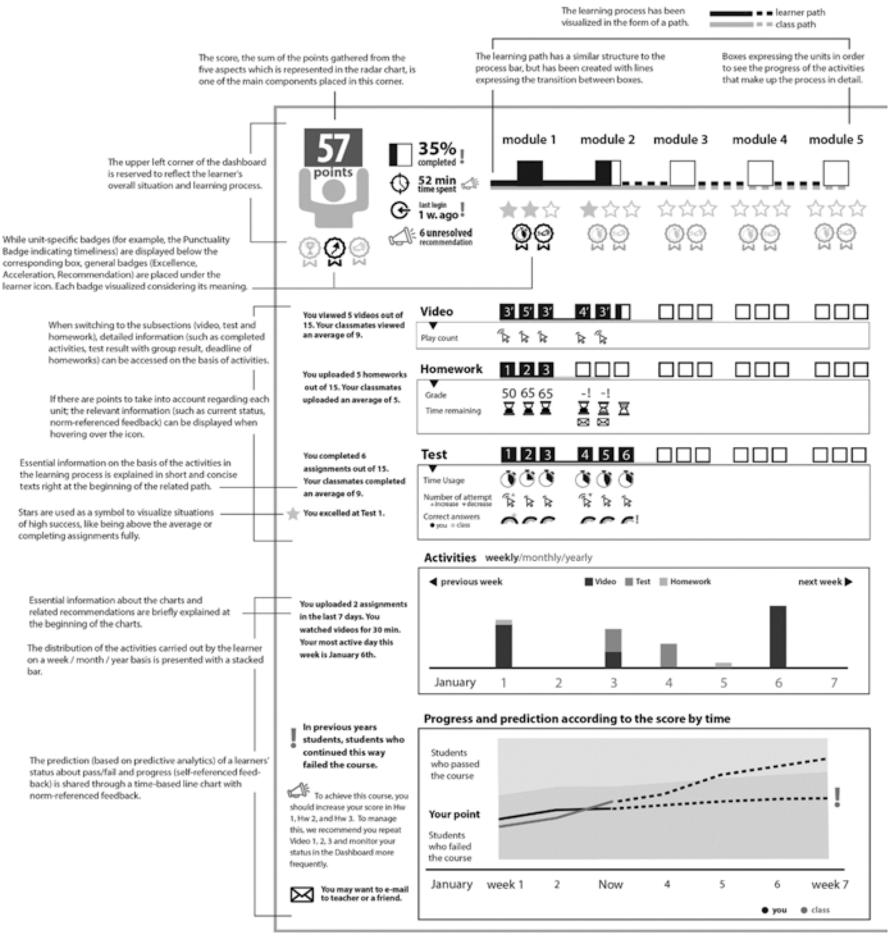


Fig. 7.1 Student-faced learning dashboard proposal (left side)

contact button was created to encourage students to get support from their peers or teachers, especially when they're below the average.

According to feedback literature, learners also need references in order to compare and make sense of their performance. However, norm-referenced comparisons are a controversial issue in the field of feedback (Jivet et al., 2020; Lim et al., 2019a; Teasley, 2017). While some studies reported negative effects of norm-referenced feedback, some highlighted positives (Aguilar, 2018; Guerra et al., 2016; Jivet et al., 2018; Mumm & Mutlu, 2011; Shute, 2008). In LA dashboard studies (Bodily et al., 2018; Schumacher & Ifenthaler, 2018), it is reported that students prefer comparison. Consequently, we provided comparison for each indicator. Leaderboard was one of the included components for comparison and used the learners' score as its indicator. In addition to the leaderboard, points, badges, and stars were used to

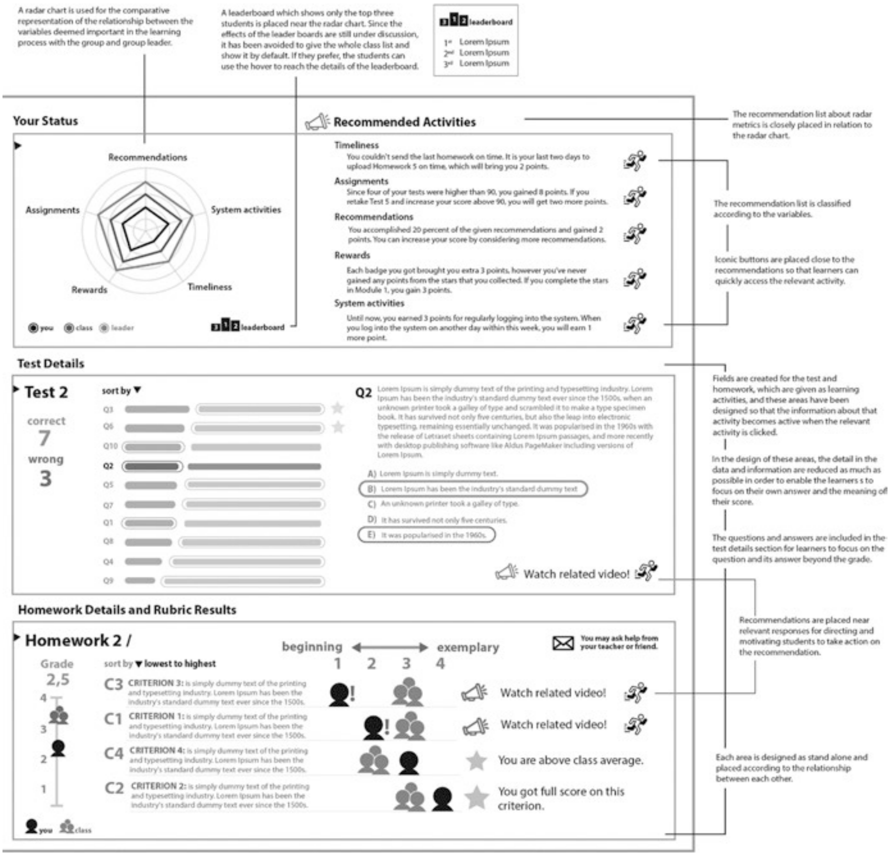


Fig. 7.2 Student-faced learning dashboard proposal (right side)

gamify the system. The game elements were planned to motivate students to follow the recommendations, to upload homework on time, and to achieve more.

Following feedback and gamification design, the design process focused on how to visualize effectively the structured learning context and process to the learners. The starting point of the visualization process was examining the design similarities between learning dashboards and graph-intense multi-block infographics. Initially, the dashboard was divided into sub-information groups that will form a meaningful big picture of the learning process as in multi-block infographics. The connections were created between blocks according to their relationship with each other. The dashboard was enhanced with iconic representations and scaffolding texts. In order to ensure that the learner focused on learning as much as possible, scaffolding text-supported iconic representations were used instead of data-intensive graphics to highlight the content-related feedback. Connected status information and recommendations were placed close to each other for stimulating the learner to take action.

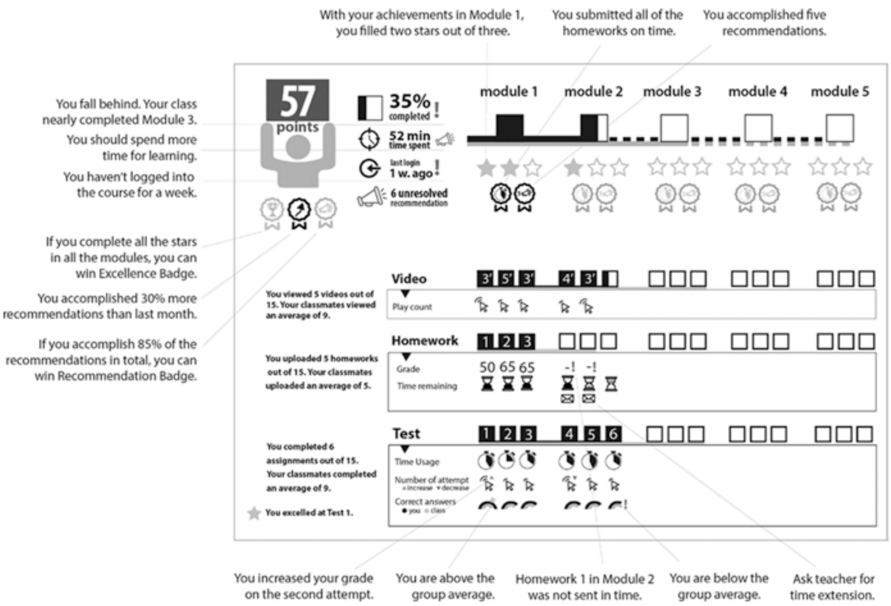


Fig. 7.3 Information presented to learners by icon hovering

Although we believe the dashboard design in Figs. 7.1, 7.2, and 7.3 might be a reference point to start to design a LAD dashboard, since each dashboard design must be unique according to the learning context, we're also aware the suggestions and examples listed in this study remained limited. Plus, these design ideas have never been tested. As expected, there is a need for experimental or design-based research to examine the presented opinions' effects. From a broader perspective, another limitation of this study is not covering the perspective of self-regulated learning (SEL), which is one of the most commonly used theoretical frameworks. Focusing SEL in the LAD design is planned within future studies of ours.

References

Aguilar, S. J. (2018). Examining the relationship between comparative and self-focused academic data visualizations in at-risk college students' academic motivation. *Journal of Research on Technology in Education, 50*(1), 84–103. https://doi.org/10.1080/15391523.2017.1401498

Albers, M. J. (2015). Infographics and communicating complex information. In A. Marcus (Ed.), *Design, user experience, and usability: Users and interactions* (DUXU 2015. Lecture notes in computer science, Vol. 9187). Springer. https://doi.org/10.1007/978-3-319-20898-5_26

Black, P., & Wiliam, D. (1998). Assessment and classroom learning. *Assessment in Education, 5*(1), 7–74. https://doi.org/10.1080/0969595980050102

Bodily, R., Ikahihifo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598. https://doi.org/10.1007/s12528-018-9186-0

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: The challenge of design. *Assessment & Evaluation in Higher Education, 38*(6), 698–712. https://doi.org/10.1080/02602938.2012.691462

Brookhart, S. M. (2008). *How to give effective feedback to your students*. ASCD.

Brown, M., McCormack, M., Reeves, J., Brooks, D.C., Grajek, S., Alexander, B., Bali, M., Bulger, S., Dark, S., Engelbert, N., Gannon, K., Gauthier, A., Gibson, D, Gibson, R., Lundin, B., Veletsianos, G., & Weber, N. (2020). *2020 EDUCAUSE horizon report, teaching and learning edition*. Retrieved from https://library.educause.edu/resources/2020/3/2020-educause-horizon-report-teaching-and-learning-edition

Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of Educational Research, 65*, 245–281. https://doi.org/10.3102/00346543065003245

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Charleer, S., Klerkx, J., Duval, E., De Laet, T., & Verbert, K. (2016). Creating effective learning analytics dashboards: Lessons learnt. In *European conference on technology enhanced learning* (pp. 42–56). Springer.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5–6), 318–331.

Clark, R. C., & Lyons, C. (2011). *Graphics for learning: Proven guidelines for planning, designing, and evaluating visuals in training materials* (2nd ed.). Wiley.

Dawson, S., Gašević, D., Siemens, G., & Joksimovic, S. (2014, March). Current state and future trends: A citation network analysis of the learning analytics field. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 231–240).

Dyjur, P., & Li, L. (2015). Learning 21st century skills by engaging in an infographics assessment. In P. Preciado Babb, M. Takeuchi, & J. Lock (Eds.), *Proceedings of the IDEAS: Designing responsive pedagogy conference* (pp. 62–71). Werklund School of Education, University of Calgary. http://hdl.handle.net/1880/50860

Few, S. (2006). *Information dashboard design: The effective visual communication of data*. O'Reilly Media Inc.

Fischer, M. H., Dewulf, N., & Hill, R. L. (2005). Designing bar graphs: Orientation matters. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 19*(7), 953–962. https://doi.org/10.1002/acp.1105

Fleckenstein, M., & Fellows, L. (2018). Data analytics. In M. Fleckenstein & L. Fellows (Eds.), *Modern data strategy* (pp. 133–142). Springer.

Freitas, S. D., Gibson, D., Alvarez, V., Irving, L., Star, K., Charleer, S., & Verbert, K. (2017). How to use gamified dashboards and learning analytics for providing immediate student feedback and performance tracking in higher education. In *Proceedings of the 26th international conference on world wide web companion* (pp. 429–434).

Fry, E. (1981). Graphical literacy. *Journal of Reading, 24*(5), 383–389. Retrieved from http://www.jstor.org/stable/40032373

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

Goethe, O. (2019). *Gamification mindset*. Springer.

Guerra, J., Hosseini, R., Somyurek, S., & Brusilovsky, P. (2016). An intelligent interface for learning content: Combining an open learner model and social comparison to support self-regulated learning and engagement. In *Proceedings of the 21st international conference on intelligent user interfaces* (pp. 152–163).

Han, Y., & Xu, Y. (2019). Student feedback literacy and engagement with feedback: A case study of Chinese undergraduate students. *Teaching in Higher Education*, 1–16. https://doi.org/10.1080/13562517.2019.1648410

Hattie, J., & Gan, M. (2011). Instruction based on feedback. In R. E. Mayer & P. A. Alexander (Eds.), *Handbook of research on learning* (pp. 249–271). Routledge.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*, 81–112. https://doi.org/10.3102/003465430298487

Henderson, M., Boud, D., Molloy, E., Dawson, P., Phillips, M., Ryan, T., & Mahoney, P. (2018). *Feedback for learning: Closing the assessment loop*. Department of Education and Training. Retrieved from https://ltr.edu.au/resources/ID16-5366_Henderson_Report_2018.pdf

Information Design Exchange (idX). (2007). *Information design: Core competences what information designers know and can do*. International Institute for Information Design (IIID). Retrieved from https://www.iiid.net/idx-information-design-core-competencies/

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40).

Kitto, K., Lupton, M., Davis, K., & Waters, Z. (2017). Designing for student-facing learning analytics. *Australasian Journal of Educational Technology, 33*(5). https://doi.org/10.14742/ajet.3607

Klerkx, J., Verbert, K., & Duval, E. (2017). Learning analytics dashboards. In C. Lang, G. Siemens, A. F. Wise, & D. Gaevic (Eds.), *The handbook of learning analytics* (pp. 143–150). Society for Learning Analytics Research (SoLAR).

Kocadere, S. A., & Çağlar, Ş. (2018). Gamification from player type perspective: A case study. *Educational Technology & Society, 21*(3): 1436–4522. https://www.jstor.org/stable/26458503

Kulhavy, R. W., & Stock, W. A. (1989). Feedback in written instruction: The place of response certitude. *Educational Psychology Review, 1*(4), 279–308. https://doi.org/10.1007/BF01320096

Lankow, J., Ritchie, J., & Crooks, R. (2012). *Infographics: The power of visual storytelling*. Wiley.

Lim, L., Dawson, S., Joksimovic, S., & Gašević, D. (2019a). Exploring students' sensemaking of learning analytics dashboards: Does frame of reference make a difference? In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 250–259).

Lim, L. A., Gentili, S., Pardo, A., Kovanović, V., Whitelock-Wainwright, A., Gašević, D., & Dawson, S. (2019b). What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course. *Learning and Instruction, 72*, 101202. https://doi.org/10.1016/j.learninstruc.2019.04.003

Lu, M., Wang, C., Lanir, J., Zhao, N., Pfister, H., Cohen-Or, D., & Huang, H. (2020). *Exploring visual information flows in infographics*. Paper presented at The ACM CHI conference on human factors in computing systems (CHI 2020), April 25–30, 2020, Honolulu, HI, USA. doi:https://doi.org/10.1145/3313831.3376263.

Mah, D. K. (2016). Learning analytics and digital badges: Potential impact on student retention in higher education. *Technology, Knowledge and Learning, 21*(3), 285–305. https://doi.org/10.1007/s10758-016-9286-8

Mautone, P. D., & Mayer, R. E. (2007). Cognitive aids for guiding graph comprehension. *Journal of Educational Psychology, 99*(3), 640–652. https://doi.org/10.1037/0022-0663.99.3.640

Mory, E. H. (2004). Feedback research revisited. In M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 745–783). Springer.

Mumm, J., & Mutlu, B. (2011). Designing motivational agents: The role of praise, social comparison, and embodiment in computer feedback. *Computers in Human Behavior, 27*(5), 1643–1650. https://doi.org/10.1016/j.chb.2011.02.002

Ndukwe, I. G., & Daniel, B. K. (2020). Teaching analytics, value and tools for teacher data literacy: A systematic and tripartite approach. *International Journal of Educational Technology in Higher Education, 17*(1), 1–31. https://doi.org/10.1186/s41239-020-00201-6

Nicol, D. (2010). From monologue to dialogue: Improving written feedback processes in mass higher education. *Assessment & Evaluation in Higher Education, 35*(5), 501–517. https://doi.org/10.1080/02602931003786559

Nicol, D. (2013). Resituating feedback from the reactive to the proactive. In D. Boud & E. Molly (Eds.), *Feedback in higher and professional education: Understanding it and doing it well* (pp. 34–49). Routledge.

Nicol, D. (2020). The power of internal feedback: Exploiting natural comparison processes. *Assessment & Evaluation in Higher Education*. https://doi.org/10.1080/02602938.2020.1823314

Nuhoğlu Kibar, P., & Akkoyunlu, B. (2017). Fostering and assessing infographic design for learning: The development of infographic design criteria. *Journal of Visual Literacy, 36*(1), 20–40. https://doi.org/10.1080/1051144X.2017.1331680

Nuhoğlu Kibar, P., & Pettersson, R. (2021). Making good use of pictures. In M. D. Avgerinou & P. Pelonis (Eds.), *Handbook of research on K-12 blended and virtual learning through the i²Flex classroom model*. IGI Global. https://doi.org/10.4018/978-1-7998-7760-8

O'Grady, J. V., & O'Grady, K. V. (2008). *The information design handbook*. How Books.

Özhan, Ş. Ç., & Kocadere, S. A. (2020). The effects of flow, emotional engagement, and motivation on success in a gamified online learning environment. *Journal of Educational Computing Research, 57*(8), 2006–2031. https://doi.org/10.1177/0735633118823159

Pardo, A. (2018). A feedback model for data-rich learning experiences. *Assessment & Evaluation in Higher Education, 43*(3), 428–438. https://doi.org/10.1080/02602938.2017.1356905

Pardo, A., & Dawson, S. (2015). How can data be used to improve learning practice? In P. Reimann, S. Bull, M. K. Rust, R. Vatrapu, & B. Wasson (Eds.), *Measuring and visualizing learning in the information-rich classroom*. Routledge.

Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using learning analytics to scale the provision of personalised feedback. *British Journal of Educational Technology, 50*(1), 128–138. https://doi.org/10.1111/bjet.12592

Pardo, A., Poquet, O., Martínez-Maldonado, R., & Dawson, S. (2017). Provision of data-driven student feedback in LA & EDM. In C. Lang, G. Siemens, A. F. Wise, & D. Gaevic (Eds.), *The handbook of learning analytics* (pp. 163–174). Society for Learning Analytics Research (SoLAR).

Park, Y., & Jo, I.-H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110–133.

Pettersson, R. (2021). *ID theories* (6th ed.). Institute for Infology.

Rakoczy, K., Harks, B., Klieme, E., Blum, W., & Hochweber, J. (2013). Written feedback in mathematics: Mediated by students' perception, moderated by goal orientation. *Learning and Instruction, 27*, 63–73. https://doi.org/10.1016/j.learninstruc.2013.03.002

Ramaprasad, A. (1983). On the definition of feedback. *Behavioral Science, 28*(1), 4–13. https://doi.org/10.1002/bs.3830280103

Rendgen, S. (2012). *Information graphics*. (J. Widemann, Ed.). Taschen.

Rouse, R., III. (2004). *Game design: Theory and practice*. Jones & Bartlett Publishers.

Ryan, T., Gašević, D., & Henderson, M. (2019). Identifying the impact of feedback over time and at scale: Opportunities for learning analytics. In M. Henderson, R. Ajjawi, D. Boud, & E. Molloy (Eds.), *The impact of feedback in higher education* (pp. 207–223). Palgrave Macmillan.

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science, 18*(2), 119–144. https://doi.org/10.1007/BF00117714

Sansom, R. L., Bodily, R., Bates, C. O., & Leary, H. (2020). Increasing student use of a learner dashboard. *Journal of Science and Educational Technology, 29*, 386–398. https://doi.org/10.1007/s10956-020-09824-w

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Schwendimann, B. A., Rodriguez Triana, M. J., Prieto Santos, L. P., Shirvani Boroujeni, M., Holzer, A. C., Gillet, D., et al. (2016). Understanding learning at a glance: An overview of learning dashboard studies. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 532–533). ACM.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512. https://doi.org/10.1016/j.chb.2018.05.004

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages, 50*, 19–38. https://doi.org/10.1016/j.jvlc.2018.11.002

Shneiderman, B. (2003). The eyes have it: A task by data type taxonomy for information visualizations. In B. B. Bederson & B. Shneidermann (Eds.), *The craft of information visualization: Readings and reflections* (pp. 364–371). https://doi.org/10.1016/B978-1-55860-915-0.X5000-8

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189. https://doi.org/10.3102/0034654307313795

Sommer, S., & Polman, J. L. (2018). From quantified self to building a more fit community: Data tracking and science infographics as boundary objects. In J. Kay & R. Luckin (Eds.), *Rethinking learning in the digital age: Making the learning sciences count, 13th international conference of the learning sciences (ICLS)* (Vol. 2). International Society of the Learning Sciences. https://doi.org/10.22318/cscl2018.1001

Spector, J. M., Ifenthaler, D., Samspon, D., Yang, L., Mukama, E., Warusavitarana, A., Lokuge Dona, K., Eichhorn, K., Fluck, A., Huang, R., Bridges, S., Lu, J., Ren, Y., Gui, X., Deneen, C. C., San Diego, J., & Gibson, D. C. (2016). Technology enhanced formative assessment for 21st century learning. *Educational Technology & Society, 19*(3), 58–71. https://www.jstor.org/stable/jeductechsoci.19.3.58

Subhash, S., & Cudney, E. A. (2018). Gamified learning in higher education: A systematic review of the literature. *Computers in Human Behavior, 87*, 192–206. https://doi.org/10.1016/j.chb.2018.05.028

Sychev, O., Anikin, A., & Prokudin, A. (2020). Automatic grading and hinting in open-ended text questions. *Cognitive Systems Research, 59*, 264–272. https://doi.org/10.1016/j.cogsys.2019.09.025

Teasley, S. D. (2017). Student facing dashboards: One size fits all? *Technology, Knowledge and Learning, 22*(3), 377–384. https://doi.org/10.1007/s10758-017-9314-3

Teasley, S. D. & Whitmer, J. (2017). *The impact of student-facing LMS dashboards. Technical report*, School of Information, University of Michigan and Director of Analytics-Research Blackboard, Inc. Retrieved from https://www.blackboard.com/en-mea/resources/impact-student-facing-lms-dashboards

Tenório, K., Challco, G. C., Dermeval, D., Lemos, B., Nascimento, P., Santos, R., & da Silva, A. P. (2020, July). Helping teachers assist their students in gamified adaptive educational systems: Towards a gamification analytics tool. In *International conference on artificial intelligence in education* (pp. 312–317). Springer.

Ware, C. (2013). *Information visualization: Perception for design* (3rd ed.). Morgan Kaufmann.

Werbach, K., & Hunter, D. (2012). *For the win: How game thinking can revolutionize your business*. Wharton Digital Press.

Winnie, P. H. (2017). Learning analytics for self-regulated learning. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 241–249). Society for Learning Analytics Research (SoLAR).

Winstone, N. (2019). Facilitating students' use of feedback: Capturing and tracking impact using digital tools. In M. Henderson, R. Ajjawi, D. Boud, & E. Molloy (Eds.), *The impact of feedback in higher education* (pp. 225–242). Palgrave Macmillan.

Winstone, N. E., Nash, R. A., Rowntree, J., & Parker, M. (2017). 'It'd be useful, but I wouldn't use it': Barriers to university students' feedback seeking and recipience. *Studies in Higher Education, 42*(11), 2026–2041. https://doi.org/10.1080/03075079.2015.1130032

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 203–211).

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology, 10*, 3087. https://doi.org/10.3389/fpsyg.2019.03087

Zhang, L., Huang, Y., Yang, X., Yu, S., & Zhuang, F. (2019). An automatic short-answer grading model for semi-open-ended questions. *Interactive Learning Environments*, 1–14. https://doi.org/10.1080/10494820.2019.1648300

Zichermann, G., & Cunningham, C. (2011). *Gamification by design: Implementing game mechanics in web and mobile apps*. O'Reilly Media Inc.

Chapter 8
Visualizing Your Visualizations: The Role of Meta-visualization in Learning Analytics

Ronald Dyer

1 Introduction

Learning analytics (LA) represents an interaction process informed by instructor/student input with an aim of effective utilization of data to improve teaching and learning processes. It is a sophisticated analytical tool providing a powerful way to gather intelligence on hundreds/thousands or millions of datasets and provide trends, hypotheses, and modeling of student-related information (Elias, 2011). The field of learning analytics draws from that of business intelligence and educational data mining, etc. supporting actionable insights and falling under the umbrella of technology-enhanced learning. The need for LA is driven by such factors as the rise of big data within education environments as well as the continued growth of online learning. According to Ferguson (2012), early origins of education data research go as far back as 1979 with the Survey Department of the Open University in the UK having the ability to reflect on 10 years of distance education students. Post 2003, integration of the Social Network Analysis (SNA) within the LA toolkit (Ferguson, 2012) was incorporated. Clow (2013) indicated that the central idea behind LA is a cycle commencing with learners, who generate data, which is processed into metrics that inform interventions and by extension affect learners. The data generated varies from demographic to online activities, assessment, and destination data. As it relates to the visualization of the LA data, this can take the form of graphs, charts, dashboards, and other infographics providing visual insights presented in interactive formats for user consumption. The development of visualizations derived from LA datasets while appearing simple is an array of complex design decisions with the requisite need to tell a

R. Dyer (✉)
University of Sheffield, Sheffield, UK
e-mail: ronald.dyer@sheffield.ac.uk

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_8

compelling story. Issues such as simplification and color schemes (Evergreen & Metzner, 2013) make the difference between interaction and abandonment of visual data. There are also challenges associated with data quantity reduction, i.e., grouping data based on similarity while trying to represent the best possible picture of what the visualization is trying to translate (Steed, 2017), utilizing smaller amounts of data. Regardless of the data, the principles of good visualization are key for good information dissemination. Furthermore, the need for user sense-making (Bendoly, 2016) informing effective questions and answers (Q&A) aided by creative problem-solving approaches (Hargrove & Nietfeld, 2015) as part of associated thinking strategies is a requisite. These Q&As cannot occur, however, without building the appropriate metacognitive frames to inform the visualization process. In essence, they represent a thinking process required to support creation of "good visuals" and the underlying narrative data via appropriate technology tools.

Consequently, visualization of LA datasets requires meta-capabilities, i.e., the properties required to learn, develop, and apply skills (Furlong & Johnson, 2003) which underlie core visualization competency building. These capabilities allow for questioning of the paradigms relative to the learning environment and stimulating and supporting the development of competencies that provide deeper context of visualization processes at a systems level, i.e., meta-capabilities require skill, capability, and competence in a general sense in order to effect requisite standards of good practice and efficacy of knowledge transfer. More specifically, as it relates to visualization processes within LA, the need for meta-visualization (MV) capabilities informing good practice and effective dissemination of outputs is a necessary precursor for adopters of visualization techniques to support LA visualization/dashboards.

To inform understanding of MV capability requirements, this chapter is organized as follows:

- A definition of data/meta-visualization
- Meta-visualizations linkage to learning analytics visualization and dashboards
- Meta-visualization framing to support learning analytics
- Meta-visualization example
- Discussion and conclusion

2 Data and Meta-visualization Defined

To understand the role of data visualization within LA, a clearer picture of its exact nature is required. Data visualization (DV) is not new, dating back centuries. Since the origins of humans and their struggle for survival, depictions on cave walls illustrating hunting strategies as well as statistics of how many animals/kinds they caught have existed. DV can be defined as the graphical or pictorial representation of data or information in a clear and effective manner (Brigham, 2016). Its aim is to assist the understanding of data. William Playfair is credited as one of the early pioneers of data visualization, first using and publishing bar, line, and pie charts to communicate information about data. DV is also sometimes referred to as information visualization or scientific visualization with the difference between the two being the audiences and complexity of the messages delivered. The array of visuals derived from DV can range from very simple word clouds to charts and infographics with interactive capabilities. It represents a story told requiring both an accurate representation of data and a clear point. The narrative encourages future action and/or engagement from users leading to valuable insights for decision-making. However, while DV looks aesthetically attractive, there are requirements to understanding both data sources and design principles associated with its development. The role of DV in learning analytics is similar to commercially focused organizational business intelligence criteria, and consequently well-informed/structured thinking is required for actionable information dissemination. In the realm of LA, DV techniques provide patterns and trends regarding large student datasets centered around: prediction, clustering, relationship mining, discovery, and human judgment (Avella et al., 2016). Thus, LA analysis focuses on data related to learners' interaction with course content, other students, and instructors and integrating these datasets to form relationships. The term visual analytics, i.e., the science of analytical reasoning facilitated by interactive visual interfaces, is sometimes used to refer to LA data analysis (Vieira et al., 2018). Terminology aside it leverages human perceptual and cognitive abilities through interactive visualization interfaces allowing users and data-related task more efficiency (Fekete et al., 2008). Given the nature of DV techniques and the myriad charts, etc. created, discerning graphical appropriateness of choices to ensure clear communication of data is key. Meta-visualization's role is lessening the workload of analysis. Rather than having to analyze each chart/plot or diagram separately in an unordered fashion, it provides a well-organized frame for analyst(s) to see plot similarity and thus relationships (Peltonen & Lin, 2015). No single diagram is sufficient to explore LA data; hence multiple visualizations are requisite, with numerous methods to illustrate. Meta-visualization processes reveal which diagrams possess redundant information/data. The term meta-visualization (MV) has several meanings denoting working with several visualizations (e.g., manual or interactive design) to support coordinated views within a visual system (Weaver, 2006) as well as describing visualization of algorithms. For the purpose of this chapter, the definition of meta-visualization is as follows: *a generic term that refers to a visualization that can be created based on another visualization's structure or operations* (Weaver, 2005). MV represents an understanding of the process by which to monitor and regulate internal representations of visualizations by individuals informing thinking through metacognitive and visual capabilities to make sense/synthesize relevant information associated with visualization through mental representation. The process creates metal models used to form an imagery of the problem the visualization is trying to solve (Rapp & Kurby, 2008). Furthermore, MV supports generation of inferences to make decisions based on spatial skills and the ability to describe and act on the data through a visualization process. Gilbert (2005) indicated that three MV evidences must occur to inform visualization processes, firstly, spatial intelligence proposed by Gardner in his theory of multiple intelligences presupposing seven types of intelligence: linguistic, musical, logical-mathematical, spatial, kinesthetic, and interpersonal/intrapersonal. In considering spatial intelligence as a prerequisite of MV, ability to perceive the visual world and individuals' interaction are key components. Secondly, he proposes two levels of thinking, object and meta level, which inform flows of information (objects) to the monitoring (meta) level where individuals become more cognoscente of control, retention, retrieval, and modification of images. Finally, Gilbert perceives visualization as a central thinking process essential for the construction of knowledge. Therefore, MV represents the ability to *think about the thinking* associated with visualizations, monitoring and regulating them as part of the learning process. The ability to monitor and regulate information flows is essential given the proliferation of existing student data and the need to understand it and disseminate to multiple stakeholder in a manner that conveys the message/data as a visual narrative (Miller et al., 2013). However, accomplishing both of these within an LA environment requires development of relevant mental process models supporting visual analytics for learning. While dashboards represent the most common manifestations of analytic data in LA providing current and historical accounts of learner performance to enable decision-making efficacy, without MV these visualizations processes are relatively useless. MV provides deeper meta-visual capabilities through processes that produce models to explain content. Moreover, integration of MV into LA allows for transitioning between modes of visual representation at the macro/micro level as part of overall metacognitive capabilities. LA's aim is knowledge creation towards development of new processes and tools for improving learning and teaching for individual students and instructors, coupled with integration into the practice of teaching and learning (Elias, 2011). Careful attention needs to be paid to the use of visualization for dashboard development in information dissemination. A lack of metacognitive capabilities affects the legitimacy of the information derived and consequently user trust, especially if contextualization of the data and user requirements is not grounded in cognitive process that connects the data with user requirements. The development of visual LA dashboards required models promoting awareness, reflection, and impact as it relates to student outcomes. MV's applicability rests with its ability to deepen individual interaction with data creating the ability to compose questions and answers and provide behavioral change through new meaning(s) generated by the visualization process (Verbert et al., 2013). Visualization professionals require an understanding of LA's four stage process model as part of building their MV capabilities (Verbert et al., 2013). Figure 8.1 illustrates the relationship between MV and LA in capability building, highlighting the need to transition from data-centric viewpoints to self-reflection and sense-making, ensuring the right questions are asked and answered. How dashboards and their inherent design processes create effective levels of MV within LA to derive the best possible visualizations practices is a focal point of the process.

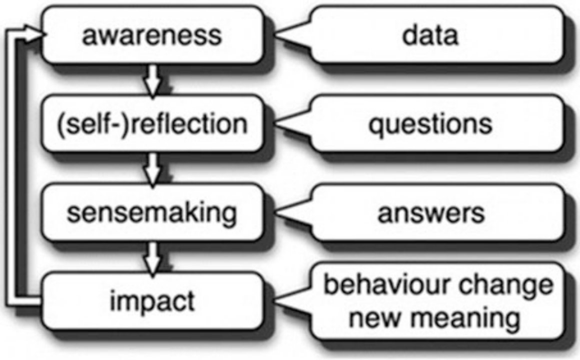


Fig. 8.1 Learning analytics process model. (Verbert et al., 2013)

3 Connecting Meta-visualizations to Learning Analytics

Analysis of collected data from learner interaction is a core component of LA showing great promise to support performance improvement. It demonstrates the ability to enable effective, automatic tracking of student engagement throughout courses as well as provision of insights regarding at-risk students, leading to timely interventions (Saqr et al., 2017). A key value of LA approaches is their timeliness, which traditional evaluation of assessment processes lacks. Consequently, dissemination of insights requires visual mechanism that not only communicates relevant LA dashboards data but also is rightly timed to support early intervention. LA represents an organizational capacity-building tool informing such elements as technology infrastructure, policies, processes, practices, and workflows (Arnold et al., 2014). It informs the premise of organizational learning supporting institutional commitment to the institution's human resources. Two questions arise therefore, regarding LA and its visualization processes. The first relates to the creation of the respective visualizations (i.e., dashboard) and the second how to lessen the workload of analysis towards creation of effective learning environments. Both questions inform institutional capacity-building capabilities utilizing data for performance improvement. Regarding the first, visualization tools require continuous human interaction enabling analytic discourse between users and data. Thereafter, users can perform analytical tasks—e.g., confirming hypotheses, exploring hypothetical situations, categorizing and organizing data, and identifying interesting features in data for further examination (Vieira et al., 2018). However, this requires a degree of introspection that *visualizes the visualization* process as mental models. These frames represent the metacognition associated with a set of processes that individuals use in monitoring ongoing cognition (task) for effective control of their behavior. Metacognitive knowledge reflects an individual's declarative knowledge/beliefs about the factors that might influence a cognitive task (Rhodes, 2019). Figure 8.2, describes the distinctions between behavior and cognition as they occur in the real world (object level) vs. individual understanding or models of cognition (meta level).

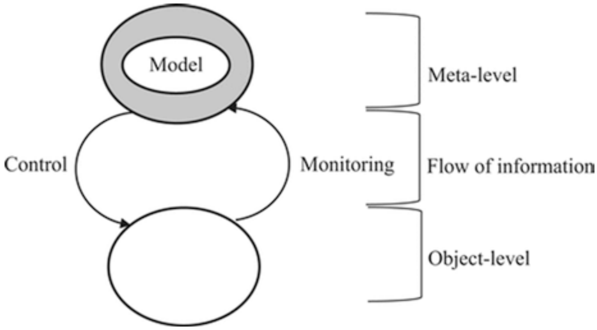


Fig. 8.2 Conceptual framework for metacognition research. (Rhodes, 2019)

The challenge of creating visualizations and dashboard design which take advantage of both behavioral and cognitive to develop effective learning environments through LA requires careful consideration inclusive of:

- Key *performance indicator* (KPI) visualizations as part of the process, specifically regarding the synthesis of the data and its ability to express achievement of the user(s) desired objectives, i.e., visualizing the quantifiable measures through the flow of information required as indicated in Fig. 8.2 to determine the extent to which these KPIs are effectively represented on the dashboards.
- Utilization of approaches which inform appropriate data hierarchies that ask/answer questions identified at the meta level. These include questions related to data structure that treats with permissions/privileges regarding administrative and academic staff access and the level of interaction these hierarchies require for effective interaction.
- Identifying appropriate dashboard design criteria in response to emerging user needs inclusive of factors such as mobility and data scalability of the dashboard as the data populating grows.
- Incorporation of filters, addressing visibility, effectiveness, and searchability factors, informing utilization of components that support frequency of queries. Additionally, identification of the filter design criteria as they relate to efficacy over need requires meta-level considerations as part of good design practice.

As part of the connection between visualizations/dashboards and effecting improved learning environments, the above supports the process as part of "good" dashboard design. The goals of dashboards in learning analytics are to support improvement of metacognitive, cognitive, and behavioral processes regarding learner competence and to support academic/administrative staff decision-making (Jivet et al., 2017). Moreover, given that dashboard design is a critical success factor in all analytics, a focus on MV is critical given the proliferation of tools available today which make dashboarding for LA or analytics generally simple. To appreciate the linkage between visualization/dashboards and effective learning, understanding design efficacy requires foundational understanding of human cognition, perception, situational awareness, and visualization technologies specifically based on how we see and think (Park & Jo, 2019). MV's model supports these dashboard design processes, with meta-level visualization of visualization processes requiring reflective process knowledge associated with individuals pondering their cognitive capabilities and processes regarding data properties and knowledge of the LA task requirements (Kavousi et al., 2020). They ascertain cognitive visualization approaches are at the core of designing effective dashboard. At the *reflective process monitoring* stage, metacognitive visualization experiences allow for contemplation of judgment regarding cognitive activity status, i.e., visualization professionals' judgment of their actions/decisions regarding the use of visualization techniques to solve a problem, e.g., utilization of specific type of chart/diagram and filters and ascertaining their appropriateness to visualize the relevant data. Finally, the reflective process control stage relates to strategy where individuals think about actions they can initiate to change the current course of their mental processing centered on activities such as data hierarchies and KPIs' approaches to provide design efficacy. Utilization of prior methodologies for implementation defines how dashboard experiences are built to perform new visualizations aligned to the MV processes. Design is complicated and thus difficult to explain due to its non-linear and recursive nature. Consequently, thinking about design, interpretation of data and provision of effective visual for communication within an MV context represent a significant contribution to the overall process. The design of visualizations follows no formulae or algorithmic processes; therefore, no recipe exists to ensure design quality (Kavousi et al., 2020). However, MV context potentially provide improved design for effect leaning environment. Utilization through contextualization and reflection on dashboard design of visualization problems applied to particular LA tasks from a metacognitive capabilities perspective assist facilitation of integration into the LA design ecosystem. While metacognition is a core contributor to the process, what differentiates generic metacognitive capabilities from those of MV is its specificity to the visualization processes. MV draws on principles of metacognition to inform the nature of dashboard design. Design education and investigation of the constructs associated with development of conceptual design models all support LA visualization and build on actions visualization professionals engage in to orchestrate the relevant visual design task. Thus, the specificity of connectivity between MV and LA dashboarding requires learning about visualization tasks implementation within the context of the data collected and mental verbalization of data prior to informing potential inferences manifested through dashboards.

In response to the second question regarding lessening the workload of analysis, LA visualization becomes an issue of capabilities and not simply visual aesthetics. MV's capabilities derive from metacognitive processes integration into LA dashboard's analytic capabilities. Visualizations and consequently their tasks support LA performance addressing workload issue as a product of ideation. They are a form of mental gymnastics utilized to create clear images for dashboard design contributing to workload reduction by allowing visualization practitioner to self-regulate representation of data for effectiveness prior to actual development of visual objects. This means that they provide the knowledge requirements concerning visualizer's own cognitive processes allowing these practitioners the ability to actively control LA dashboarding design processes and not the cognitive task such as tools to create the charts. To achieve integration of MV, thinking regarding dashboard planning provides a window into how to lessen the workload analysis through consideration of the role of users, provisions of lines of inquiry, visualization of key questions user wish to address, and establishment of goals/structures and associated tasks. This supports LA users in identification of the right frames providing appropriate approaches for planning and monitoring student activities (Chen et al., 2019) by situating user experience in MV-based deep design. LA dashboards consist of two components: knowledge monitoring and utilization strategies (Chen et al., 2019) based on overall data collection. MV allows knowledge monitoring to exist as a hierarchy of metacognitive processes informing the dashboard's role as a monitoring of learners. The dashboards' designs allow users to acquire knowledge through provision of access to recommendation related to student performance, etc. In designing effective dashboard, visualization professionals firstly need to estimate whether they can solve the LA users' problems utilizing dashboard/visualization mechanisms. A high degree of metacognitive inference through MV is required for comparisons of accuracy between estimation of what to visualize. We can think of the comparisons as multiple lens through which visualizations are assessed. The lessening of workload analysis occurs when the MV process enables estimation of known approaches to visualization, such as those that may be less accurate and unknown to establish baselines of knowledge acquisition informing LA tasks (Tobias & Everson, 2009). More specifically, the process creates opportunities to identify correct vs. incorrect judgment along a mental axis supporting visualization processes and providing users with data related to their LA requirements in form and function, i.e., usability of visualizations to interpret data and solve issues related to their student population. MV at this stage acts as a conceptual road map to aid dashboard design allowing LA users to visually summarize content. Creation of dashboards provides easy access to the requisite information, validates predictive models, and integrates, coordinates, and interprets significance of variables. Thus, MV's connection to LA practice acts as a meta-skill, i.e., *the highest-level skills that visualization designers possess and deploy in their work*. The actual visualization process is the least critical in a continuum of design skills as its agency is lower than higher meta-skills such as translation, distillation, and interpretation of LA data and user interaction. Materialization of visualizations is simply a concrete decision bound by factors as color, shape, location, and arrangement of objects. This process represents the least agency as it relates to MV capabilities given that visualization professionals cannot chose what to visualize. Its factor such as translation provides greater agency given their need to recapitulate something into another language or modality which can only occur when designers meta-visualize, e.g., translation of a data structure into a specific type of visual and assigning choices interaction to support representation. Designers afford more agency due to choice, influencing how users view/translate dashboard items. Agency processes contribute to visualization professionals' ability to sub-segment data disaggregating critical content through reduction while maintaining comprehensibility. Only through MV processes does the designer possess abilities to represent complex variables via dashboards by thinking about which components best provide significance for visualization of unsorted information. Finally, interpretation allows reflection on distilled information through novel forms, previously unseen cementing MV's requirements as control mechanism via design regarding what/how to represent LA data. This degree of latitude can only occur if dashboard design professionals trust their collaboration processes and possess abilities to contextualize dashboard efficacy through MV prior to visual manifestation of requisite data.

4 Meta-visualization Framing in Learning Analytics

Just as metacognition is thinking about thinking, meta-visualization focuses on visualizing your visualizations as a precursor to actual cognitive processes associated with designing them. Its specificity lies in the visualization process, informed by good design thinking principles. MV assists visualization professionals through its ability to assess and categorize their thoughts hierarchically. The process is ongoing with a large part of the problem-solving process occurring through mental pre-assessment followed by monitoring of manifested dashboards outputs. From an LA perspective, it allows designers to map task through thought, allowing the application of other processes (computational or other) later. Integration of visualizations into LA as an evaluation strategy requires that visualization professionals ask structured questions such as the following:

- What am I trying to accomplish through visualization (of LA data)?
- What strategies will I utilize?
- How well am I using them?
- What else can I do? (i.e., alternative approaches)

These all represent metacognitive approaches, providing preparation and planning, strategy implementation, and utilization of tactics for monitoring and evaluation (Hargrove & Nietfeld, 2015). MV represents a capability for strengthening creative thinking through practice and promotion of divergent thought processes culminating in a mental model of a dashboard. The essence of activities such as brainstorming, synthesis, attribution, and idea checklist provides fundamental skills requisite for LA problem-solving. Moreover, studies such as Garaigordobil (2006) revealed significant advantages of distributed practice in creative thinking over time. Consequently, effective LA dashboard visualization requires MV to effect visual ideation fluency. Enabling MV to effect ideation fluency requires the following Table 8.1.

Utilization of meta-visualization helps designers gain understanding to speed up processes for innovative dashboard designs, resulting in insights, leading to action (Kernbach et al., 2018). It represents part of the design thinking process making it easier to build ideas, visually map dashboard dialogue, and overcome cognitive constraints such as information overload (Kernbach et al., 2018). MV informs

Table 8.1 Benefits of Meta-visualization in learning analytics

Cognitive functions	Facilitation of elicitation/synthesis Enable new perspectives Comparison Recall ease
Emotional functions	Engagement Inspiration Evidence
Social functions	Perspective integration Identification of interdependencies

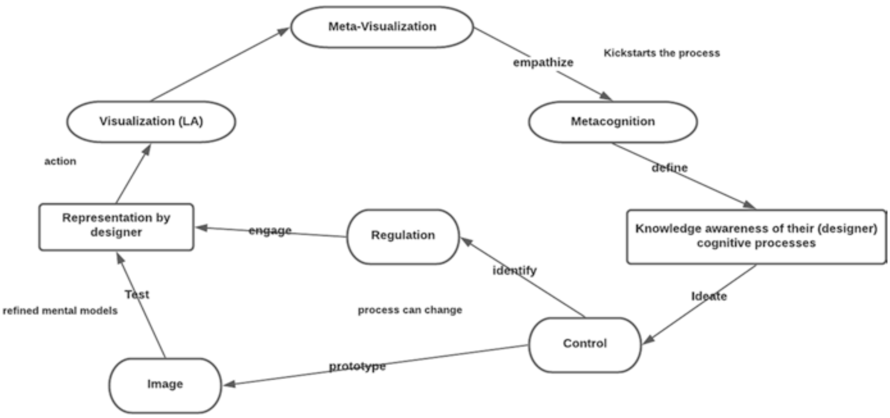


Fig. 8.3 Conceptual Meta-visualization model for learning analytics

sense-making, allowing the cognitive, emotional, and social factors listed above to improve the overall design process and contextualize design thinking by allowing designers to build effective dashboards. Without MV they lack the requisite cognitive approaches to visually map dashboards. Informing this process are more detailed factors such as the ability to empathize, define, ideate, prototype, and test the mental models created through MV. These detailed factors borrow from Stanford d.school's five stages approach regarding the design thought model designed by Hargrove and Nietfeld (2015).

The MV model (Fig. 8.3) allows a multidimensional approach to LA dashboard design processes empathizing identification of the right users, their needs, and potential emotions associated with the use of LA. Defining provides visualization professionals with the ability to unpack user needs and establish the scope of visualization towards problem-solving. Ideation creates a stream of convergent/divergent ideas to select from informing materialization of the visuals while prototyping acts as a translation of MV thinking (ideas) into tangible objects enabling users of the LA system to effectively interact. At the testing stage, MV processes refine the solution(s) and allow visualization professionals to feedback on their process of development as well as learn more about what they discovered and how to action. The action stage establishes a working definition of their mental models and how to approach LA dashboard design task while remaining aware of the cognitive processes associated with delivery of LA dashboard artifacts to end users. During this process, MV acts as a series of checks and balances (control and regulation) providing opportunities for adjustment of mental models before implementation. This is the stage at which MV provides a clear mental image of the dashboard leading to development of appropriate visualizations, which meet the requirements of user interaction. In its entirety, MV is about thinking, monitoring, and regulating all components of dashboarding in LA as part of a learning process. This meta-visual capability occurs representing the requirements for effectively situated practice in dashboard creation, leading to conceptual templates which can be consistently synthesized across several dashboard projects.

5 Meta-visualization in Practice

While the chapter provides discourse regarding meta-visualization, it is equally important to illustrate. Locatelli and Davidowitz (2021) provide a useful example of MV utilization through their research with six students participating in investigative activity on a Chemistry Teaching Practices II course, a compulsory subject for the degree in chemistry. The study considered preexisting coding schemes to evaluate clay models constructed by students with subsequent revisions made by the students and compared to drawings constructed by the first researcher for consideration of differences/similarities between models. The research was qualitative in nature utilizing a case study format. A simple investigative activity was proposed, based on a topic drawn from everyday life with the objective of engaging the students in the process. They were presented with a problem situation requiring a solution using the materials available. This activity represents the macro level of the chemical phenomenon, where they were instructed to formulate a work plan to test their hypothesis of how they would solve the problem using evidence. I.e., a small portion of soil from each of the two pots, placed in different test tubes, water added and testing of the mixtures with an aqueous solution of silver nitrate using a few drops in each case. After this they were invited to construct an explanatory model at the submicro level using the modeling clay. The submicro representation is an example of a diagram depicting the reaction, and students were told that other diagrams exist to represent this phenomenon. The next step in the process was to compare the clay model constructed with the submicro diagram presented to them, identifying similarities and differences. Based on this reflection, students reassembled the clay models which would reveal any reconstruction of ideas. Finally, students carried out an assessment of the activity as well as a self-assessment. The task was designed to allow them to verbalize their feelings during the activity by answering questions such as "What did you think about this activity?" It should be noted that throughout the process, students were instructed to express verbally whatever they were thinking, so that their dialogues could be analyzed later. The most important aspect of the activity was analysis of the process for the purpose of reconstructing knowledge. When the first model was compared to their final drawings, their ideas provided indictors regarding revision and potential self-regulation through their thought processes as they worked through various iterations of the activity. The value of having the students draw several versions of the model made it possible for students to reconstruct concepts through a combination of visualization and metacognition. They were able to take control and regulate learning through reflection and reconstruction of ideas. Additionally, students demonstrate competence regarding the reconstructive process when they hypothesized. The relevance of this example is in highlighting that images are not self-explanatory and as such designers need to consider the obstacles to interpretation by their audiences despite the efficacy of conceptualization. Moreover, there is value in mental revisions of visual representations utilizing MV which can contribute to formation of sufficient mental models required for visualization prior to implementation.

6 Discussion and Conclusion

The value of meta-visualization represents an interplay between macro and micro mental symbolism. To understand learning analytics, dashboarding tasks and its constituent knowledge properties visual thinking processes associated with meta-visualization require an upfront mental investment. Requisite for general visualization practice is the need to address questions such as the type of content that needs representation, the expected advantages of a visualization process, appropriate formats to use, and their integration as part of design thinking. It also answers conditions (Fekete et al., 2008) such as the following:

- Is there a good underlying structure so that items close to each other can easily be inferred?
- How users interact with unfamiliar content?
- When users have limited understanding of the system/data, what organization exists to reduce cognitive load?
- How do the visualizations assist user difficulty verbalizing underlying information in datasets?
- Do visualizations make the data easier to recognize and describe?

These conditions represent good criteria, and MV is a crucial component to inform visualization relevance and efficacy. Visualization supports amplification of cognition through increasing memory resources and search reduction and increasing attention to mechanisms for monitoring. Thus, MV acts as a catalyst to support implementation. Moreover, meta-visualization role is framing of the delineation between knowledge visualization and design thinking processes (Kernbach et al., 2018). The frame provides indicators of the information to be visualized, their main function, and benefits. Application of visualization within learning analytics is a function of tool use for problem-solving. Today there are myriad tools to support the dashboarding process such as Tableau, Microsoft BI, Alteryx, etc. with significant visualization capabilities. What these tools cannot provide are the capabilities to support effective dashboarding.

Firstly, from a reflection and foresight perspective regarding effectively communicating learner performance, interventions regarding problems associated with learning to support innovate solutions or treat with the elegance of human-centered design processes in LA require deep cognitive processes. It is one thing to consider LA and dashboard visualizations from a technological perspective aimed at efficacy and efficiency; however, LA dashboarding competence goes well beyond tools that provide insights into students' learning and success. A human-centered LA (HCLA) approaches require careful design through identification of stakeholders, their relationships, and the context within which the dashboards will function (Shum et al., 2019). Given the growing body of work on HCLA, the challenges of creating interactive systems incorporating effective interaction, analytics, and user discourse are required to produce co-created learning analytics platform. The co-creation value rests in creation of participatory design frameworks where users and designers ensure simplification of task through mutual working knowledge of the end product (Dollinger et al., 2019). MV potentially improves participatory design as the dashboard designer(s) spend more time understanding the user context, information requirements, and constraints associated with gaining optimum benefits from the LA system. In preparing learning analytics dashboards for educational practice, designers require metacognition (understanding, agreement, and reflective capabilities) and cognition to inform dashboard performance and a clear understanding of tool usability to aid operationalization (Jivet et al., 2018). Dashboards should be designed as pedagogical tools, enhancing awareness and reflection aimed at creating change in competence. MV utilization removes assumptions that all dashboards have the same effect on users or follow the same data-driven design principles. They seek instead to use the process as determinant of how to design, ensuring learners benefit the most from these customized dashboards. Moreover, MV provides an opportunity for designers to seamlessly integrate data into learning environments by focusing on information which supports goals and usability of data. Visualization is an empiric science, and as such, thinking about visualizations through meta-visualization lenses is of significant interest to not only allow for improved analytics but also justify adoption to leverage predictive capabilities in learning. Consequently, MV capabilities are required to assess the visual resources necessary for solving education problems. Access to tools is insufficient given their proliferation and ease of use. It is the meta-design capabilities associated with visually matching need and scalability requirements to provide solutions that represent core visualization competence. Without these capabilities, LA potentially remains a repository of large amounts of education information, unusable and lacking the opportunity to benefit students, academics, and administrators.

6.1 Implication

A key implication of this approach is its opportunity to inform improved training for visualization professionals as well as research into the role of meta-visualization as part of visual design processes. More specifically, it provides LA adopters with an appropriate lens through which to view insights and support improvement in prototyping visualization that effect actionable result. The need for LA adopters to move beyond familiarization with data and its potential capacity to one of capability building through "deep thinking" cannot be underscored. Moreover, understanding meta-visualization's associated change capabilities from a skill perspective has implications for teaching, administration, and potential prejudices (student/teachers) common with learning analytics adoption. A core implication is improved customizability of dashboard because designers are situated in the design process and can provide users with greater control over learning analytics data towards self-regulation and academic achievement. Moreover, MV-related approaches provide context of usage through developer's better understanding usage patterns, improving training to support adoption and improving overall perception of LA dashboards by taking human-centered approaches. This process represents an excellent starting point for MV as a rational stage-gated process for thinking about dashboard design, removal of silos, and identification of the "right" mindset informed by visual approaches to data communication supporting end users.

6.2 Future Direction

The future direction of meta-visualization is ensuring the process is well embedded in designer competence from the perspective of understanding learning analytics stakeholders and relieving tensions between stakeholder perception of learning analytics regarding access, use, and analysis of data. To accomplish this requires, firstly, more empirically focused research to map meta-visualization capabilities among visualization professionals and quality assure such methods for best practice opportunity identification. Specific research interest should examine the role of metacognitive capabilities, their requirements and benefits, and/or the effect that various meta-visualization approaches have on use/adoption of learning analytic visualization efficacy to inform decision-making.

References

Arnold, K. E., Lynch, G., Huston, D., Wong, L., Jorn, L., & Olsen, C. W. (2014). Building institutional capacities and competencies for systemic learning analytics initiatives. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/2567574.2567593

Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Journal of Asynchronous Learning Network*. https://doi.org/10.24059/olj.v20i2.790

Bendoly, E. (2016). Fit, bias, and enacted sensemaking in data visualization: Frameworks for continuous development in operations and supply chain management analytics. *Journal of Business Logistics*. https://doi.org/10.1111/jbl.12113

Brigham, T. J. (2016). Feast for the eyes: An introduction to data visualization. *Medical Reference Services Quarterly*. https://doi.org/10.1080/02763869.2016.1152146

Chen, L., Lu, M., Goda, Y., & Yamada, M. (2019). Design of learning analytics dashboard supporting metacognition. *16th international conference on Cognition and Exploratory Learning in Digital Age, CELDA 2019*. https://doi.org/10.33965/celda2019_201911l022

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*. https://doi.org/10.1080/13562517.2013.827653

Dollinger, M., Liu, D., Arthars, N., & Lodge, J. M. (2019). Working together in learning analytics towards the co-creation of value. *Journal of Learning Analytics*. https://doi.org/10.18608/jla.2019.62.2

Elias, T. (2011). Learning analytics: Definitions, processes and potential. *Proceedings of the 1st international conference on Learning Analytics and Knowledge – LAK'11*, 23. https://doi.org/10.1.1.456.7092

Evergreen, S., & Metzner, C. (2013). Design principles for data visualization in evaluation. *New Directions for Evaluation*. https://doi.org/10.1002/ev.20071

Fekete, J. D., Van Wijk, J. J., Stasko, J. T., & North, C. (2008). *The value of information visualization*. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). https://doi.org/10.1007/978-3-540-70956-5_1.

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*. https://doi.org/10.1504/IJTEL.2012.051816

Furlong, G. P., & Johnson, L. (2003). Community of practice and metacapabilities. *Knowledge Management Research & Practice*. https://doi.org/10.1057/palgrave.kmrp.8500011

Garaigordobil, M. (2006). Intervention in creativity with children aged 10 and 11 years: Impact of a play program on verbal and graphic-figural creativity. *Creativity Research Journal*. https://doi.org/10.1207/s15326934crj1803_8

Gilbert, J. K. (2005). Visualization: A metacognitive skill in science and science education. *Visualization in Science Education*. https://doi.org/10.1007/1-4020-3613-2_2

Hargrove, R. A., & Nietfeld, J. L. (2015). The impact of metacognitive instruction on creative problem solving. *Journal of Experimental Education*. https://doi.org/10.1080/00220973.2013.876604

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). *Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice*. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). https://doi.org/10.1007/978-3-319-66610-5_7

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3170358.3170421

Kavousi, S., Miller, P. A., & Alexander, P. A. (2020). Modeling metacognition in design thinking and design making. *International Journal of Technology and Design Education*. https://doi.org/10.1007/s10798-019-09521-9

Kernbach, S., & Svetina Nabergoj, A. (2018). Visual design thinking: Understanding the role of knowledge visualization in the design thinking process. *Information visualisation – Biomedical visualization, visualisation on built and rural environments and geometric modelling and imaging, IV 2018*. https://doi.org/10.1109/iV.2018.00068

Locatelli, S. W., & Davidowitz, B. (2021). Using metavisualization to revise an explanatory model regarding a chemical reaction between ions. *Chemistry Education Research and Practice*. https://doi.org/10.1039/d0rp00339e

Miller, B. D. A., Cook, E., Kennedy, E., McGuire, S. Y., Lindsey, B. A., Nagel, M. L., … Stevens, R. H. (2013). Metavisualization an important skill in the learning chemistry. *Journal of Chemical Education*.

Park, Y., & Jo, I. H. (2019). Correction to: Factors that affect the success of learning analytics dashboards (Educational Technology Research and Development, (2019), 67, 6, (1547–1571), https://doi.org/10.1007/s11423-019-09693-0). *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-019-09703-1

Peltonen, J., & Lin, Z. (2015). Information retrieval approach to meta-visualization. *Machine Learning*. https://doi.org/10.1007/s10994-014-5464-x

Rapp, D. N., & Kurby, C. A. (2008). The 'ins' and 'outs' of learning: Internal representations and external visualizations. *Visualization: Theory and Practice in Science Education*. https://doi.org/10.1007/978-1-4020-5267-5_2

Rhodes, M. G. (2019). Metacognition. *Teaching of Psychology*. https://doi.org/10.1177/0098628319834381

Saqr, M., Fors, U., & Tedre, M. (2017). How learning analytics can early predict under-achieving students in a blended medical education course. *Medical Teacher*. https://doi.org/10.1080/0142159X.2017.1309376

Shum, S. B., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centred learning analytics. *Journal of Learning Analytics*. https://doi.org/10.18608/jla.2019.62.1

Steed, C. A. (2017). Interactive data visualization. *Data Analytics for Intelligent Transportation Systems*. https://doi.org/10.1016/B978-0-12-809715-1.00007-9

Tobias, S., & Everson, H. T. (2009). The importance of knowing what you know: A knowledge monitoring framework for studying metacognition in education. In *Handbook of metacognition in education*.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*. https://doi.org/10.1177/0002764213479363

Vieira, C., Parsons, P., & Byrd, V. (2018). Visual learning analytics of educational data: A systematic literature review and research agenda. *Computers and Education*. https://doi.org/10.1016/j.compedu.2018.03.018

Weaver, C. (2005). *Visualizing coordination in situ. Proceedings – IEEE symposium on information visualization, INFO VIS*. https://doi.org/10.1109/INFVIS.2005.1532143

Weaver, C. (2006). Metavisual exploration and analysis of DEVise coordination in improvise. *Proceedings – Fourth international conference on coordinated and multiple views in exploratory visualization, CMV 2006*. https://doi.org/10.1109/CMV.2006.14

Part II
Practices and Evidence from the Learner's Perspective

Chapter 9
User-Centered Design for a Student-Facing Dashboard Grounded in Learning Theory

Stephanie D. Teasley, Matthew Kay, Shannon Elkins, and Jackson Hammond

1 Introduction

The development of dashboards designed for student use follows from the growth of analytics-based visualizations across many economic sectors. Dashboards quickly became ubiquitous in industry for "business intelligence" (Negash, 2004) before moving into the realm of education, where they were used by university administrators for "academic analytics" (Campbell et al., 2007). With the advent of learning analytics, dashboards have become a popular way to support educators, such as academic advisors (e.g., Krumm et al., 2014; Gutiérrez et al., 2020) and instructors (e.g., Van Leeuwen, 2015; Wise & Jung, 2019). These dashboards, also called "learning analytics dashboards" (LADs), are increasingly being designed specifically for student users. In fact, student-facing LADs are already a standard feature in commercial learning management systems, like BlackBoard and Moodle.

Student-facing learning analytics dashboards promise to improve learning by presenting students with actionable information grounded in how they (and their peers) engage with a course. Yet guidelines for effective dashboard design are nascent. Despite the rapid growth in the popularity of student-facing dashboards, their development has outpaced our understanding of what good ones look like and how they do or don't support learning. Bodily and Verbert (2017) conducted a comprehensive review of 93 student dashboards, finding serious deficits in the use of—or at least reporting of—effective design methods in dashboard development. They concluded that "Future research

S. D. Teasley (✉) · S. Elkins · J. Hammond
School of Information, University of Michigan, Ann Arbor, MI, USA
e-mail: steasley@umich.edu; srelkins@umich.edu; jbhammon@umich.edu

M. Kay
Computer Science and Communication Studies, Northwestern University, Evanston, IL, USA
e-mail: mjskay@northwestern.edu

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_9

should focus not only on evaluating the final product of a reporting system, but also on evaluating the design and development process" (p. 417). This paper and other meta-reviews (e.g., Yoo et al., 2015; Schwendimann et al., 2016) call for a better articulation of the methods used to develop student dashboards and the criteria by which they are evaluated. A recent article by Verbert et al. (2020) specifically called out this problem, "The process to design and evaluate dashboards has received very little attention from the Learning Analytics research community" (p. 35). The absence of learning theory, effective design methods, and principles of good data visualization in LAD design presents challenges to producing effective student dashboards.

Following the reviews of dashboard research that have identified missing elements in the design of many learning analytics-based dashboards, we combined principles from three areas—learning theory, human-computer interaction, and information visualization—to develop design requirements for a student-facing dashboard. We then built *My Learning Analytics* (MyLA), a dashboard with three views aimed at helping university students to plan their efforts for upcoming assignments, identify course materials they might have missed, and understand their course performance relative to classmates while preserving students' privacy and anonymity (see also Kia et al., 2020).

In this paper we provide a detailed account of the design and development of MyLA. We describe our six MyLA design guidelines, grounded in theory and methods from the learning sciences, education, human-computer interaction, and information visualization. We describe our multi-modal, iterative, user-centered design process and then describe each dashboard view in MyLA in detail. We then discuss the major themes arising from user feedback gathered during the various phases of our design process. We conclude with recommendations for the development of future student-facing dashboards.

2 Background and Prior Work

The earliest learning analytics dashboards demonstrated the feasibility of creating visualizations based on activity data generated by learning management systems (e.g., Arnold, 2010; Duval, 2011) but rarely included justifications for design choices (Bodily & Verbert, 2017; Jivet et al., 2018). When the intended users are academic advisors or instructors, there is an expectation that they have the necessary training to understand these displays and the relevant experience to know what to do with the information provided. However, the data generated by online learning platforms has also opened up new opportunities for providing students with direct feedback (Bienkowski et al., 2012; Young, 2016).

Although the impact of student dashboards is as yet unclear (Ifenthaler et al., 2019), they are generally assumed to be tools for supporting agency (Winstone et al., 2017) and meta-cognition (Durall & Gros, 2014). Specifically, student-facing dashboards are expected to improve performance by supporting awareness, self-reflection, and sense-making (Verbert et al., 2013; Sedrakyan et al., 2019), behaviors which have been characterized as central to self-regulated learning (SRL, see Butler & Winne, 1995). The visualizations shown by dashboard displays provide students with feedback to plan for, to evaluate and monitor their current progress, and to adjust their learning strategies. However, it is also important to examine the relationship between the information student dashboards provide and how these may produce differential effects depending on student-specific factors, such as their current level of performance and course goals. For example, in earlier work (Brown et al., 2016), we found that the level of academic difficulty experienced by students was related to the effectiveness of strategies for academic recovery. Specifically, students who were experiencing moderate academic difficulty benefited more from tools that helped them plan their time compared to students experiencing more severe academic difficulty.

In addition to SRL, Achievement Goal Theory (AGT, see Maehr & Zusho, 2009) can also be a valuable approach for understanding how the design of a dashboard may have differential effects on students. AGT describes the different goal orientations that motivate students: mastery (focus on understanding and improvement) and performance (focus on comparisons with peers) (e.g., see Barron & Harackiewicz, 2001; Beheshitha et al., 2016). Research has shown that compared to performance-orientated students, mastery-oriented students are more likely to focus on developing an understanding of the material (Elliot & McGregor, 2001) and have higher self-esteem (Shim et al., 2012). In our prior research on an advisor-facing dashboard (Lonn et al., 2014; Aguilar et al., 2020), we found that students' achievement orientation was negatively impacted when academic advisors shared their dashboard during meetings with students. Specifically, some students—the most academically vulnerable—moved from a mastery orientation to a more performance orientation, a change that may negatively impact their performance.

Based on the relevance of both SRL theory and AGT for understanding when and why students might benefit from feedback displayed in a dashboard, we aimed to develop displays that provide a general, but customizable, framework for students to engage in SRL-related behaviors and to support a mastery orientation toward learning. This required that we develop a set of design guidelines that were consistent with these goals; we also followed the recommendation by Jivet et al. (2017) to support multiple reference frames (social, achievement, and progress). To do so, we engaged in iterative, user-centered design (Nielsen, 1993), involving student users in the design process. Lack of student input in a tool designed for their use has been a critique of prior dashboard reports (De Quincey et al., 2016; Bodily & Verbert, 2017) and specifically called for in several recent papers (Ahn et al., 2019; Buckingham Shum et al., 2019).

3 MyLA Design Guidelines

Based on our review of the literature on student-facing dashboards, designs for previous learning analytics dashboards, information visualization design principles, and our experience with user-centered design methods, we generated the following general design guidelines for the My Learning Analytics (MyLA) dashboard.

DG1: Support Self-Regulated Learning and Mastery Orientation by Displaying Points not Grades

Self-regulated learning theory has emerged as the primary theoretical basis for LADs (Matcha et al., 2019; Jivet et al., 2020). There are three key elements of self-regulated learning theory that we wanted our dashboard to support: planning, monitoring, and evaluating (Butler & Winne, 1995; Winne, 1997, 2018). Further, following Achievement Goal Theory (Maehr & Zusho, 2009), we sought to avoid representations that focused on grades and used the percentage of points earned instead to represent how much students had learned rather than how well they had performed. As the data utilized to create the visualizations came from the logs generated by our campus learning management system (Canvas), we could leverage the system's grade book to provide these calculations. All students at our university ultimately receive a grade for their course which is represented on their official transcript as both a letter grade and summed as a numerical value from 0 to 4.0 to represent performance across courses. However, how the percentage of points earned translates to a specific letter grade is determined by the individual instructor. Thus, using point percentages had the benefit of being consistent with AGT theory and the LMS gradebook tool, as well as agnostic about how any individual instructor determined the final letter grade for the course.

DG2: Allow for Student Control over What They See

We wanted to encourage students to engage with course content in ways they could not do in standard LMS views. Giving students tools for planning and monitoring allows them to strategize about what they have done and what they could do differently. To ensure that students feel a greater sense of agency when they use MyLA, we wanted to give them some control over the data shown in the visualizations. The ability for students to choose how their information is displayed by the dashboard is both consistent with SRL theory and recommended in several prior dashboard studies (e.g., Sluijter & Otten, 2017; Schumacher & Ifenthaler, 2018).

Chatti et al. (2020) observed that "dashboards … are predominantly static and, in general, afford very little interaction" (p. 72). However, when students have the ability to manipulate dashboard visualizations, they have more freedom to meet their own needs and accomplish their own tasks (Stephanie, 2017). In a recent meta-review aimed at assessing the effectiveness of learning analytics in supporting study success, Ifenthaler and Yau (2020) concluded that visualizations that have been documented to support study success were those that included meaningful information about learning tasks and progress of learning toward specific goals. Because students often have different reasons for their choice of classes with specific goals for each (Regan & DeWitt, 2015), we wanted students to be able to change various dimensions of the visualizations—both to display information that they determine is meaningful and to determine how they want to highlight the features of their progress that are relevant to their own goals. This is particularly important as goals play an important role in students' interpretation of feedback (Shim & Ryan, 2005).

DG3: Support Social Comparison

Despite generalized concerns about the effects of providing students with information about their performance relative to their peers, most dashboards do so by at least providing representations of where students fall in the distribution of grades. Studies on AGT have shown that seeing one's own data compared to others' can be helpful for some students but might be disliked by others (Ames & Archer, 1988; Barron & Harackiewicz, 2001). In order not to force these comparisons on students, our dashboard gives them the choice to hide direct comparisons to other students. We also wanted to give students control over which students they wanted to be compared with should they desire to do so. Social comparison theory (Festinger, 1954) has shown that students' comparisons with others who perform worse (downward comparison) have been shown to lead to feelings of superiority and positive affect (Major et al., 1991) while comparisons with others who perform better (upward comparisons) can evoke negative affect and lower academic self-concept (Dijkstra et al., 2008). In MyLA, the Resources Accessed view (Sect. 5.2) allows students to choose their own reference group by filtering the visualization to show data on other students who have a specific standing in the class.

DG4: Use a Simple, Consistent Visualization/Interaction and Vocabulary

In addition to grounding our dashboard design in theory, we employed user-centered design techniques and the state of the art in information visualization design principles. Sedrakyan et al. (2019) found that an aggressive simplification of visualization designs and features is needed to make visualizations widely accessible to people with varying levels of visualization literacy. A part of such simplification involves establishing a consistent *visual vocabulary*: common chart types (e.g., bar, pie, line chart) used consistently across different views (consistent visualization *schemas*, Padilla et al., 2018); common color schemes, icons, and other visual design elements used always to reference the same concepts; a common high-level structure to each dashboard page; and a common set of interaction idioms used across the interface.

Wakeling et al. (2015) found that users were better able to answer questions of higher difficulty using bar charts than other chart types in a visualization dashboard. Bar charts also use the most perceptually effective visual encoding: they map data values onto *position* (the position of the endpoint of the bar) or *length* (Cleveland & McGill, 1984; Heer & Bostock, 2010). Given the need for a consistent visual vocabulary and the unique combination of familiarity and perceptual effectiveness held by bar charts, we adopted bar charts as the fundamental visual encoding across the dashboard.

DG5: Preserve Privacy

An important consideration in the design of our dashboard—which exposes both grade data and data on students' interactions with online course content compared to other students—is privacy. These concerns were particularly salient in our design of the grade view, as we did not want to disclose the students with the lowest grades to their peers. As described in the section below, we prototyped numerous approaches to partially anonymizing a grade histogram. We ultimately grounded our solution in the principle of k-anonymity (Sweeney, 2002), an established principle in privacy design.

DG6: LMS Integration for Scalability and Adoption
Consistent with the recommendation of Sedrakyan et al. (2019), a primary goal of MyLA was that it be a system that can be deployed broadly. We wanted MyLA to be able to support students in any course on our campus without needing to be configured by instructors, with the eventual goal that it could be adopted easily on any campus that uses Canvas. Thus, it should not require use of any special data sources not available through Canvas or any other educational system that does not conform to the IMS Global standards for tool interoperability. Our close collaboration with staff in the campus information technology services helped us scope designs to features that can actually be built atop Canvas and other data sources (e.g., video lecture capture systems), which could be as agnostic as possible to the variety of types of courses offered on our campus.

4 Design Process

Our design process proceeded through several phases.

Phase 1: Idea Generation We began with a brainstorming session among the design team, including experts in learning and motivation, learning analytics, information visualization, human-computer interaction, and software design (members of the information technology team who would implement the dashboard), as well as their students (undergraduate through doctoral levels). This session sets the template for future meetings with the team; researchers, designers, implementers, and students were represented at virtually all meetings and design sessions in order to ensure all perspectives were included.

During this phase we focused on *tasks we wanted students to be able to accomplish*, aiming not to reject ideas too early. We used existing literature and examples of student dashboards as jumping-off points in brainstorming, generating a variety of paper sketches of possible dashboards and a tentative list of students' tasks. In later phases of brainstorming, we narrowed design options based on our design guidelines. In particular, **DG1: Support Self-Regulated Learning and Mastery Orientation** led us away from designs that focused too heavily on grade maximization. Having a close collaboration between the researchers, designers, and implementers helped us quickly identify designs that would either not satisfy our theoretical focus (**DG1**) or be infeasible due to technical constraints (**DG6: LMS Integration for Scalability and Adoption**). Often, for example, IT members on our team would run queries in response to design questions to see what feature sets are used across courses at our institution (such as assignment groups that allow students to drop the lowest grade) so we could understand how many classes might be negatively or positively impacted by a particular design. This integration was invaluable for developing a feasible, scalable design.

Phase 2: Visualization Design Workshop To gather further design inspiration from stakeholders for the dashboards, we conducted a visualization design session following a modified version of the VizitCards protocol (He & Adar, 2016) at a campus workshop as part of a larger event on improving teaching and learning through the integration of technology and pedagogy. Participants at this “Design Jam” workshop ($n = 17$) included students, teaching support staff, IT developers, and members of the research team. The VizitCards protocol is a 1.5-hour visualization design workshop in which participants are given a design “brief,” asked to identify tasks users might wish to perform with a visualization, and then led through a series of paper prototyping exercises in small groups to develop a visualization to help users accomplish their desired tasks. We asked participants to design a student-facing learning analytics dashboard and used this protocol to generate further design ideas for our dashboard.

Phase 3: High-Fidelity Prototypes and Implementation Following paper prototyping from phases 1 and 2, we developed high-fidelity mockups of dashboards using Tableau. The MyLA front end is written in JavaScript using React, with Material-UI as the component library and D3 for data visualization. Jest was used as the testing framework. The MyLA backend uses the Django framework and a MySQL database, and a cron job is used to get Canvas data and live events. MyLA can be run as a stand-alone tool with SAML (Security Assertion Markup Language) support, or as a Canvas LTI (Learning Tools Interoperability) tool.

Phase 4: Pilot We piloted the dashboard in Fall 2018 in three classes during the fifth week of a 14-week term. Two classes (105 students total) were graduate-level classes, one in information and the other in public health. For the third course, an undergraduate introductory course in information, the instructor decided (1) not to turn on the Grade Distribution view, (2) to turn on MyLA for only 1 month, and (3) to offer students an option to write an assessment of MyLA as assignment for the course. Framed by the instructor as a user evaluation report, students reported pain points they experienced using MyLA, positive aspects of use, and suggestions for new functionality. Of 208 students in this course, 50 gave us permission to access to their written assignment. These assignments were analyzed for general thematic content regarding usability issues.

Phase 5: Deployment In three subsequent academic terms (Winter 2019 through Winter 2020), we deployed MyLA to courses where instructors volunteered to have their class participate. Students were informed about MyLA via an in-class demonstration conducted by one of researchers for the pilot and first term, and via a recorded demonstration video in the subsequent two terms. Faculty also posted an announcement about MyLA to their course website. Students received no further reminders about its availability.

Term 1: 10 classes (8 undergraduate, 2 graduate classes from multiple disciplines), opened between weeks 6 and 11, to 860 students. Class size varied from 19 to 265 students. The instructor for one course elected not to turn on the Grade Distribution view.

Term 2: 12 classes (5 undergraduate, 7 graduate classes from multiple disciplines), opened between weeks 5 and 8, to 1106 students. Class size varied from 16 to 233 students. The instructors for three courses elected not to turn on the Grade Distribution view; one instructor elected not to turn on the Assignment view.

Term 3: 12 classes (9 undergraduate, 3 graduate classes from multiple disciplines), opened between weeks 6 and 8, to 1037 students. Class size varied from 15 to 151 students. The instructors of five courses elected not to turn on the Grade Distribution view. This academic term was affected by the pandemic: all classes went fully online starting the tenth week of the term.

After each term, we administered surveys via email to assess students' dashboard usage and to elicit feedback on the dashboard. Respondents who did not use MyLA were also asked why they did not use it. Participation was voluntary, and students who completed the survey were entered into a drawing to win a gift card for a popular e-commerce website. The survey response rate averaged 20% over the three terms; 49% were from MyLA users and 51% were non-users.

We continuously improved the dashboard design between terms based on student feedback and guided by the six design guidelines described above.

Phase 6: User Experience Interviews After the end of Term 3, 12 students (10 undergraduate, 2 graduate; 11 female, 1 male) participated in a user experience interview and received a gift card to a popular e-commerce website for doing so. Two participants had used MyLA in multiple terms. All interviews were conducted remotely via Zoom and took 30–45 min. After a set of introductory questions, students were shown each of the dashboard views from their course showing their own data. The interviewer asked the student to walk through how they used the dashboard view during their most recent MyLA visit, and then followed up with questions to learn why they came to that specific view and how they used it. Responses to the questions about each view were clustered and analyzed with affinity diagramming techniques (Lucero, 2015) to iteratively uncover and refine themes (described in Sect. 6).

5 MyLA Design

As our design evolved continuously throughout the design process described above, we focus here on the final design of the three MyLA views.

5.1 Assignment Planning View

The goal of the Assignment Planning view is to give students the ability to (1) see the progress they have made so far in the class and (2) help them plan for future assignments or tests. These two goals lead to its two main components: a progress bar showing a student's progress through the class (top) and a table showing all the items that will contribute to the student's overall course grade (bottom).

Influenced by **DG1: Support Self-Regulated Learning and Mastery Orientation**, the progress bar does not show the student's current grade. Instead, it shows the ongoing total percentage of points they have accumulated toward a final percentage score. Graded assignments are shown in blue, and the size of the graded bars is proportional to the percentage points of the final grade the student earned in that assignment. Ungraded assignments are shown in gray, and the size of the ungraded bars is proportional to the total percentage points of the final grade the student would earn if they received 100% in that assignment. Thus, stacked horizontally, the total of the blue plus gray bars (graded plus ungraded assignments) is the total percentage the student would receive if they got 100% on all remaining assignments. This allows students to quickly see what assignments have a large or small potential impact on their final grade.

The lower portion of the display provides details to aid in planning: the week, due date, title, and percent of final points for each assignment (or the points earned if the assignment has been graded). This facilitates monitoring and planning (**DG1**) for individual assignments. By default, the current week is highlighted in yellow on the lower and upper panels. Following **DG4: Use a Simple, Consistent Visualization/Interaction and Vocabulary**, we use the same color scheme in both panels for graded assignments (blue), ungraded assignments (gray), and the current week (yellow); we also use the same visual encoding (bar length) to indicate percentage points earned toward final grade. This reduces the size of the visual vocabulary students must learn to be able to interpret this view.

5.2 Resources Accessed View

The goal of the Resources Accessed view is to allow students to (1) identify resources that other students in the classes are using that they might not have looked at (**DG3: Support Social Comparison**) in order to (2) plan usage of class resources (**DG1: Support Self-Regulated Learning and Mastery Orientation**).

The view allows students to analyze the files, media, and other resources their instructor provides for them in Canvas. The time slider (top) allows students to select a desired time period (**DG2: Allow for Student Control over What They See**). The bottom view lists all resources (files, videos, etc.) that students in the class have accessed on Canvas during that time period, and the bars show what percentage of students who accessed each resource. For consistency with other views

(**DG4**), we use bar charts to show percentages, highlight resources the student has looked at in blue, and show resources the student has not looked at in gray (paralleling color usage in the Assignment Planning view). Each resource is a hyperlink to that resource's location on the course website.

This view facilitates planning (**DG1**) by allowing students to see what resources are popular but which they might have overlooked. For example, in the weeks leading up to a midterm, a student might select the pre-midterm time window to see what resources their classmates are using to study that they have not used (**DG3**). Students can use a dropdown to further filter results to see which resources particular groups of students were using (e.g., students with grades between 90% and 100%, 80% and 89%, or 70% and 79%) to calibrate their own performance (**DG2**).

5.3 Grade Distribution View

The goal of the Grade Distribution view is to help students (1) monitor their performance in a class (**DG1**) and (2) understand their performance relative to the performance of their classmates (**DG3**).

In text, this view displays four key statistics: the average grade, the median grade, the class size, and the student's current grade (as a percentage). The main feature of the view is a histogram of percentage points earned by all students in the class, which indicates the student's current grade with a yellow line (see Fig. 9.1). Students can see approximately how many students have grades above and below the average and where their grade sits in the distribution (**DG3**).

This view was particularly contentious during our design process due to tensions between supporting social comparison (**DG3**) and encouraging a mastery orientation (**DG1**). Course grade distributions are a typical feature in many LADs (Jivet et al., 2017), and the view serves as a potential draw for students to come to the dashboard (Young, 2016) where students could potentially benefit from functionality in other views. Based on feedback we got from students during the pilot, and to address some of the potential shortcomings of direct social comparison, we also gave students the option to hide their grade on the distribution (**DG2: Allow for Student Control over What They See**). If the student disables the display of their grade, this choice is remembered as their default so that when they load the screen in the future it is not shown unless/until they re-enable it.

Another important consideration of this view is to satisfy privacy concerns (**DG5**). One advantage of the histogram is that students can see how other students are performing without us explicitly representing the scores of individual students. However, this benefit is not guaranteed: a lone student might fall in a single bin in the histogram, which is particularly concerning if that student has a low grade. We consulted with a privacy expert and prototyped a variety of privacy-preserving methods for transforming the histogram view, including outlier

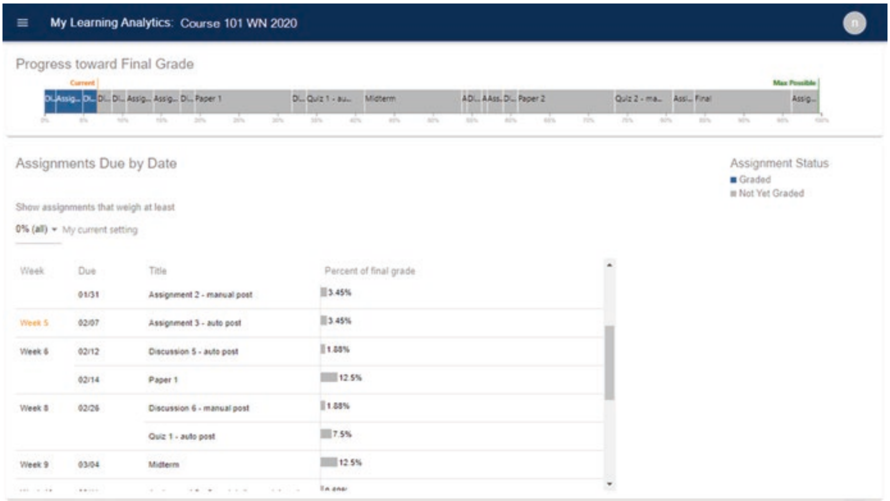


Fig. 9.1 Assignment Planning view

detection methods and heuristics based on k-anonymity. We applied several of these heuristics to real course data so that we could examine the pros and cons of these different heuristics on actual data.

We found that outlier detection methods were too unreliable, often producing histograms that either binned too much or too little data. Ultimately, we found that our primary concern should be preserving the privacy of students with low grades, so we adopted a k-anonymity approach (Sweeney, 2002) for anonymizing the lowest-performing students. On the histogram, we group the lowest five students' grades together and do not depict exactly where they lie (only that they are less than the highest student in the lowest group of five). For example, Fig. 9.3 shows that the bottom five students in the class have a grade of 67% or less but does not show exactly what their grades are. In addition, if the entire class has unusually high grades (currently defined as all students having 98% or above), no binning occurs.

6 Themes Arising from the Design and User Feedback

In this section we describe major themes arising from user feedback gathered during the various phases of our design process (Sect. 4), including **student reports** as an optional assignment in one course (Pilot Term), **surveys** (all terms), and user experience **interviews** (following Term 3). Quotes from surveys are indicated using the term the survey was conducted in (T1, T2, T3), and quotes from interview participants are indicated using participant numbers (P1, P2, etc.).

6.1 Usage Triggers and Viewing Habits

To better understand key facets of the students' monitoring and planning habits, we asked students why they visited MyLA when they did and what they were hoping to learn.

Students' reported usage of MyLA is partly event driven. Many students checked the Grade Distribution view after larger graded items had been released for the purposes of self-assessment and monitoring (**DG1**) or social comparison (**DG2**): "It was after our second test, and I wanted to gauge how I was doing in the class compared to the other students" (T3). This example illustrates how social comparison (**DG3**) can motivate usage; several students described how they would check the Grade Distribution view after major tests or assignments to see their standing in the class. Usage of the Resources Accessed view was also triggered by tests; one student described using that view to "... see what resources students were using to study with" (T2) prior to major assignments, i.e., for planning purposes (**DG1**). In contrast to this *event-triggered usage*, only a small number of students described using MyLA in some sort of weekly or daily routine.

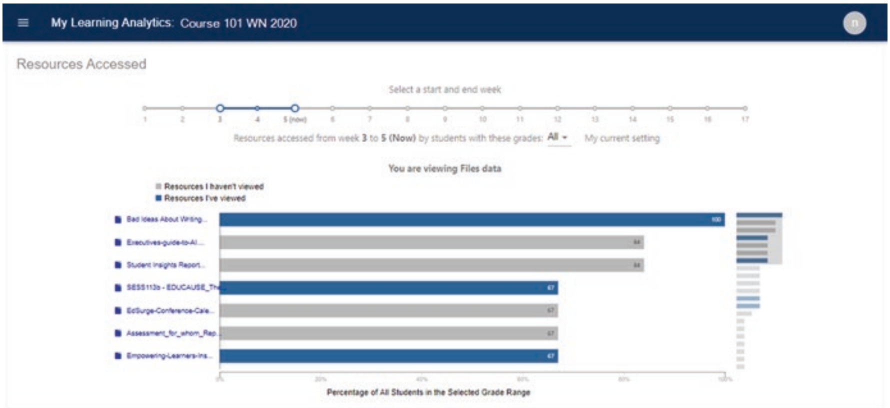


Fig. 9.2 Resources Accessed view

Table 9.1 Usage of MyLA across three deployment terms

Term	Total unique MyLA users (% of total population)	Resources Accessed users (% of total MyLA users)	Assignment Planning users (% of total MyLA users)	Grade Distribution users (% of total MyLA users)
1	449 (52%)	256 (57%)	242 (54%)	391 (87%)
2	432 (40%)	222 (51%)	206 (48%)	392 (91%)
3	469 (45%)	252 (54%)	318 (68%)	377 (80%)

Note. Term 3 was affected by the COVID pandemic, and the university transcript only reported "pass" or "no record-COVID for all classes"

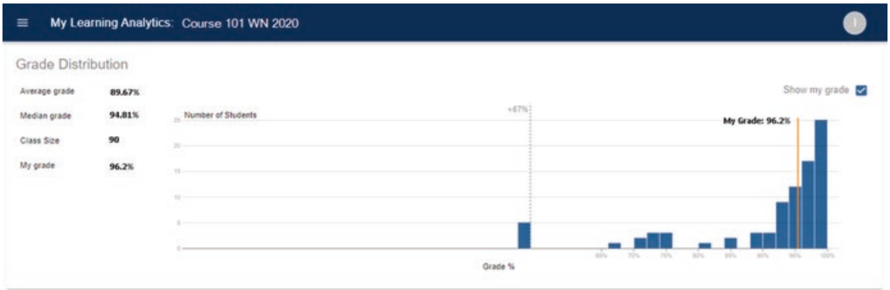


Fig. 9.3 Grade Distribution view

Usage statistics for MyLA across our three deployments are shown in Table 9.1. Students indicated that a common barrier to use was that MyLA was hard to find on the Canvas course site. The most common reason reported in surveys for not using MyLA (89% of the non-users) was that students either forgot MyLA was on their course site or that they did not know it was available. This finding was consistent across all three deployment terms. We have suggested that instructors position MyLA near the Grade tool in the tool listing in Canvas. However, without reminders that MyLA is on the course website, we have not seen an increase in visibility or usage.

6.2 Monitoring and Planning

In every semester, students must manage their effort across multiple courses, and they described various ways they used MyLA to assess their status (monitoring) and plan future actions (**DG1: Support Self-Regulated Learning and Mastery Orientation**).

6.2.1 Keeping Performance "on Track"

Students in the user experience interviews expressed a worry about "staying on track" or "keeping up with others," meaning that they were at or above the class average (**DG3:** Support Social Comparison), and used the Grade Distribution view to better assess their performance in the class: "This tool helped me feel less anxious because I could feel like I was doing well in the course instead of wondering/worrying about how I was doing" (T3). P9 confirmed that this view helped her monitor her performance; she used it to "see if I was on the right track to achieve the grade that I'm hoping for"; i.e., monitoring (**DG1**).

6.2.2 Discovering and Prioritizing Resources

Some students reported that the Resources Accessed view helped them discover and prioritize resources. The simplest usage involved *discovery* of important resources they had not accessed yet: “There was a document I hadn’t looked at that helped me complete the assignment” (T2). While some students simply opened the view to see what resources they had not used, other students used the popularity of resources for *prioritization* (**DG3: Support Social Comparison**), learning of potentially important resources they had overlooked. P2 noted, “A lot of these things are things I hadn’t really noticed in the class…especially this one with the highest one [% of students who had accessed it].” P4 reported that their instructor provided examples for one assignment in their class but not enough time to review each one; they explained, “this [Resources Accessed view] gives us a good idea of what to look at first, instead of just blindly picking.” By identifying popular files using the Resources Accessed view, students are better able to calibrate their activities with their peers and the instructor’s expectations (**DG3**) and to prepare for lectures and assignments more efficiently (**DG1: Support Self-Regulated Learning and Mastery Orientation**).

6.2.3 Using Percent of Final Grade for Planning and Monitoring

The “% of final grade” value for each graded item in the Assignment Planning view was a key piece of data students used to monitor how much they have progressed through a class and how much is yet to be completed (**DG1**): “I learned how the class grades were structured and therefore could manage my time more efficiently” (T3). This helped students plan time allocation and put grades in a broader context: “I would have less stress…if I didn’t do as well on something, I could see all these other opportunities to do well on them to help my grade, because there are a couple things worth the same amount” (P3). Students in the Pilot Term liked how the progress bar provided a visual representation of assignment weighting, remarking that it allowed them to prioritize their assignments in order of importance; this sentiment was echoed in the surveys: “It really helped plan out my studying goals - I knew how much each assignment counted for in my grade, so I could set priorities” (T2). While students could have calculated the “% of final grade” value themselves using information from the course syllabus, students reported being happy the view did the math for them. Students also suggested that this view could provide a visualization of what scores they would need on upcoming assignments to obtain a certain grade, a feature we have built into an upcoming version of MyLA (for a discussion of this approach to “gameful learning” see Aguilar et al., 2018; Holman, et al., 2015).

6.3 Changing Defaults Was Rare, Except for "My Grade"

In the design of MyLA, we wanted to provide settings that students could customize to improve the usefulness of each view and to give them some autonomy (**DG2**). However, we found that in our first deployment of MyLA students interacted very little with these settings: in Term 1, only 12 MyLA users (3%) changed a default setting 16 times in total (min = 1, max = 5). This lack of interaction with the visualization settings does not indicate overall *usage* was low but echoes recent findings about interactive visualizations in journalism: that while many readers engage with visualization content, few use interactive controls embedded in the visualizations (Fulda, 2018).

We suspect this may be related to the perceived utility of the interactive controls. After Term 1, we introduced a new setting that allowed students to hide their grade in the Grade Distribution view, as a way to let students change the visualization if they had negative reactions to seeing their grade directly in the class distribution (**DG3: Support Social Comparison**). After this change, we saw a substantial uptick in students changing defaults: in Term 2, 36% of users changed a default setting 692 times in total (min = 1, max = 18); in Term 3, 37% of users changed a default setting 653 times in total (min = 1, max = 22).

6.4 Social Comparison

Investigating the potential for social comparison (**DG3**) to help students by exposing them to anonymized data from Canvas was one of the original motivations for MyLA. While we were concerned that social comparison in MyLA could have unintended consequences, the behaviors reported related to social comparison were generally positive as detailed below.

6.4.1 Comparing with the Whole Rather than the Top

As described in Sect. 6.2.1, many students were concerned about "staying on track" for the grade they wanted or "keeping up with others." However, that sentiment stopped short of specifically wanting to do better than others (described in AGT as a performance-approach orientation). Survey comments did not focus on wanting to see that they were the best in the class, but instead focused on students' own mastery goals: "I learned [from the Grade Distribution view] that I was below average, which really motivated me to study harder" (T1). Similarly, P7 said the Grade Distribution view helped with "making sure you're not…falling to the left side of the spectrum." Like many of the comments in the survey, nine interviewees explained that they liked seeing that their grade was at or above average, without expressing a desire to be at the top of the distribution.

Students also checked the Grade Distribution view when new grades were entered to determine if the shape of the distribution—and their position in it—had changed. "After big tests or papers, I would check it to see where I was standing in comparison to the class" (T3). Some students explained that this comparison helped them feel better about their performance when they received grades lower than they hoped, a positive monitoring behavior (**DG1**) made possible by social comparison (**DG3**); P3 checked the view "right after our past big test had gone in, and I hadn't done as well as I wanted to do on it…so I went in here to see…and the average grade, at least from when I had looked at it previously, had dropped so that kinda clued me into that a lot of people had struggled with the test like I did. So it made me feel a little bit better and I was still on track with everything."

6.4.2 Social Comparison Utility Varies

Compared to the Grade Distribution view, the utility of the social comparison features in the Resources Accessed view had more variance across students. As discussed in Sect. 6.2.2, some students used the popularity of resources in this view to identify potentially important items they had missed. However, other students found this view less useful: P8 had used it when "I was as a freshman and I wasn't sure how much reading to do for class." Now a sophomore, P8 felt more confident that her social networks could tell her what resources are important: "word of mouth is more popular than using something like this." We suspect the utility of popularity-based comparison features depends on educational context and students' social networks. In online courses or for students with smaller social networks, being able to see what classmates are reading may have greater utility.

6.5 Match Between the System Language and the Users' Language

A crucial consideration in the design of interactive systems is how well the system's *language* or *model* (the vocabulary and operations the system uses) matches up to the users' *task language* and *model*. The smaller the gap between these, the easier the system should be to use (Hutchins et al., 1985). In deploying MyLA, we discovered some subtle mismatches between our system language and that of our users which suggest future directions for improvement.

6.5.1 Completed Work Means Progress

The Assignment Planning view was designed to give students a tool to monitor their course progress and plan for future assignments. The view relies on assignments being graded, and distinguishes primarily between *graded* and *ungraded* assignments. However, some students wanted the view to summarize what work they have submitted (whether or not it has been graded) and what was yet to be completed. P4 explained: "my understanding of this page is…an assignment planning page, but right now it's more towards a 'what grades are in?' page." Showing progress through assignments only after a grade is received did not properly reflect the work they felt they had completed, and several students suggested that the view have an additional color for "submitted but not graded" assignments.

6.5.2 Semantic Milestones vs. Week Numbers

The Resources Accessed and the Assignment Planning views both use the week numbers of a term as units of time. While many instructors base lectures and assignments on week numbers, week numbers were not strong indicators of time for students. Five interviewees wanted the Resources Accessed view to organize items with respect to other structural features of the course, such as assigned chapters, lecture topics, or exams. For example, P1 stated, "Week 11 we…went over 'card sorting', it would be nice to just click on that [the lecture topic]." When she explained how she would like the Resources Accessed view to be organized by which resources would help her study, P11 explained, "I don't know what week…chapter 4 was." This suggests using semantic milestones in addition to (or instead of) week numbers as time points across MyLA may improve students' ability to orient themselves to the information displayed. This presents a tension with **DG6**: **LMS Integration for Scalability and Adoption**, as not all instructors use Canvas in a way that supports extracting meaningful metadata for use as semantic milestones.

7 Conclusion

With the goal of creating a dashboard that would allow university students to make informed, actionable decisions about their learning, we created MyLA to integrate seamlessly into our campus learning management system and designed it to scale broadly. Given the many shortcomings described in the existing literature on learning analytics dashboards (LADs), particularly those designed for students, we anchored our design process in learning theory and careful empirical methods for system development. Specifically, we drew on expertise in the learning sciences, education, human-computer interaction, and information visualization to generate design guidelines for MyLA and followed a development process firmly grounded in user-centered design. The three visualizations we designed, the Assignment Planning view, the Resources Accessed view, and the Grade Distribution view, provide students with information designed to encourage ongoing reflection on their course activity and performance. In this paper we have presented our design guidelines and described how the phases of our iterative design process allowed us to make changes to the views driven by student usage and feedback.

Several of our design guidelines follow closely from prior dashboard research. **DG1: Support Self-Regulated Learning (SRL) and Mastery Orientation** reflects the theoretical frame advocated in a number of papers that have theory-based designs (Jivet et al., 2020; Matcha et al., 2019). Here we add Achievement Goal Theory (AGT) as well, so that MyLA use does not unintentionally lead students away from a mastery approach to learning (Aguilar et al., 2020). Indeed, while grading activity was a major trigger for MyLA use, students suggested that their interest in the grade distribution was not focused on being at the top of the class but rather making sure their performance kept them on track with their course goals. **DG2: Allow for Student Control over What They See** is consistent with SRL theory but a component of only a few other dashboards (e.g., Roberts et al., 2017; Sluijter & Otten, 2017; Schumacher & Ifenthaler, 2018). Here we found that students primarily changed default settings to customize information when they wanted to discover or prioritize resource use, or to see how the overall grade distribution changed over time. However, we found that more students began changing settings only after we responded to specific feedback (e.g., remove the self-performance line on the Grade Distribution view) and when we made the settings more visually salient.

Perhaps the most contentious aspect of dashboard design involves the issue of social comparison (Stephanie, 2019). Despite the popularity of views that support social comparisons (Matcha et al., 2019), the evidence is mixed about when and for whom such feedback is beneficial. We included **DG3: Support Social Comparison** as our response to the ubiquity of this form of reference frame (Jivet et al., 2017), but we kept with **DG2: Allow for Student Control over What They See** so that students could make individual decisions about if and when to seek comparisons with their peers and to pick with whom they wanted to be compared. Ethics should be at the forefront of any learning analytics intervention (Slade & Prinsloo, 2013), and **DG5: Preserve Privacy** also addresses ethical issues related to social comparison by ensuring that the lowest-performing individuals cannot be identified in any performance comparisons (using a k-anonymity approach, Sweeney, 2002). These efforts were driven primarily by our own ethical values and as a response to instructor concerns about the Grade Distribution view. Interestingly, students did not express concerns about privacy in any of the feedback activities across our design phases. And, as with so many LADs (Fritz, 2011; Young, 2016), this was the most frequently used view in MyLA.

The remaining two design guidelines, **DG4: Use a Simple, Consistent Visualization/Interaction and Vocabulary** and **DG6: LMS Integration for Scalability and Adoption**, reflect our experience with the field of information visualization and our commitment to developing an easy-to-use student dashboard that could be implemented broadly across our campus learning management system (LMS). Although the field of learning analytics has raised a number of important questions about the value of using LMS-based data (Verbert et al., 2020), we wanted to provide an information resource for students where they expect to find course-related information. In addition, by focusing our system architecture on interoperability standards, we allow for inputs to MyLA views from multiple sources, such as etextbooks, library usage, and other campus resources, as well as the potential for data from other sources used in "multimodal learning analytics" (Blikstein & Worsley, 2016).

In our future work, we are continuing to improve MyLA. As discussed above, (1) students want confirmation that assignments have been received and not just that they have been graded, and (2) information displayed in the three MyLA views need to be organized around more meaningful milestones than week designations. We have already rolled out a new Assignment Planning view that shows submitted as well as graded assignments and allows students to set individual goals for each assignment to calculate the impact of those goals on their final grade. In addition, as MyLA is now being adopted by other universities in the United States, we can address the main limitation of this project; while being tested with many courses taught across multiple disciplines, our research on MyLA to date only represents students on our campus. As a large, research university with highly competitive admissions, we recognize that our students do not necessarily reflect the needs and preferences of students everywhere. Although it is too early to make strong claims about the overall impact of MyLA on student learning, positive feedback from hundreds of student users and multi-institutional adoption suggests we are on the right track. The development of our design guidelines reflecting a theoretical framework and important practical issues such as privacy and scalability, as well as the value of a user-centered approach, provides a promising path forward for future learning analytics dashboards.

Acknowledgments We wish to recognize the important contributions of two collaborators, Stuart Karabenick and John Johnston, who passed away before this project was completed. We also acknowledge our colleagues in the Teaching & Learning team at UM's Information Technology Service without whom this dashboard would only be a dream. The Learning, Education & Design Lab is supported by funds from the UM Provost Office.

References

Aguilar, S., Holman, C., & Fishman, B. J. (2018). Game-inspired design: Empirical evidence in support of gameful learning environments. *Games and Culture, 13*(1), 44–70.

Aguilar, S., Karabenick, S., Teasley, S. D., & Baek, C. (2020). Associations between learning analytics dashboard exposure and motivation and self-regulated learning. *Computers & Education*.

Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6*(2), 70–85.

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80*(3), 260.

Arnold, K. E. (2010). Signals: Applying academic analytics. *ECUCAUSE Quarterly, 33*(1), 1.

Barron, K. E., & Harackiewicz, J. M. (2001). Achievement goals and optimal motivation: Testing multiple goal models. *Journal of Personality and Social Psychology, 80*(5), 706.

Beheshitha, S. S., Hatala, M., Gašević, D., & Joksimović, S. (2016). The role of achievement goal orientations when studying effect of learning analytics visualizations. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 54–63). ACM.

Brown, M. R., DeMonbrun, M., Lonn, S., Aguilar, S., & Teasley, S. D. (2016). What and When: The Role of Course Type and Timing in Students' Academic Performance. *Proceedings of the 6th International Conference on Learning Analytics & Knowledge* (pp. 459–468). Edinburgh, Scotland: ACM.

Bienkowski, M., Feng, M., & Means, B. (2012). Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. *US Department of Education, Office of Educational Technology, 1*, 1–57.

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220–238.

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418.

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centered learning analytics. *Journal of Learning Analytics, 6*(2), 1–9.

Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of Educational Research, 65*(3), 245–281.

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *Educause Review, 42*(4), 40.

Chatti, M. A., Muslim, A., Guliani, M., & Guesmi, M. (2020). The LAVA model: Learning analytics meets visual analytics. In *Adoption of data analytics in higher education learning and teaching* (pp. 71–93). Springer.

Cleveland, W. S., & McGill, R. (1984). Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American Statistical Association, 79*(387), 531–554.

De Quincey, E. J., Turner, M., Williams, N., & Kyriacou, T. (2016). Learner analytics; the need for user-centered design in learning analytics. *EAI Endorsed Transactions on Ambient Systems, 16*(9), E8.

Duval, E. (2011). Attention please! Learning analytics for visual recommendation. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 9–17). ACM.

Durall, E., & Gros, B. (2014). Learning analytics and a metacognitive tool. In *Proceedings of the 6th international conference on Computer Supported Education (CSEDU)* (pp. 380–384).

Dijkstra, P., Kuyper, H., van der Werf, G., Buunk, A. P., & van der Zee, Y. G. (2008). Social comparison in the classroom: A review. *Review of Educational Research, 78*, 828–879.

Elliot, A. J., & McGregor, H. A. (2001). A 2 X 2 achievement goal framework. *Journal of Personality and Social Psychology, 80*, 501–519.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117–140.

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise awareness of underperforming peers. *The Internet and Higher Education, 14*(2), 89–97.

Fulda, J. (2018). Interactivity to the rescue. In *Digital investigative journalism* (pp. 123–135). Palgrave Macmillan.

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*, 105826.

He, S., & Adar, E. (2016). Viz it cards: A card-based toolkit for Infovis design education. *IEEE Transactions on Visualization and Computer Graphics, 23*(1), 561–570.

Heer, J., & Bostock, M. (2010). Crowdsourcing graphical perception: Using mechanical turk to assess visualization design. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 203–212).

Holman, C., Aguilar, S. J., Levick, A., Stern, J., Plummer, B., & Fishman, B. (2015, March). Planning for success: How students use a grade prediction tool to win their classes. In *Proceedings of the fifth international conference on learning analytics and knowledge* (pp. 260–264).

Hutchins, E. L., Hollan, J. D., & Norman, D. A. (1985). Direct manipulation interfaces. *Human–Computer Interaction, 1*(4), 311–338.

Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990.

Ifenthaler, D., Mah, D. K., & Yau, J. Y. K. (2019). Utilising learning analytics for study success: Reflections on current empirical findings. In *Utilizing learning analytics to support study success* (pp. 27–36). Springer.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017, September). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In *European conference on technology enhanced learning* (pp. 82–96). Springer.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018, March). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40).

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Kia, F. S., Teasley, S. D., Hatala, M., Karabenick, S., & Kay, M. (2020). How patterns of students' dashboard use are related to their achievement and self-regulatory engagement. In *Proceedings of the 10th international conference on learning analytics & knowledge* (pp. 340–349). ACM.

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). Using data from a learning management system to support academic advising in undergraduate engineering education. In J. A. Larusson & B. White (Eds.), *Learning analytics from research to practice: Methods, tools, and approaches* (pp. 103–119). Springer.

Lonn, S., Aguilar, S., & Teasley, S. D. (2014). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior, 47*, 90–97.

Lucero, A. (2015, September). Using affinity diagrams to evaluate interactive prototypes. In *IFIP conference on human-computer interaction* (pp. 231–248). Springer.

Maehr, M. L., & Zusho, A. (2009). Achievement goal theory: The past, present, and future. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of motivation in school* (pp. 77–104). Routledge.

Major, B., Testa, M., & Bylsma, W. H. (1991). Responses to upward and downward social comparisons: The impact of esteem-relevance and perceived control in social comparison. In J. Suls & T. A. Wills (Eds.), *Contemporary theory and research* (pp. 237–260). Erlbaum.

Matcha, W., Gasevic, D., & Pardo, A. (2019). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies*.

Negash, S. (2004). Business intelligence. *Communications of the Association for Information Systems, 13*, 177–195.

Nielsen, J. (1993). Iterative user-interface design. *Computer, 26*(11), 32–41.

Padilla, L. M., Creem-Regehr, S. H., Hegarty, M., & Stefanucci, J. K. (2018). Decision making with visualizations: A cognitive framework across disciplines. *Cognitive research: principles and implications, 3*(1), 1–25.

Regan, E., & DeWitt, J. (2015). Attitudes, interest and factors influencing STEM enrolment behaviour: An overview of relevant literature. In *Understanding student participation and choice in science and technology education* (pp. 63–88). Springer.

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*(3), 317–333.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407.

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages, 50*, 19–38.

Shim, S., & Ryan, A. (2005). Changes in self-efficacy, challenge avoidance, and intrinsic value in response to grades: The role of achievement goals. *The Journal of Experimental Education, 73*(4), 333–349.

Shim, S. S., Ryan, A. M., & Cassady, J. (2012). Changes in self-esteem across the first year in college: The role of achievement goals. *Educational Psychology, 32*(2), 149–167. https://doi.org/10.1080/01443410.2011.627837

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.

Sluijter, J., & Otten, M. (2017, March). Business intelligence (BI) for personalized student dashboards. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 562–563).

Stephanie Danell, Teasley (2017). Student Facing Dashboards: One Size Fits All? *Technology Knowledge and Learning, 22*(3), 377–384. https://doi.org/10.1007/s10758-017-9314-3

Stephanie Danell, Teasley (2019). Learning analytics: where information science and the learning sciences meet. *Information and Learning Sciences, 120*(1/2), 59–73. https://doi.org/10.1108/ILS-06-2018-0045

Sweeney, L. (2002). k-anonymity: A model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 10*(05), 557–570.

Van Leeuwen, A. (2015). Learning analytics to support teachers during synchronous CSCL: Balancing between overview and overload. *Journal of Learning Analytics, 2*, 138–162. https://doi.org/10.18608/jla.2015.22.11

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509.

Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A., & De Laet, T. (2020, March). Learning analytics dashboards: The past, the present and the future. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 35–40).

Wakeling, S., Clough, P., Wyper, J., & Balmain, A. (2015). Graph literacy and business intelligence: Investigating user understanding of dashboard data visualizations. *Business Intelligence Journal, 20*(4), 8–19.

Winne, P. H. (1997). Experimenting to bootstrap self-regulated learning. *Journal of Educational Psychology, 89*(3), 397.

Winne, P. H. (2018). Cognition and metacognition within self-regulated learning. In D. H. Schunk & J. A. Greene (Eds.), *Educational psychology handbook series. Handbook of self-regulation of learning and performance* (pp. 36–48) Routledge/Taylor & Francis Group.

Winstone, N. E., Nash, R. A., Parker, M., & Rowntree, J. (2017). Supporting learners' agentic engagement with feedback: A systematic review and a taxonomy of recipience processes. *Educational Psychologist, 52*(1), 17–37.

Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics, 6*(2), 53–69. https://doi.org/10.18608/jla.2019.62

Yoo, Y., Lee, H., Jo, I., & Park, Y. (2015). Educational dashboards for smart learning: A review of case studies. In *Emerging issues in smart learning* (pp. 145–155). Springer.

Young, J. R. (2016). What clicks from 70,000 courses reveal about student learning. *The Chronicle of Higher Education, 63*(3).

Chapter 10
Learning Analytics for Students

A Field Study on Giving Students Access to Their Own Data

Sebastian Hobert and Florian Berens

1 Introduction

Feedback is an important driver of learning processes (Hattie, 2015; Winstone & Carless, 2020). Feedback enables students to reflect on their learning effectiveness and efficiency. This way, it acts as a driver for improving learning. To provide feedback, it is required to have information about the students' learning processes. One standard measure to provide feedback in university teaching is the final examination at the end of the lecture term. This is an effective feedback tool but has the disadvantage that students cannot adapt their learning during the lecture term. Thus, early and continuous feedback is required to allow students to reflect and adapt their learning processes constantly.

This is typically not too much a problem in small courses as instructors or teaching assistants interact with their students closely. Thus, they get to know each other and can support the students' learning processes through personal, individualized feedback. In contrast to that are large-scale lectures in which often hundreds of students participate – mainly in a more passive way (i.e., listening to the lecturer). It is hard for lecturers to provide individual feedback in such learning settings as there is typically (almost) no direct interaction between the lecturer and each individual student.

S. Hobert (✉)
University of Göttingen, Chair of Application Systems and E-Business, and Campus-Institute Data Science, Göttingen, Germany
e-mail: shobert@uni-goettingen.de

F. Berens
University of Göttingen, Center of Methods in the Social Sciences, and Campus-Institute Data Science, Göttingen, Germany
e-mail: florian.berens@uni-goettingen.de

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_10

This is particularly challenging during the COVID-19 situation, which resulted in safety measures and precautions that were established worldwide (Desvars-Larrive et al., 2020; World Health Organization, 2020). As a result, educational institutions were closed, and in-class teaching in lectures was impossible (Crawford et al., 2020; Weeden & Cornwell, 2020). The COVID-19 situation changed many learning settings and often resulted in less personal contact among students and instructors. Due to the pandemic situation, teaching in lectures was typically moved to digital learning settings like synchronous video conferences or asynchronous video-based teaching (Crawford et al., 2020; Sun et al., 2020). Those video-based teaching offers were often supported by further learning materials offered by lecturers like exercises, scripts, or lecture slides provided via learning management systems. This increased digitalization of learning and teaching provides new potentials for giving individual feedback to students. As all learning activities were moved from in-class instruction to digital learning environments, learning-related data could be collected and analyzed to provide feedback.

In current research, learning analytics is often used among others to analyze and predict students' learning processes, successes, and influencing factors (Chatti et al., 2012; Ifenthaler, 2015; Ifenthaler & Yau, 2020; Long & Siemens, 2011). These research activities are often conducted after the lecture term has ended. From a scientific point of view, these approaches are interesting and seem to be promising in order to understand learning. From a practice-oriented perspective, this has, however, the problem that the current students participating in the course do not benefit from these insights. Thus, we followed a different approach by focusing on a learning analytics dashboard stream of research (see, e.g., Verbert et al., 2020 and Schwendimann et al., 2017). Thus, we designed a learning analytics dashboard for students that enables them to access their own data directly. The developed learning analytics dashboard offers the students the possibility to analyze their learning processes individually at any given time during the semester. In comparison to traditional learning settings, this provides students new opportunities to reflect on their learning. However, from a scientific point of view, it is interesting whether the students actually use these possibilities when getting access to it in a long-term field study and whether the students perceive these insights as beneficial for their learning.

To this end, we report findings from a field study conducted during the COVID-19 pandemic situation in two courses. We analyze how students interacted with a learning analytics dashboard that visualized their individual learning processes during an online semester in a large-scale educational setting. We further report findings from a quantitative survey among the students in which we asked them about their opinion and assessment of the new learning analytics possibilities. One notable difference from many other prior studies is that we did not conduct the survey until the students had the opportunity to use the dashboard extensively during the course of a semester. Thus, we are not asking students in an artificial, laboratory-like setting, what they expect, but we ask them after they actually used a learning analytics dashboard for quite some time. Thus, we report data from the field.

To achieve this, the remainder of this paper is structured as follows: In the next section, we provide an overview of related research on learning analytics dashboard targeting students, discuss it, and derive our research questions for the conducted study. Subsequently, we outline our research design by describing our case situation, briefly give an overview of the used learning analytics dashboard, and outline the methods used for collecting usage data and quantitative survey data. We then present the results of our analyses in Sect. 4 and discuss them subsequently. Finally, we summarize our study results, outline limitations, and point out future research directions.

2 Related Research

2.1 Basic Concepts of Learning Analytics

Learning analytics aims to investigate students' learning processes, identify relations to learning success, improve learning environments, and provide data for well-grounded decision-making (Chatti et al., 2012; Ifenthaler, 2015; Long & Siemens, 2011). Depending on the specific focus of the analyses of learning-related data, multiple closely related fields of research are somehow overlapping, like educational data mining and academic analytics (Long & Siemens, 2011).

Whereas learning analytics is a broad and interdisciplinary field of research covering different research approaches, goals, and methods, the present study focuses mainly on the subfield of learning analytics dashboards. In prior research, learning analytics dashboards are also known under different terms like educational dashboards or learning dashboards (Schwendimann et al., 2017). Commonly, learning analytics dashboards are referred to as graphical user interfaces (most often as web-based applications) that aggregate learning-related data and results of conducted analyses with the aim of visualizing them appropriately for a given target audience. Most often, the target audience of learning analytics is lecturers or teachers (Schwendimann et al., 2017). The aim of learning analytics dashboards is to visualize the students' learning progress and their learning processes and eventually provide feedback on improving learning. Thus, a learning analytics dashboard's task can be seen as the collection, aggregation, and visualization of interesting analyses for the specified target audience. This is in line with common learning analytics processes like the process described by Chatti et al. (2012), who propose three main steps in learning analytics: data collection and pre-processing, analytics, and post-processing. To achieve the aim of presenting students useful information that actually supports their learning and decision-making, it is often required to simplify the underlying complex scientific learning analytics methods and results in order to focus on a user-centric presentation of insights. This user-centric approach is essential when designing learning analytics dashboards.

Recently multiple reviews have been published analyzing different learning analytics perspectives. For instance, Ifenthaler and Yau (2020) focused on how learning analytics can be used to foster students' study success in higher educational settings. To this end, they conducted a literature review with the aim to investigate success factors and interventions for supporting students' study success. In another review, Larrabee Sønderlund et al. (2019) also surveyed interventions. Also, by conducting a literature review, Schwendimann et al. (2017) mainly focused on prior research on learning dashboards. Their results show, among others, that learning analytics dashboards are most often designed for teachers, but with a trend towards also offering students access to dashboards. Finally, by conducting a workshop discussion with researchers, Verbert et al. (2020) outline a future research agenda that includes, among others, design patterns and the aspect of responsibility in data collection and analyses.

Summarizing the existing reviews briefly, it has been shown by the authors of the reviews that learning analytics is a broad field of research in which different perspectives and approaches are researched. The reviews outline that in each specific field of research, limitations and needs for future research exist. In the present paper, we will particularly focus on investigating learning analytics dashboards targeting students, which are an interesting target audience but still often not the main focus of learning analytics research (Schwendimann et al., 2017). In particular, we will focus on collecting survey and usage data from the field to analyze the students' perception of the influence of a learning analytics dashboard on learning processes. As a basis for the following study and to discuss related research and to specify our research objectives, in the following, we will first outline exemplary related research studies targeting data ownership as this is a prerequisite for doing learning analytics. Then, we will focus on the design of learning analytics dashboards.

2.2 Data Ownership

One of the important critical aspects that researchers face when conducting field studies in learning analytics is data gathering and data ownership. Whereas in artificial studies fictional data can be used to illustrate how a learning analytics dashboard works, in field settings, real data from students is needed. Without appropriate data, no individualized analyses can be conducted, and thus, students cannot get individualized feedback that supports their learning processes.

In prior research, the aspect of data ownership and privacy has been addressed in few studies. For instance, Ifenthaler and Schumacher (2016) surveyed in an exploratory study how students perceive privacy aspects related to learning analytics. They showed that students, on the one hand, like to have personalized analyses but also are a bit reserved when sharing their data. The authors argue that it is important to include all stakeholders when developing and introducing learning analytics dashboards. With a more general perspective, Drachsler and Greller (2016) proposed a checklist that can support the implementation of learning analytics (not only with a focus on dashboards for students). The checklist should support implementing trusted learning analytics systems considering privacy aspects.

Even though this aspect is essential for learning analytics, only a few studies have been conducted. One key aspect that has been shown is that transparency is important. Due to this, we argue that students should get access to their own data in learning analytics research studies. Using learning analytics dashboards for students is one promising possibility to achieve this. It is, however, the question, whether students value this aspect. To research this aspect of getting access to their own data, we base on the students' experience after using our learning analytics dashboard in our field study and ask them how they perceive this particular topic of data ownership. Thus, we ask the following research question:

How do students perceive accessing their own learning-related data after using a learning analytics dashboard in a long-term field study?

2.3 Design and Features of Learning Analytics Dashboards

As previously outlined, learning analytics dashboards are often designed for supporting lecturers or teaching advisers (Schwendimann et al., 2017). In prior research, multiple studies on the design of such lecturer-centric systems have been presented. One recent exemplary study focusing on the creation of such a system is presented by Gutiérrez et al. (2020). They designed and evaluated the LADA system and showed it to be useful. Fewer studies focus particularly on the design of learning analytics dashboards for students, which is the focus of the present paper. One example is the LAPA Dashboard designed and presented by Yeonjeong Park and Il-Hyun Jo (2015).

Regarding the design of student-centric dashboards, few studies have recently been conducted. For instance, Schumacher and Ifenthaler (2018) in two consecutive studies empirically surveyed learning analytics features that students perceive as useful. To this end, they conducted qualitative interviews and a quantitative survey among students. They showed that students expect multiple features (like offering self-assessments or providing personalized learning analytics analyses) to be beneficial. Also, taking a student perspective, Roberts et al. (2017) analyzed which features might be interesting to students. Based on surveys, they showed, for instance, that comparative analyses are interesting for some students, but others might be reserved. Recently, Jivet et al. (2020) focused on features for learning analytics dashboards using empirical methods. The study focused mainly on sense-making and conducted a qualitative pre-study and a consecutive quantitative study to derive three main latent variables relevant for sense-making.

Summarizing the presented studies, it can be concluded that some studies exist that focus on the design of learning analytics dashboards that were provided particularly for students. However, it needs to be remarked that most studies survey design aspects without giving the students the possibility to use learning analytics dashboards under real settings (e.g., during a complete lecture term). Many existing studies survey the design using quantitative instruments or qualitative interviews without giving students the possibility to use and interact with learning analytics dashboards for a longer time. Thus, we argue that we need further insights from students who actually interacted with learning analytics dashboards in real settings.

Only a few studies report actual data from learning analytics targeting students from the field. For instance, Haynes (2020) presented first results from a pre- and post-survey about the students' perception of learning analytics dashboards. Additionally, Kim et al. (2016) analyzed whether interacting with learning analytics dashboards affects learning success. They could, for instance, showed that some positive effects exist.

Summarizing these findings, we argue that there is a need to survey students' actual interaction with learning analytics dashboards not only in laboratory settings using fictional data or with mockups but to conduct research in the field. This enables learning analytics researchers to observe the students' interaction in the long-term use and to conduct surveys using post-intervention questionnaires to get more valuable feedback. To this aim, we will focus on the following two research questions related to the design of dashboards and their implications for learning processes:

How do students interact with a learning analytics dashboard during long-term use in large-scale lectures?

How do students perceive the usefulness of a learning analytics dashboard for supporting their learning processes?

3 Research Design

To conduct a field study where we can gather actual usage and survey data from students interacting with a learning analytics dashboard, we developed a learning analytics dashboard targeted specifically for students and introduced it in two large-scale university courses. To address the research questions derived in Sect. 2, we analyzed the usage of the dashboard and conducted a quantitative survey. Before outlining the methods for collecting and analyzing the data (i.e., usage data and survey data), we briefly outline the two cases in which we introduced the learning analytics dashboard. Subsequently, we provide a brief overview of the learning analytics dashboard for students.

3.1 Investigated Cases

The field study was conducted at a larger German university and took place in two independent introductory courses addressing undergraduate students from various study programs. Typically, more than 700 students participate in each of the courses. Thus, both courses can be classified as large-scale learning settings that target fundamental knowledge (basic statistics and research methods).

Usually, the courses are taught in class by experienced lecturers. As the courses took place during the COVID-19 pandemic, both courses could not be taught in class. Instead, both courses were switched to online settings and can thus be classified as e-learning courses. Instead of in-class lectures, the lectures were pre-recorded by lecturers on video and delivered via a web-based video player. Additionally, the students got access to formative assessments that they could use for practicing their skills. The students could solve all formative assessments digitally to get instant automatic feedback. Even though it was highly recommended to use those quizzes to deepen the students' skills, it was voluntary.

Further, the students could download the lecture slides. All course materials (i.e., videos, formative assessments, and slides) were delivered via the course's learning management system that integrated all aspects in a web-based app. The identical app but with different contents was available for students of both courses. The students could use it on both desktop computers and mobile devices to allow flexibility for learning, even in times when the university's campus was closed due to impacts of the coronavirus.

As the learning app was the central point of access to the courses' learning materials, we assume that most of the students' learning activities took place using the app. This is somehow different from the typical situations in both courses before the COVID-19 pandemic. In the past, a substantial part of learning took place in-class during the lectures and tutorial sessions. The current situation seems, however, beneficial for learning analytics activities as more data about the learning processes is available as all formative assessments are provided in a digital learning environment. Thus, it is most likely that the learning analytics analyses are more helpful for the students as more learning-related data provides feedback.

3.2 Introduction of a Learning Analytics Dashboard

As both courses are taken by approx. 750 students per year, providing individual learning support is nearly impossible, as already outlined in the introduction section. Due to the COVID-19 pandemic, this becomes particularly more challenging as all in-class sessions were canceled. Thus, the lecturers decided to give the students the possibility to get access to automated feedback. To this end, a learning analytics dashboard (see Fig. 10.1) was implemented and introduced in both courses. It was developed during the lecture break in early 2020 when the protection measures against the spread of COVID-19 were initiated at the university. The development of the dashboard could be finished before the start of the lecture term.

The learning analytics dashboard was implemented as a web-based application. Due to this, the dashboard could be integrated directly into the learning management system. This allows the students to access the learning analytics dashboard easily. The dashboard provides students multiple possibilities to get insights into their learning activities. To this end, it analyzes the available learning-related data of the courses' learning app (see Sect. 3.1). In total, several 100,000 log entries (e.g., quiz activity or downloads of lecture slides) form the basis of the analyses during the lecture terms of both courses. First, the students

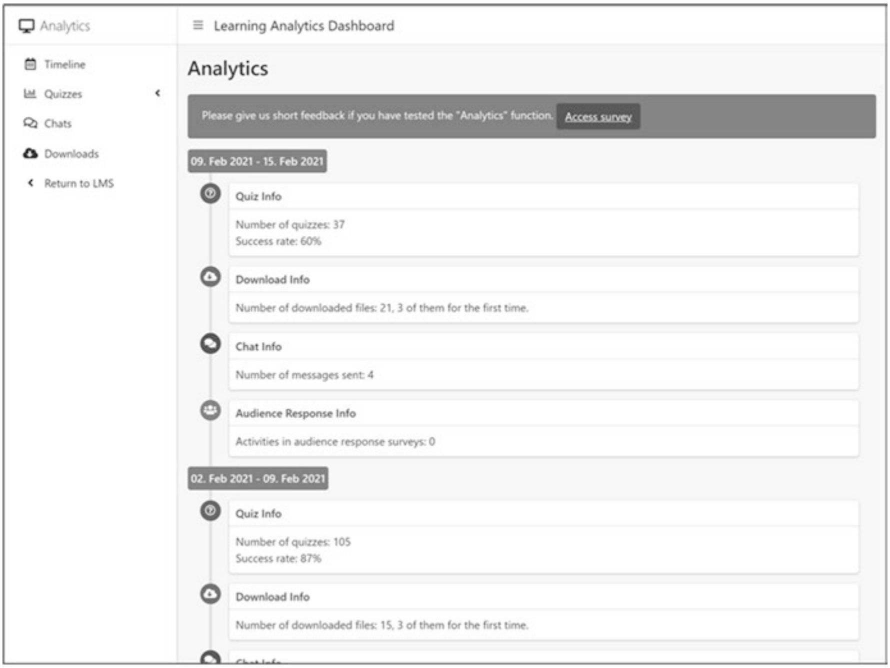


Fig. 10.1 Screenshot of the developed learning analytics dashboard

can get a summarized overview of their learning activities in the form of a timeline (see Fig. 10.1), which aggregates the activity types (e.g., quiz activity or download of files) on a weekly basis. For each activity type, the students can get further detailed analyses. For instance, the quiz section provides an overview that shows key indicators (like the total number of solved quizzes or the success rate) and a line chart of the quiz activity for each week. Students can access further analyses on a single quiz or per group of quizzes to get more information. Those analyses show the success rate for each quiz resp. each group and analyses of the required time to solve a quiz (using box plots). Finally, a comparative overview of the success rates for each quiz and each group is shown to the students utilizing a heatmap. This visual representation of the successes with a comparison to the average of all fellow students gives the possibility to assess and reflect the learning activities.

3.3 Method

We introduced the implemented learning analytics dashboard during the COVID-19 pandemic situation in two courses as a field study based on the described case setting. After releasing the learning analytics dashboard, the students were notified of the existence of the analysis functionalities. A short message was displayed in the courses' app to promote the learning analytics dashboard further.

After the students had the opportunity to use and interact with the learning analytics dashboard for several weeks, we made a survey available in the courses' app. With this questionnaire survey, we intended first to get feedback from the students about the dashboard implementation. Second and more important, we aimed at analyzing whether the students perceive getting access to their own data using a learning analytics dashboard is actually desirable and beneficial for their learning processes.

The survey design consisted of two parts relevant for this study: First, we used the standardized and validated User Experience Questionnaire by Laugwitz et al. (2008) and Team UEQ (2020) to measure the students' user experience about the dashboard implementation. We expanded this survey section by further in-depth questions about the dashboard's specific implementation details (like whether students liked the dashboard page or the visualization of the quiz results). For the given research questions, the actual evaluation of the dashboard's user experience might not be too relevant at first glance. It is, however, essential to identify whether the dashboard provides a suitable tool. If the students evaluate the user experience with a negative score, our subsequent analysis results might not be valid and transferable to other learning analytics dashboards. Thus, we assume this first part of the questionnaire as a necessary prerequisite for the subsequent analysis.

To conduct the user experience analysis, we used the Data Analysis Tool provided by the authors of the User Experience Questionnaire (Team UEQ, 2020). This analysis tool provides an estimate of the questionnaire results. Thus, we can use this estimate to determine whether the dashboard implementation is suitable. If we receive positive results, we argue that our other survey part and the collected usage data are also valid for other dashboards.

In the second part of the questionnaire study, we asked the students to provide us feedback on five major topics related to the effects on the students' learning processes: general feedback, access to own data, benefits for learning processes, evaluation of the comparison functionalities, and overall evaluation of learning analytics. A complete overview of the relevant items is depicted below in Table 10.1 in Sect. 4.3.

Participation in the survey was voluntary and not linked to any incentives for the students. We showed each student who logged into the learning app during the survey period an advertising banner and asked them to give us feedback to promote participation.

In addition to this survey, we collected data about the students' interaction with the learning analytics dashboard. The collected usage data gives us insights into how the students used the dashboard. We can get insights into how the students who agreed to share their usage data for scientific purposes in an anonymized form navigated through the dashboard and how frequently they accessed data. During the data collection period, we gathered usage data from 802 individual students. 8.5% of them participated in the voluntary survey, which is considered a typical response rate.

Table 10.1 The students' perception of the learning analytics dashboard and its implication on learning processes

Item	Mean	Median	St.D.
General			
Enjoyment to use the dashboard	+1.31	2	1.60
Having a dashboard is useful	+1.94	2	1.42
Analytics results are easy to understand	+1.45	2	1.43
Access to own data			
Like to have access to own learning data	+2.00	2	1.36
Having access supports learning	+1.17	2	1.73
Having access increases motivation to reflect	+1.24	2	1.75
Having access increases motivation to learn	+0.89	1	1.78
Benefit for learning processes			
Is helpful to get an overview of the current learning status	+0.90	1	1.86
Provides a useful addition to traditional teaching offers	+1.85	2	1.32
Evaluation of the comparison functionalities			
Comparison with fellow students are useful	+0.92	1	1.69
Comparison with fellow students is motivating	+0.68	1	1.66
Comparison with fellow students is stressful	−0.19	0	1.85
Overall evaluation of dashboard			
Recommendation for providing a dashboard	+1.85	2	1.47
Overall evaluation	+2.08	3	1.34

4 Results

The presentation of this study's results is based on the case-based field study in which we collected data using a questionnaire-based survey and usage data. In the following, we first outline the survey data results by addressing the dashboard implementation. Subsequently, we give insights into the students' interaction with the learning analytics dashboard. Finally, we are focusing on the impacts on the students' learning processes. This three-folded analysis provides insights into how students perceive and use a learning analytics dashboard in times dominated by distance learning using e-learning tools (due to the pandemic situation induced by COVID-19). The results and their implications are discussed subsequently in the discussion section.

4.1 Dashboard Implementation

In the first part of the survey evaluation, we asked the students to provide feedback on the dashboard implementation using the User Experience Questionnaire (Laugwitz et al., 2008; Team UEQ, 2020). The analysis of the standardized questionnaire reveals that the students evaluated the dashboard implementation in terms of the six scales (attractiveness, perspicuity, efficiency, dependability, stimulation,

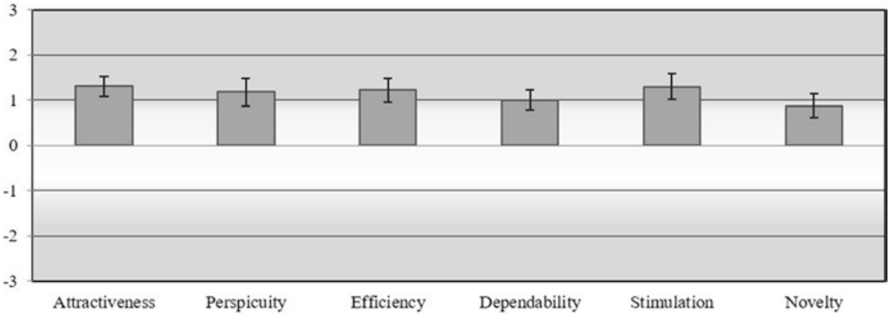


Fig. 10.2 Results of the UEQ computed using the UEQ Data Analysis Tool (Team UEQ, 2020)

and novelty) as positive according to the UEQ Data Analysis Tool (Team UEQ, 2020) with values ranging from +1.305 to +0.877 on a scale ranging from −3 to +3 (see Fig. 10.2). The students evaluated the attractiveness as the most positive, whereas novelty received the lowest rating. This does not seem surprising as analytics dashboards are known from other contexts (like gamified apps). By further aggregating the scales as proposed by the Data Analysis Tool, it can be stated that the pragmatic quality, as well as hedonic quality, receives values larger than +1 (1.13 resp. 1.09).

The feedback gathered using the User Experience Questionnaire informs this study that the implemented learning analytics dashboard using the field evaluation provides an adequate user experience. These positive results are also confirmed by further questions on the design of the analytics dashboard's specific functionalities that we asked the students. For instance, the students rated the visualization of the analyses of formative assessments as positive with a value of +1.302.

Overall, this first part of the survey indicates that the developed dashboard is appropriate for the given purpose to offer students the possibility to access their own learning-related data and get feedback about their learning activities. Due to this, we argue that analyzing the impact on the students' learning processes is valid. Thus, we focus on this in the following using the collected usage data and the second part of the questionnaire.

4.2 Analysis of Usage Data

In both courses, approx. 50% of the enrolled students used the learning analytics dashboard. This results in a total population of 802 students that used the dashboard during our data collection period. The students used the dashboard in approx. 4200 session.[1] Thus, on average, each user of the learning analytics dashboard used it more than five times.

[1] A session is defined in our setting as the sum of all unique users per day, i.e., if an individual student accesses the dashboard multiple times shortly after the other, this is only counted as one.

Each student performed on average approx. 80 interactions within the dashboard. In each session, this results in approx. 15 interactions. This number of interactions on average is comparatively high compared to traditional websites and (e-learning) apps, which indicates the intensity of the students' use of the dashboard.

The students were mainly interested in analyzing their performance in formative assessments. Approximately 67% of all accessed analyses are related to formative assessments. In these analyses, the students were mainly interested in getting aggregated statistics about groups[2] of multiple formative assessments and the aggregation of all formative assessments. Both kinds of analyses show analyses of the students' own performance compared to the average performance of all fellow students. In addition to these analyses focusing on comparative aspects, the students also requested several hundreds of analyses of single formative assessment quizzes in each course (approx. 700 in course 1 and approx. 900 in course 2). The individual quizzes analyses give the students in-depth insights about their performance (e.g., feedback on success and time to complete the quiz). The number of views of those very specific analyses ranges from only accessed by a single student up to approx. 70 students accessing a specific analysis. This indicates that most of the students in our field study are interested in getting aggregated information that includes comparative aspects to overview their current state of knowledge in the course. Nevertheless, a large amount of very specific analyses was requested. A close look at the specific learning analytics analyses revealed that analyses were particularly requested for more complex formative assessment questions.

In addition to analyses of formative assessments, the timeline that provides an overview of the personal learning activities receives a lot of attention, which is not surprising as this is the start page of the dashboard. All other analyses (e.g., download activity of learning materials) were only accessed to a minor extend (only up to less than five percent).

Overall, we can conclude that students are mainly interested in getting feedback on formative assessments in our field study. This does not seem surprising as formative assessments allow students to practice. As practicing gives students the possibility to succeed or to fail, it is not surprising that getting feedback on this aspect is interesting. Our analyses also show that students are actively interested in getting comparative overviews that show how they perform compared to their fellow students. This is in line with the results of our survey questionnaire.

4.3 Impact on Learning Processes

If learning analytics is directed at students, it is not only about analyzing the numbers correctly. Equally important is whether the analyses are helpful for the students. Thus, the students' perception of the effects on their learning has a substantial impact on the success of learning analytics activities directed at students.

[2] Each group of formative assessments aggregates all individual quizzes that cover a certain topic.

Due to this, we first gather the students' general assessment of the learning analytics dashboard. The results shown in Table 10.1 indicate that the students enjoyed working with it (+1.31) and perceive having a learning analytics dashboard as useful (+1.94). Important as well is that the provided analyses are understandable by the students, which is the case in our survey (+1.45). This aspect seems most notable as (complex) scientific analyses and predictions seem not useful for a learning analytics dashboard directed at students when the results are not visualized in an (for non-experts) easily understandable format.

Subsequently, we focused on the aspect of giving students access to their own learning-related data that is collected during their use of the e-learning tool. The survey results clearly show that the students like this idea and appreciate the efforts to provide a learning analytics dashboard (+2.00). The students stated that having access to their learning-related data supports their learning (+1.17) and increases their motivation to reflect on their learning processes (+1.24). Interestingly, this has only a slightly positive effect on the students' motivation to learn (+0.89). This seems surprising at first glance but might not be too critical as some of the students might get the feedback that they are at the top of the course. Thus, they do not need to increase their learning activities further (as long as they do not decrease them).

Besides these motivational aspects, we also directly asked the students whether the learning analytics dashboard is actually useful to overview their current learning state. The students acknowledged this by a slightly positive result of +0.90. With a value of +1.85, the students perceive the dashboard as a very good addition to the traditional learning offers. The discrepancy between both items seems interesting and surprising as those items seem to be quite similar. As noted before, learning analytics dashboards are only capable of analyzing learning-related data that is provided appropriately. If students are learning traditionally (i.e., using supplementary books) or using additional learning materials (like videos from commercial video portals), we could not collect relevant data. Thus, the learning analytics dashboard might only observe an incomplete part of the students' state of knowledge, which could be reflected in the observed difference.

A topic that is controversially discussed among lecturers and practice-oriented learning analytics developers is whether providing students comparative analyses is beneficial. On the one hand, comparisons with fellow students seem to be a good indicator to assess the own state of knowledge. If students perform below average, additional learning effort seems obviously advisable. However, it must be taken into account that a below-average performance attested by a learning analytics dashboard might also have negative implications on motivation. To gather the students' feedback on this, we asked them to evaluate such comparative functionalities. First of all, we asked the students whether they perceive the provided comparisons with fellow students as useful (e.g., in the formative assessment analyses that indicate how well the students perform compared to all other fellow students). The students rated this functionality with a value of +0.92 as positive, with more than 50% of the students rated it as +1 or better.

Interestingly, the results of these comparisons seem to be motivating, but to a lower extent (+0.68). In this case, we also have a median of 1, i.e., at least 50% of the students rate the comparisons as motivating. A common point of criticism about comparisons with fellow students in teaching settings is the effect on the perceived level of stress. Our survey data indicates that the students do not perceive the comparisons as stressful. Interestingly, the median value is 0, and almost 42% of the students perceive the comparisons as stressful, whereas 47% perceive it as not stressful. This seems to be an interesting point for discussions and further research.

Finally, we asked the students about an overall evaluation of learning analytics activities. First of all, we wanted to get feedback on whether the students would recommend that the effort to provide a learning analytics dashboard for further courses should be taken. With a value of +1.85 and a median value of 2, this can definitively be acknowledged. Second, we asked the students about an overall evaluation of the field study's learning analytics activities within the dashboard. The students rated the learning analytics with exceptionally positive results of +2.08, where 88.7% of all students participating in the survey used the top score.

5 Discussion

In the following, we discuss the results of both the questionnaire-based survey and the usage data analysis. To this end, we combine both by focusing on four major aspects: (1) the suitability of learning analytics dashboards for students, (2) negative implications of learning analytics dashboards for students, (3) data ownership, and (4) implications for the design of learning analytics dashboards for students.

5.1 Suitability of Learning Analytics Dashboards for Students

First of all, from a pedagogical or didactical point of view, it can be questioned whether automated learning analytics dashboards are suitable to support students enough actually to improve the students learning processes. In contrast to personal feedback from lecturers who are informed in detail about the students' individual learning process, automated learning analytics-based feedback will most likely perform worse. However, there is usually no possibility for students to get in-depth individual feedback from the instructor in large-scale lectures. If several hundreds of students attend a lecture, individual feedback is typically simply not possible due to resource constraints. In these cases, automated feedback based on learning analytics dashboards for students seems to be promising and one of the best options to get at least some feedback.

The results of our field study confirm this argument. The students clearly stated that having access to the learning analytics dashboards encourages them to reflect on their learning. They perceive it as a beneficial addition to the other teaching offers. This is also reflected in the usage data. The data reveals that students are actively seeking in-depth information about formative assessment. We believe this indicates that students are actively engaged in learning and seek further analyses and information about formative assessments.

Nevertheless, it must also be acknowledged that the survey also showed that even though the high values indicating that students reflect on their learning (+1.24), only lower effects on increased learning activities (+0.89) can be captured. It can only be speculated whether face-to-face conversations with a lecturer about reflections on students' learning process would lead to higher impacts on the students' learning processes. We assume that personal learner-lecturer interaction could result in a stronger influence. This might be an interesting aspect for future research. Nevertheless, even if this would be the case, in large-scale lecture settings, this would still not be feasible due to resource constraints. Thus, we argue that learning analytics might still be one of the best options to provide students individualized feedback.

5.2 Negative Implications of Learning Analytics Dashboards for Students

Even though we are quite optimistic about the benefits of learning analytics dashboards for students, it must be acknowledged that negative aspects might be implied by it. It can be argued that too many comparisons with fellow students might increase the level of perceived stress substantially. A negative stressful learning experience might additionally be hindering a positive learning process.

Due to this, when conceptualizing and designing learning analytics dashboards, this should be taken into account. Our survey results indicate that, on average, the students do not feel that the learning analytics dashboards result in more stressful learning. Nevertheless, a deeper analysis of the data reveals that almost 42% of the participants stated that they perceive it (at least as a little bit) stressful. Only 5.7% of them strongly agreed that it results in stress while the others see only a low effect. Even though this number does not seem high, in a large-scale lecture, at least some students might be affected. Due to this, we encourage designers and lecturers to think about the negative implications of feedback as early as possible during the conceptualization phase. In our case, we offered students the possibility to discuss the learning analytics results with a trained teaching assistant to get feedback. At least some students used this offer to reflect on their learning analytics results.

Even though some negative implications should be considered, we assume that access to learning analytics dashboards for students is nevertheless beneficial, which is also supported by our survey.

5.3 Data Ownership

In addition to the effects of learning analytics on feedback and negative implications, a critical aspect of learning analytics is the gathering of learning-related data. Without getting access to learning-related data that reflects the students' learning progress or the learning activities, learning analytics is not possible. In many studies that focus on learning analytics, the data is used for scientific or management purposes to improve learning and decision-making in the long term. To this end, researchers ask students to consent to conduct the research. This is a valid approach. We nevertheless argue that it might be a matter of fairness that if the students help to improve learning in the long term, they should also benefit from the learning analytics activities directly. To this end, we argue that a learning analytics dashboard targeting students is a fair and suitable approach to give students access to their own data. In doing so, the students can actually benefit themselves from providing data.

Our survey reveals that the students acknowledge this as they stated that they like the idea of getting access to their own learning-related data. Additionally, as already discussed in Subsection 5.1, this also has positive effects on the motivation to reflect and improve learning processes.

5.4 Implications for the Design of Learning Analytics Dashboards for Students

In the previous subsections, we discussed positive as well as negative impacts of learning analytics dashboards and valued giving students access to their own data. In addition to these aspects, it needs to be questioned whether the results have concrete implications for the design of a learning analytics dashboard targeting students.

First of all, we could show that learning analytics dashboards have added value for students in large-scale educational settings. This justifies the development of dashboards as it might help to improve teaching and learning. Our analysis of the usage data further reveals that students are not only interested in basic comparative analyses with fellow students but also use the opportunity to deep dive into very specific analyses. In our field study, some analyses of specific formative assessments were only accessed by one single student, whereas others were requested by a large number of students. This shows that a large variety of analyses seem to be beneficial as students request even specific ones. Thus, we argue that comparative overviews should be implemented, but deep dives into learning activities seem to be relevant as well. Whereas comparative overviews can give students a good impression of their learning progress compared to the fellow students, they might also have negative impacts due to resulting stress if the analyses show poorer performance than expected. Deep dives into specific analyses have the benefit that students might reflect on and explore their learning processes.

Finally, we encourage learning analytics researchers to consider providing students analyses that are beneficial for their current learning processes. Getting access to data of value is crucial for scientific learning analytics research. If students support such research, it seems to be a matter of fairness to offer them appropriate analyses that support their learning as well.

6 Conclusion

In this research project, we conducted a field study where we introduced a self-developed learning analytics dashboard to students to analyze whether students benefit from it. To this end, we surveyed the users of the dashboard in two large-scale lecturers at a German university. Additionally, we analyzed usage data to understand how students actually access such a learning analytics dashboard.

Our results reveal that students positively evaluate the possibility to access their own data and corresponding learning analytics analyses. The analyses help the students to motivate themselves to reflect on their learning processes and to increase learning activities. We also showed that comparative results are helpful in this task but have the challenge that a not small number of students might perceive this as stressful. Finding a balance between comparative analyses and deep dive analyses seems to be an appropriate way to prepare learning analytics results for students. These results are an addition to the available body of research on the design of learning analytics dashboards (see Sect. 2) as this study provides insights into the actual use of learning analytics dashboards in the field.

Based on the discussion of these results, we propose the following recommendations: When designing learning analytics dashboards, not only aggregated basic analyses should be provided, but also more in-depth analyses should be available as well. This combination of analyses allows students to analyze their learning at different levels in detail. Additionally, we recommend to provide comparative analyses as well. Comparisons with the average of all fellow students enable students the possibility to reflect on and improve their individual learning. Overall, we encourage learning analytics researchers to give students the possibility to access their own data and to provide corresponding analyses.

References

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5/6), 318–331. https://doi.org/10.1504/IJTEL.2012.051815

Crawford, J., Butler-Henderson, K., Rudolph, J., Malkawi, B., Glowatz, M., Burton, R., … Lam, S. (2020). COVID-19: 20 countries' higher education intra-period digital pedagogy responses. *Journal of Applied Learning & Teaching, 3*(1). https://doi.org/10.37074/jalt.2020.3.1.7

Desvars-Larrive, A., Dervic, E., Haug, N., Niederkrotenthaler, T., Chen, J., Di Natale, A., … Thurner, S. (2020). A structured open dataset of government interventions in response to COVID-19. *Scientific Data, 7*(1), 285. https://doi.org/10.1038/s41597-020-00609-9

Drachsler, H., & Greller, W. (2016). Privacy and analytics. In D. Gašević, G. Lynch, S. Dawson, H. Drachsler, & C. Penstein Rosé (Eds.), *Proceedings of the sixth international conference on Learning Analytics & Knowledge – LAK '16* (pp. 89–98). ACM Press. https://doi.org/10.1145/2883851.2883893

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., de Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*(8), 105826. https://doi.org/10.1016/j.chb.2018.12.004

Hattie, J. (2015). The applicability of visible learning to higher education. *Scholarship of Teaching and Learning in Psychology, 1*(1), 79–91. https://doi.org/10.1037/stl0000021

Haynes, C. C. (2020). The role of self-regulated learning in the design, implementation, and evaluation of learning analytics dashboards. In D. Joyner, R. Kizilcec, & S. Singer (Eds.), *Proceedings of the seventh ACM conference on learning @ scale* (pp. 297–300). ACM. https://doi.org/10.1145/3386527.3406732

Ifenthaler, D. (2015). Learning analytics. In *The SAGE encyclopedia of educational technology* (2nd ed., pp. 447–451). Sage.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. https://doi.org/10.1007/s11423-016-9477-y

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*(1), 100758. https://doi.org/10.1016/j.iheduc.2020.100758

Kim, J., Jo, I.-H., & Park, Y. (2016). Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(1), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2019). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology, 50*(5), 2594–2618. https://doi.org/10.1111/bjet.12720

Laugwitz, B., Held, T., & Schrepp, M. (2008). Construction and evaluation of a user experience questionnaire. In A. Holzinger (Ed.), *Lecture notes in computer science. HCI and usability for education and work* (Vol. 5298, pp. 63–76). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-89350-9_6

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review, 46*(5), 30–40.

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*(3), 317–333. https://doi.org/10.1007/s10758-017-9316-1

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*(1), 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522

Sun, L., Tang, Y., & Zuo, W. (2020). Coronavirus pushes education online. *Nature Materials, 19*(6), 687. https://doi.org/10.1038/s41563-020-0678-8

Team UEQ. (2020). *User Experience Questionnaire (UEQ)*. Retrieved from https://www.ueq-online.org/

Verbert, K., Ochoa, X., de Croon, R., Dourado, R. A., & de Laet, T. (2020). Learning analytics dashboards: The past, the present and the future. In C. Rensing & H. Drachsler (Eds.), *Proceedings of the tenth international conference on Learning Analytics & Knowledge* (pp. 35–40). ACM. https://doi.org/10.1145/3375462.3375504

Weeden, K., & Cornwell, B. (2020). The small-world network of college classes: Implications for epidemic spread on a university campus. *Sociological Science, 7*, 222–241. https://doi.org/10.15195/v7.a9

Winstone, N. E., & Carless, D. (2020). *Designing effective feedback processes in higher education: A learning-focused approach. Society for research into higher education series*. Routledge, an imprint of the Taylor & Francis Group.

World Health Organization. (2020). *Coronavirus disease 2019 (COVID-19): Situation Report – 72*. Retrieved from https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200401-sitrep-72-covid-19.pdf?sfvrsn=3dd8971b_2

Yeonjeong Park, & Jo, I.-H. (2015). Development of the learning analytics dashboard to support Students' learning performance. *Journal of Universal Computer Science, 21*(1), 110–133. https://doi.org/10.3217/jucs-021-01-0110

Chapter 11
Students' Emotional Reactions to Social Comparison via a Learner Dashboard

Liz Bennett and Sue Folley

1 Introduction

The context for this chapter is a growing policy agenda that is focussed on addressing student well-being amid a rise in reported student mental health (Thorley, 2017; Universities UK, 2020). Concomitantly learning analytics is a burgeoning area of development with increased attention being given to the opportunities that the increased availability of data can and should have on higher education. However, it has been noted that learning analytics policies have not, as yet, addressed the well-being agenda (Ahern, 2020).

Well-being is a complex term which is easier to describe than to define (Dodge et al., 2012). Aspects which contribute to well-being include autonomy; environmental mastery; positive relationships with others; purpose in life; realisation of potential; and self-acceptance (Dodge et al., 2012). The focus for this chapter is students' emotions and motivations which are central components of managing well-being, as they are linked to a sense of purpose and to managing self-acceptance. The significance of emotions and motivation is not just in terms of well-being but also in terms of the role that they play self-regulated learning in which control of negative emotions (such as anxiety and boredom) promotes positive self-regulated learning (Shields, 2015; You & Kang, 2014).

The chapter focusses on students' responses to seeing data about their study behaviours (such as the number of books taken from the library, attendance on campus) and attainment presented via a student dashboard. Studies of students' responses to other sorts of feedback have identified a strong emotional component which includes both positive emotions including pride, confidence, motivation, and

L. Bennett (✉) · S. Folley
University of Huddersfield, Huddersfield, UK
e-mail: e.bennett@hud.ac.uk; s.folley@hud.ac.uk

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_11

enjoyment alongside a range of emotions that are negatively linked to learning including anxiety, fear of failure, and thereat to self-esteem (Shields, 2015).

The power of learning analytics is that this data can be captured and manipulated at scale, which enables students to have new ways of seeing information about themselves presented in graphical form. In particular this chapter focusses on how dashboards enable students to see their performance compared to other students: that is, it allows for social comparison. The use of student dashboards is an emergent practice and a growing area of research interest, and the application of social comparisons within the field of learning analytics and its impact on student well-being is an under-researched area (Jivet et al., 2020). The chapter addresses this gap through a small-scale empirical study. The study sets out to better understand how students respond to seeing their learning data presented on a student-facing dashboard and to answer the following questions:

- How are students' emotions and hence identity affected by accessing a student dashboard?
- How are visualisations of social comparison experienced by a range of students from across a cohort?
- How is students' motivation affected by accessing a student dashboard?

2 Social Comparison Theory and Student Identity

In this chapter we apply social comparison theory to understand student identity. Social comparison is a sociopsychological process identified by Festinger (1954) based on observations of people's behaviour. Festinger's social comparison theory relates to the 'process of thinking about information about one or more other people in relation to the self' (Wood, 1996), and in the absence of this process of self-comparison, Festinger suggested that a person's opinions are unstable (Festinger, 1954, p.119). A key feature of self-comparison is the notion of the frame of reference, which means those who are used as the reference for the comparison process. Upward comparison occurs when the comparison with someone whose abilities or status are perceived as better, and the converse is known as downward comparison. A meta-analysis identified that when given a choice, the dominant frame of reference was upward comparison; however, this generally results in disappointment and feelings of self-deflation (Gerber et al., 2018).

Social comparison has been widely recognised within psychology studies (Gerber et al., 2018) and also applied to a range of sociological studies (Margolis & Dust, 2019; Schneider & Schupp, 2014). It has also been applied to educational contexts to understand how pupils' self-concept is influenced by their perception of the standing of the school that they attend, as well as their perception of their position within a class (Trautwein et al., 2009; Rogers et al., 1978). Trautwein et al. (2009) conclude that there is compelling evidence that "students actively seek out information about their own standing and the standing of their class and integrate that information into their academic selfconcepts." (p.864). Hence these studies suggest that social comparison data may well be useful part of supporting a student's identity development.

The chapter draws on the notion of student identity which is made up of dispositions and personal history. In doing so we take a sociocultural view of students and their learning (Wenger, 1998) and note that identity formation is a dynamic process that is developed from and shaped by engagement with educational practices (Tett, 2014; Turner & Tobbell, 2018). We refer to identity work, a term used to describe the personal project associated with managing one's sense of self (Bhatt & de Roock, 2014), which consists of self-concept and self-esteem, and of managing one's emotional world.

3 Visualisations of Social Comparison

With the advancement of digital technology, it is now possible to provide students with social comparison data, and this can be achieved in a systematic way through the adoption of student-facing dashboards. There are a range of ways that social comparison can be achieved including rank order, cohort comparison, and comparison to a particular group. These are considered in turn and are shown in Fig. 11.1a

a

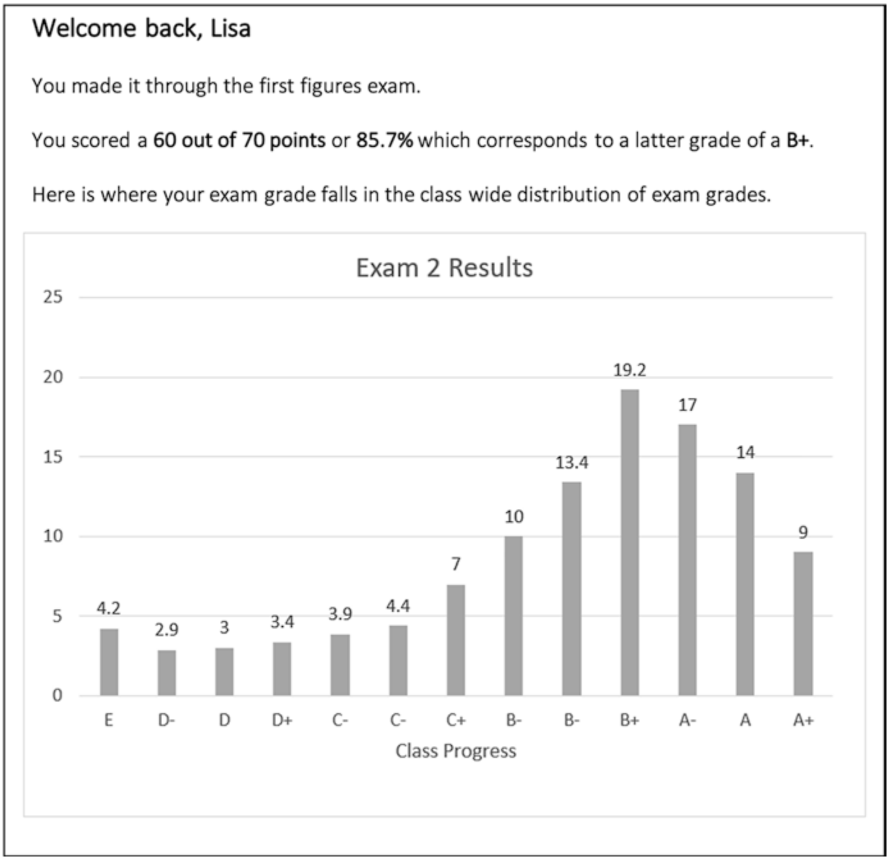


Fig. 11.1 a–e Different forms of social comparison. (**a**) Bar chart showing individual performance in rank order. (**b**) Table showing comparing individual performance to cohort average, (**c**) Scatter diagram showing cohort comparison. (**d**) Leader board showing ranking and badges gained. (**e**) Radar diagram showing key performance indicators compared to the cohort average

b

Metric	Your Data (Week X)	Class Average (Week X)	Observations
Range of Participation	***5 days***	6 days	
# of sessions	***7***	14	
Average session length	***34 min***	50 min	
% of sessions with posts	***70%***	51%	
# of posts made	***9***	11	
Average post length	***151 words***	130 words	
% of posts read	***83%***	90%	
# of reviews of own posts	***24***	15	
# of reviews of others' posts	***9***	115	

c

d

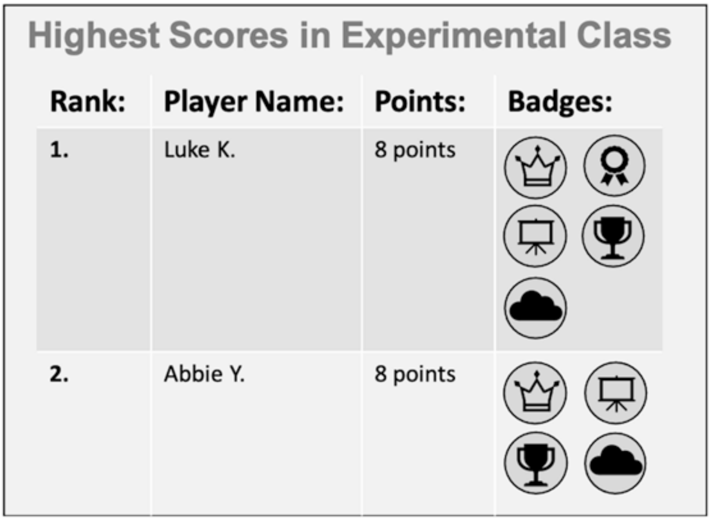


Fig. 11.1 (continued)

e

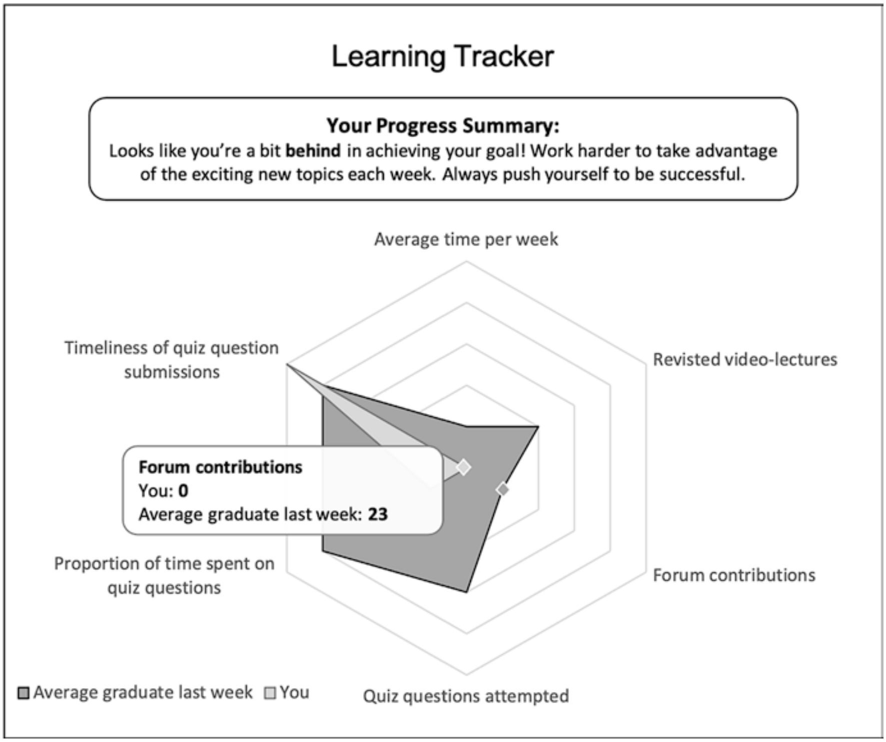


Fig. 11.1 (continued)

to e. *Rank order* is where students are given details of where they stand in order within the cohort, e.g. 10th out of 180 which can be give numerically or visually (see Fig. 11.1a used by Teasley, 2017 and Smith, 2019). More frequently dashboards provided students with information about how they compare to the whole cohort, *cohort comparison* (Jivet et al., 2017). Figure 11.1b and c shows cohort comparisons (used by Wise et al., 2013 and Teasley, 2017). Alternatively, students can be compared to a particular group of students, for instance, those in at the top of the class. For instance, Davis et al. (2017) designed a student dashboard that compared learners to those who had been successful on the course in the previous year. Similarly, dashboards can use a 'leader board' by showing those students who are achieving highest in the group and hence allow students to compare their achievement to their high-performing peers (used by Krause et al., 2015; see Fig. 11.1e).

There is contradictory evidence of the impact of social comparison on students. Frequently there is concern for, and attention paid to, those who are the bottom of the cohort as to the impact of social comparison. Wise et al. (2013) identified that low performers were discouraged by social comparison; however, in direct contrast, other studies found that social comparison was motivating, especially for low-performing students (Teasley, 2017). Whereas Tan et al. (2016) reported mixed motivational outcomes in students who were performing below the class average, for some the dashboard stimulated competition through ‘healthy peer pressure’, but for others these data were ‘demoralising’. A study by Davis et al. (2017) offered some insight into the reasons for these differences when they concluded that it was those with higher levels of prior education accrued the benefits of the social comparison dashboard compared to their peers with less prior education. This is supported by Smith (2019) whose study focussed on high-attaining students (postgraduate doctors undertaking specialist training) and identified that social comparison was experienced as motivational by this particular cohort. An alternative hypothesis that was suggested by Gašević et al. (2015) is that the negative impact of comparison is experienced by students with low levels of self-efficacy rather than simply those who are the low attainers. Hence there is conflicting empirical evidence on the impact of social comparison on students’ motivation to study, and this is the gap the study aims to address.

4 Methodology

The study was a small-scale qualitative study based on semi-structured interviews with 24 undergraduate students that aimed to understand how students interpreted and responded to feedback via a learner dashboard. We wanted to uncover the range of responses to various dashboard elements and the student dispositions that led to these responses to address the gap identified in the literature.

The dashboard was designed to display seven descriptive elements: Fig. 11.2 shows four of these elements, and Fig. 11.3 illustrates the other three elements. Note that the ‘on-track’ display (bottom left of Fig. 11.2) averages the marks that the student has received and this appears to be a form of prediction. However, it is not prediction in the sense of using machine learning and hence is classified as part of a descriptive dashboard. The elements of social comparison used in our dashboard were shown in the top right display on Fig. 11.2 which shows rank order, i.e. 9 out of 17, and on the bottom right display which shows the same information in a line graph format. Figure 11.3 element top right compares the student’s engagement with the VLE against the cohort average.

The sample was final year undergraduate students within the Department of Education at a single case study UK higher education institution. The sample for the first round of interviews was self-selecting and consisted of 10 students from the cohort of 178. For the second round, the sample consisted of a nearly complete cohort (14 out of 16). The dashboard presented each student with their performance in a recent assignment. The students’ attainment in this assignment ranged from 1st to 168th out of 178 in the first group and in the second from 1st to 16th in a cohort of 16 students. The dashboard displayed the degree classification that the student was on track to achieve, ranged from 51% (low 2:2) to 74% (1st) for the first round,

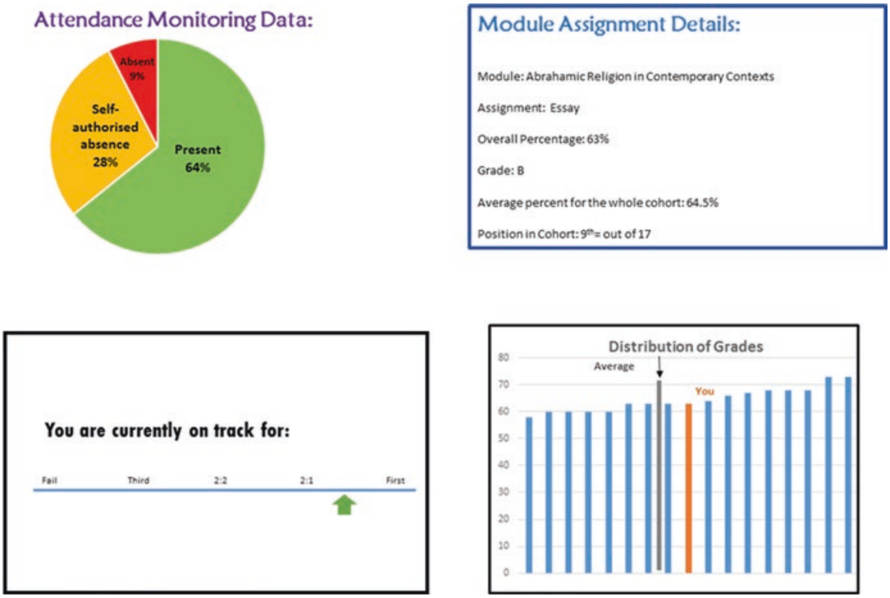
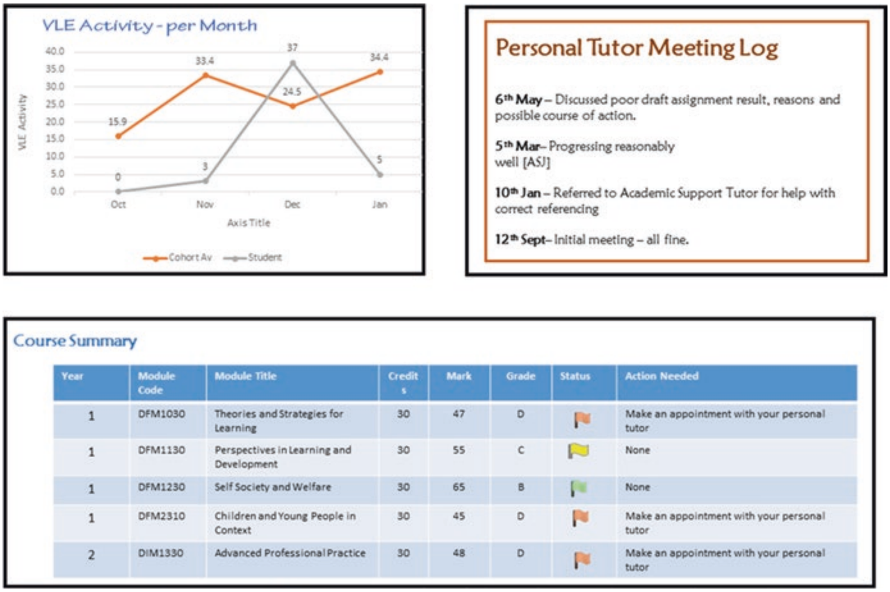


Fig. 11.2 Four elements of the learner dashboard used in our study



Year	Module Code	Module Title	Credits	Mark	Grade	Status	Action Needed
1	DFM1030	Theories and Strategies for Learning	30	47	D		Make an appointment with your personal tutor
1	DFM1130	Perspectives in Learning and Development	30	55	C		None
1	DFM1230	Self Society and Welfare	30	65	B		None
1	DFM2310	Children and Young People in Context	30	45	D		Make an appointment with your personal tutor
2	DIM1330	Advanced Professional Practice	30	48	D		Make an appointment with your personal tutor

Fig. 11.3 Three further elements of the student dashboard used in our study

and the range of participants in the second round was from 60% (border of 2:1 and 2:2) to 76% (1st). Slightly more students were doing worse in the assignment presented on the dashboard than their overall on-track score. Thus, the sample had the potential to uncover a range of emotional responses to the assignment data, not just being pleased that this assignment was bringing their average mark up or disappointment that it was lowering their mark.

This was the first time that the students had seen their data presented in this way, and the semi-structured interview, immediately after being presented with their dashboard, enabled them to gain clarification and reassurance about their interpretation of their data. This approach has influenced the findings, leading to a more nuanced understanding of the challenges for students in using dashboards, and influenced our choice of analytical framework in that we conceptualise dashboard feedback as a dialogic process (Carless & Boud, 2018). The interviews lasted between 10 and 30 min (typically 15 min) and asked students about their response to seeing the dashboard elements. Students talked about their feelings, their responses to the dashboard, and how they would act as a result of seeing the data presented in this way. The semi-structured interview allowed for follow-up questions and students to share feelings that arose as they made sense of the data and its presentation. Data was coded thematically (Braun & Clarke, 2006) based on the analysis using an interpretive framing. The trustworthiness of the data and the analysis is based on students having trust in the interviewers, who were not part of their teaching team, bringing a neutral and critical eye to the analysis process (Lincoln & Guba, 1981).

The study was sensitive in nature, given its focus on students' academic performance. BERA (2018) ethical principles informed the study. Participation was voluntary, and students' identity has been anonymised through the use of pseudonyms. We were aware of the responsibility that we had for supporting students and did this by preparing carefully to ensure that all the data presented were valid and by helping students to interpret their data in a way that would encourage positive outcomes, for instance, explaining how the on-track score was calculated and how it will change according to future module results. We also encouraged students to reflect on their progress and plan how to approach their final year of study. Ethical permission was given by the Ethics Committee of the School of Education at the case study university.

The study has some methodological limitations in that it involved a small sample of final year students from one academic discipline in one UK university. However, a particular strength of the study is that nearly a whole cohort was interviewed (14 out of 16 students) in the second round, thus avoiding the bias that arises from self-selecting samples. The interviews provided a rich source of insight into students' responses that enables the details of individual's dispositions, experiences of study, and other factors to be considered.

5 Findings

5.1 Social Comparison and Student Identity

It was evident that dashboards elicited emotional and identity work. For some students seeing their dashboard data appears to have a positive impact on their self-confidence (Esme) or reinforce aspects of their learner identity (Claire) or provided reassurance (Asmah). Please note the students' names have been changed:

> That's quite a surprise because I didn't really think I was very good at it. (Esme, 9th equal out of 16)

> Knowing your position in a class is always a nice thing because you know where you are, what you need to, do you need to move up or you just need to, are you keep, are you on the right track? Are you following other classmates? (Claire, 25th out of 178)

> I honestly didn't think I'd done very well on the essay. So seeing that it [her mark just below the average] does make me feel a bit better to be honest. (Asmah, 9th equal out of 16)

In these quotations students are using the positional data for self-evaluation, and it appears to develop their identity or to reinforce their existing self-concept. Asmah recognised she had not done as well in that assignment, so was pleasantly surprised to be in the middle of her cohort. It had beneficial and reinforcing impact on her self-esteem. In the following quotes, other students appeared to have a negative impact on their self-identity of the social comparisons: Marcia talks about seeing herself as a student with the ability to achieve a '2:1 or first' and feeling concerned at the way the dashboard appears to show her as doing less well. Similarly, Ingrid feels a sense of dejection at seeing her profile:

> Oh am I really going to graduate with a 2:2? […] Because I've always seen it as hoping to aim for a 2:1 or a first. (Marcia, 53rd out of 178)

> The saddest one is the core summary overall because looking back on grades that you've previously had – you can't really change them anymore so you can't really do anything. (Ingrid, 168th out of 178)

Hence social comparison data can provide students with feedback that helps them to locate themselves within their cohort. Whilst this appears to have been reassuring and reduce anxiety (for Esme and Asmah and Claire), in line with Festinger's theory (Festinger, 1954), it is also emotionally charged. For some it may have diminished their self-esteem, with feelings of sadness, or feeling resigned to their position in the cohort. Similarly, Raat et al. (2013) suggest as well as having the capacity to improve a student's self-efficacy, social comparisons also have the potential to diminish it.

5.2 Does Position Matter?

Perhaps surprisingly the position in the cohort was not a good way to predict how a particular student responded to seeing their social comparison data. Justine who was 15th in the group of 178 felt upset and angry by being given information about her position in the group:

> 14 other people have still done better than me…I had thought I'd really, really topped it, I've maxed out here. And it's taken away a bit from that feeling of elation. (Justine, 15th out of 178)

At the end of the interview, when Justine was asked if there was anything else she wanted to add, she returned to he topic of social comparison:

> If I'd have been eighty out of a hundred and seventy-eight I might've thought, oh okay that's fine, but because I know now actually how many people did better than me it makes me feel a little bit worse actually. (Justine, 15th out of 178)

In contrast, whereas India, who was at the bottom of her group, interpreted her information more positively and focussed on a holistic picture of where she was overall and the broader ways of interpreting the data that would support her in moving forward:

> India: I think it gives me motivation to try harder
>
> Interviewer: You pointed out straight away to the on-track slider
>
> India: Straight away, yeah. This is what I'm more focused on…I want to see the overall, where I am working at the moment. (India, 16th out of 16)

These examples illustrate that negative impact on a students' self-esteem was not necessarily predicted by position in the cohort. Justine, despite being a high attainer (15th out of 178), focusses on the negative aspects of being 15th with 14 people ahead of her, rather than reflecting on her success of her high-achieving score of 83% which was above the average of her other module marks and hence was bringing up her overall grade point average (GPA) score.

The majority of students, by definition, will appear to be in the middle of a cohort rather than being towards the top (as was Justine) or towards the bottom (as was India). For these students they grappled with the notion of being 'average':

> I'm closer to average. It's annoying anyway because I feel I've always been average, so this to me is more personal. (Jenny, 9th equal out of 16)
>
> Yeah, I would like to know that information, yeah, because I want to be on the average board with everyone else as well. Because if they're able to do it … ..I think I'll be able to do it as well. (Harry, 5th out of 16)

The process of identifying yourself as 'average' differs between students and results from upward and downward comparison. Jenny appears to see herself as an above-average student, so was disappointed by her dashboard displaying her scores as being average. This discussion supports the idea that students should be given choice as to the 'frame of reference' that preferred by the student, a position also supported by Roberts et al. (2017). The data also suggest both the fragile nature of the identity work that students engage in as they negotiate their position in the cohort and also the significance that students take from finding out this information. As Festinger's social comparison theory notes, being able to know where you stand amongst your peers is both sought out as a normal part of being in a group and also a mechanism to that helps to reduce uncertainty (Festinger, 1954): as Harry comments, he likes to know where he is in the group. The challenge for dashboards is to support this process of social comparison but to do so whilst promoting positive approaches to self-esteem and well-being. We return to this notion in the section on implications for dashboard design.

5.3 Motivation to Act Differently

As students interpreted their dashboard, it invoked a range of ways that they would act in response. This section looks broadly at the responses to dashboards that showed students' intention to act on the basis of receiving their data, as well as examining how the notion of competition played out through providing social comparison.

For some students it appeared as though the social comparison stimulated and reinforced competition that already existed within the group (Esme) whereas for others (Sarena) were less competitive in their response.

> I think it's actually a good idea [getting comparative data] … Because I think, especially in my course, we're all quite competitive with each other …. I feel like it would definitely push us. (Esme, 9th out of 16)

> Yeah, I never expect to be top anyway…..Well I'm more or less average with everybody else. (Sarena, 8th out of 16)

This finding was also found in Tan et al.'s (2016) study in that some students saw the dashboard as positively stimulating competition, therefore encouraging students to do better, whereas other students were demoralised by them.

More broadly the study showed that some students' responses indicated that they would take action in response to seeing their data presented in this format. The quotations appear to demonstrate that many students felt more motivated and determined to do better and to prioritise their academic study:

> I think as soon as I saw it I decided I'm taking a month off [paid] work to just get on with my dissertation. (Marcia, 53rd out of 178)

> I'd work even harder to get my last module to be like, so hopefully I would get a first type of thing. (Sarah, 65th out of 178)

> I'd definitely just do more reading and work a little bit harder than I already do. It's a bit of a kick up the backside. But then on the other side it's a little bit demotivating at the same time. (Esme, 9th out of 16)

Much of the literature on use of dashboards has focussed on their potential to support self-regulated learning, such as goal setting, meta-cognition, and motivation (Jivet et al., 2017), and our data also suggest there is some potential for this, for instance, Marcia saying she would take time off paid work and Sarah and Esme saying they would work harder. However, as Esme comments that is not the whole story and she also feels demotivated. Dashboard visualisations have significant limitations: they do not guide and support in the way that highly personalised feedback can do. As Esme alludes, it only gives part of the picture; it does not provide structure and support that will help to enhance attainment. Whilst motivation is part of what students need, students also need opportunity to make sense of the data, to understand what it means for them, and to identify actionable insights that will lead to improvements in performance.

There is a danger that the data-driven information that is provided via a dashboard might lead to action that might be of questionable value. The largest number of comments focussed on attendance data, its accuracy, and the fairness of self-reported absences and needing to remember to self-report absences. This investment in time to correct attendance data could be seen as effort that could be better spent on other learning-related activities. It also appeared to raise anxiety levels:

> The absences are because I've lost my card. I've not officially missed any …It just shows that I'm always losing things and that I need to go and get them [the absences authorised]. (Sannah, 1st out of 16)

> The three per cent absent makes me quite cross, and that's because there was a problem, my card wasn't swiping me in. (Jayne, 74th out of 178)

It illustrates MacFarlane's (2017) notions of student presentism, whereby students feel compelled to attend lectures because they are being monitored rather than because they believe that they will be a valuable learning opportunity and demonstrates how an institution's policies and practices shape students' behaviours. Hence providing students with more data about their performance might not lead to productive time spent on task, but rather to compliant behaviours or increased worry based on 'obsessively check[ing]' (Fritz, 2011, p.92).

5.4 Implications for Dashboard Design

Our findings illustrate that students' responses to their learner dashboard is highly individual and reflects their individual disposition influenced by their personal history (compare Justine and India's responses), and other studies support this (see, e.g. Tan et al., 2016; Raat et al., 2013; Schneider & Schupp, 2014). Students cannot be treated as though they are a homogenous body or as though there is an inevitability in the way that they respond to seeing their achievements and behaviours presented back to them. Instead, our findings illustrate the need for a more nuanced picture. Sutton talks about grades being polysemic, in that they signify different meanings to different students (Sutton, 2012), and this polysemic nature of student's response to learner dashboards is one of the significant findings from this study.

Our findings suggest the potential of learner dashboards to support student motivation but draw attention to the need to implement with caution in relation to how social comparison is operationalised. Whilst for most students they appeared to support a positive response, there were one or two who felt that comparing their performance to others in their cohort was unnecessary and/or emotionally challenging. We suggest that students need to be given choice in the ways of viewing their data that suits their personal dispositions: this would enable the competitive student to see how they were fairing alongside their cohort and allow a student who finds competition off-putting to focus on their personal trajectory. Hence students need to make appropriate choices and customisation whether they see their performance compared to others and also who they are compared to, the frame of reference, a position supported by Roberts et al. (2017). In a previous paper, we also argue that learner dashboards need to be designed with student agency and empowerment as central tenet of their design (Bennett & Folley, 2019).

There is a tension between the motivational potential of social comparison and its potential for negatively affecting some students. Jivet et al. (2018) have suggested that there is a need to tread cautiously in relation to implementing social comparison. However, once social comparison is enabled, the clock cannot be turned back, and, like an itch that demands to be scratched, human nature suggests that students will be drawn to looking at comparisons even if they know that they are likely to be demoralising, or worse emotionally destabilising. As Fassl et al. (2020) note, students who have low self-esteem tend to engage in social comparison processes more frequently. We suggest that institutions only implement social comparison features if they have a well-established approach to well-being. This, we suggest, should include a strong personal academic tutorial programme whereby students meet with a member of faculty regularly to build up a personal relationship that would enable them to discuss their response to the dashboard information and in particular to attend to a student's emotional response to information about where they stand in the cohort. Personal academic tutors would need to be adequately trained so that they were aware of the unpredictable nature of response to social comparison and to be attentive to the impact and how it can be experience from students irrespective of their position in the cohort, rather than the natural tendency to focus on those towards the bottom.

The study raises questions about the use of machine learning to develop predictions about students' outcomes. Our findings demonstrated that students' responses to their data were often unpredictable: for instance, we anticipated that the students with high grades would be positive about their feedback and those with less satisfactory results would react negatively. However, this was not the case, and those with lower results often took a pragmatic approach and found the data motivating, whilst some with average results were delighted in being 'average' and others disappointed.

This lack of predictability in a student's response suggests that machine-derived predictions of students' outcomes and responses are likely to be limited and certainly the research to date has failed to show the accuracy of deriving predictions (Beheshitha et al., 2016; Pardo et al., 2015; Wilson et al., 2017). In addition, there is an ethical question about using predictions because of the emotional impact that data has on students' self-concept, as we have illustrated, that also is likely to affect a student's behaviour in ways that may not be anticipated. For instance, the high-achieving student, such as Justine, may become demoralised by a prediction of a less than top score. Whereas the learning analytics community has argued that we need better algorithms to predict students' responses more accurately (Strang, 2017; Teasley, 2017), instead we argue that simple descriptive dashboards might be preferable to predictive dashboards because of the inaccuracy of prediction and of its power to impact on students' well-being. We suggest that prediction may become more accurate as machine learning improves but the emotional responses to the data will remain far from predictable.

6 Limitations of the Study

The study was based on a sample of students from the final year who were studying on a range of courses within an education faculty, and further work is needed to establish the generalisability of the findings. In particular, how do students from first and second year undergraduate and postgraduate courses respond to their dashboard, and how is this different or similar to our study which is based on final year students? In what ways does the discipline and institutional context in which dashboards are used by students shape their potential to support students' positive engagement?

Whilst learner dashboards appear to support student motivation to learn and provide them with particular ways that they might act, for instance, they might suggest taking more books out of the library, or spending longer on the VLE, they do not of themselves guarantee that students will act. As Winstone et al. (2017) have identified, knowing about the support and opportunities available is not the same as having the willingness to make use of it. Similarly, Broos et al. (2019) identified that students liked their dashboard, but it did not change their behaviour or result in deeper learning. Hence further longer-term study would be needed to establish the actual impact that dashboards have on students' behaviour.

7 Conclusion

The use of social comparison within learner dashboards is something of a 'Pandora's box' whereby once the potential is released the impact may be different from what was intended. The intention behind using dashboards with students is to support their motivation and hence to enhance their well-being, yet this chapter has shown that their use results in a range of potential responses. Many are positive and motivational, reinforcing Festinger's theory of social comparison which suggests people need to know where they sit in a group (Festinger, 1954), and it reduces their uncertainty to do so. However, for a few it was shown to have a negative impact on their emotions. Interestingly the chapter has highlighted that the position in the cohort is not always the main determinant of how a student responds to the social comparison aspect of the dashboard, that is, those at the top of the cohort might be negatively impacted, and those at the bottom respond more positively to being compared to the rest of the cohort. Hence predicting the emotional and motivational responses based on position appears to be inaccurate, and responses are more nuanced being influenced by individual disposition and their personal history. Previous studies have called for caution when implementing the emotional challenges of social comparison (Jivet et al., 2018) and to allow students to choose their 'frame of reference' for the comparison (Roberts et al., 2017), and the evidence from this study supports this. However, our study has shown that social comparison invoked strong emotional responses so we argue that it is important that an institution has a well-embedded approach to student well-being to complement the use of social comparison.

Acknowledgements The Society for Research into Higher Education provided funds to support this study.

References

Ahern, S. J. (2020). Making a #Stepchange? Investigating the alignment of learning analytics and student wellbeing in United Kingdom higher education institutions. *Frontiers in Education, 5*(174). https://doi.org/10.3389/feduc.2020.531424

Beheshitha, S., Hatala, M., Gašević, D., & Joksimović, S. (2016). *The role of achievement goal orientations when studying effect of learning analytics visualizations*. In Paper presented at the LAK'16, Edinburgh, Scotland.

Bennett, L., & Folley, S. (2019). Four design principles for learner dashboards that support student agency and empowerment. *Journal of Applied Research in Higher Education, 12*(1), 15–26. https://doi.org/10.1108/JARHE-11-2018-0251

Bhatt, I., & de Roock, R. (2014). Capturing the sociomateriality of digital literacy events. *Research in Learning Technology, 21*(0). https://doi.org/10.3402/rlt.v21.21281

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101.

British Educational Research Association. (BERA). (2018). *Ethical guidelines for educational research*. Retrieved from Nottingham: https://www.bera.ac.uk/researchers-resources/publications/ethical-guidelines-for-educational-research-2018

Broos, T., Pinxten, M., Delporte, M., Verbert, K., & De Laet, T. (2019). Learning dashboards at scale: Early warning and overall first year experience. *Assessment and Evaluation in Higher Education, 45*(6), 1–20. https://doi.org/10.1080/02602938.2019.1689546

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education*, 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Davis, D., Jivet, I., Kizilcec, R., Chen, G., Hauff, C., & Houben, G.-J. (2017). *Follow the successful crowd: raising MOOC completion rates through social comparison at scale*.
Dodge, R., Daly, A. P., Huyton, J., & Sanders, L. D. (2012). The challenge of defining wellbeing. *International Journal of Wellbeing, 2*(3).
Fassl, F., Yanagida, T., & Kollmayer, M. (2020). Impostors dare to compare: Associations between the impostor phenomenon, gender typing, and social comparison orientation in university students. *Frontiers in Psychology, 11*, 1225–1225. https://doi.org/10.3389/fpsyg.2020.01225
Festinger, L. (1954). A theory of social comparison processes. *Human Relations (New York), 7*(2), 117–140. https://doi.org/10.1177/001872675400700202
Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *The Internet and Higher Education, 14*(2), 89–97. https://doi.org/10.1016/j.iheduc.2010.07.007
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71.
Gerber, J. P., Wheeler, L., & Suls, J. (2018). A social comparison theory meta-analysis 60+ years on. *Psychological Bulletin, 144*(2), 177–197. https://doi.org/10.1037/bul0000127
Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). *Awareness is not enough. Pitfalls of learning analytics dashboards in the educational practice*. In Paper presented at the Data Driven Approaches in Digital Education. EC-TEL 2017.
Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). *License to evaluate: Preparing learning analytics dashboards for educational practice*. In Paper presented at the LAK '18, Sydney, Australia.
Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758. https://doi.org/10.1016/j.iheduc.2020.100758
Krause, M., Mogalle, M., Pohl, H., & Williams, J. J. (2015). *A playful game changer: Fostering student retention in online education with social gamification*. In Paper presented at the Proceedings of the Second (2015) ACM Conference on Learning @ Scale, Vancouver, BC, Canada. doi:https://doi.org/10.1145/2724660.2724665.
Lincoln, Y. S., & Guba, E. G. (1981). Criteria for assessing the trustworthiness of naturalistic inquiries. *Educational Communication and Technology Journal, 29*, 75–91.
MacFarlane, B. (2017). *Freedom to learn*. Routledge.
Margolis, J. A., & Dust, S. B. (2019). It's all relative: A team-based social comparison model for self-evaluations of effectiveness. *Group & Organization Management, 44*(2), 361–395. https://doi.org/10.1177/1059601116682901
Pardo, A., Ellis, R., & Calvo, R. (2015). *Combining observational and experiential data to inform the redesign of learning activities*. In Paper presented at the LAK15, Poughkeepsie, USA.
Raat, A. N., Kuks, J. B. M., van Hell, E. A., & Cohen-Schotanus, J. (2013). Peer influence on students' estimates of performance: Social comparison in clinical rotations. *Medical Education, 47*(2), 190–197. https://doi.org/10.1111/medu.12066
Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*(3), 317–333. https://doi.org/10.1007/s10758-017-9316-1
Rogers, C. M., Smith, M. D., & Coleman, J. M. (1978). Social comparison in the classroom: The relationship between academic achievement and self-concept. *Journal of Educational Psychology, 70*(1), 50–57. https://doi.org/10.1037/0022-0663.70.1.50
Schneider, S. M., & Schupp, J. (2014). Individual differences in social comparison and its consequences for life satisfaction: Introducing a short scale of the Iowa–Netherlands comparison orientation measure. *Social Indicators Research, 115*(2), 767–789. https://doi.org/10.1007/s11205-012-0227-1
Shields, S. (2015). 'My work is bleeding': Exploring students' emotional responses to first-year assignment feedback. *Teaching in Higher Education, 20*(6), 614–624.

Smith, P. (2019). Engaging online students through peer-comparison progress dashboards. *Journal of Applied Research in Higher Education, 12*(1), 38–56. https://doi.org/10.1108/JARHE-11-2018-0249

Strang, K. D. (2017). Beyond engagement analytics: Which online mixed-data factors predict student learning outcomes? *Education and Information Technologies, 22*(3), 917–937. https://doi.org/10.1007/s10639-016-9464-2

Sutton, P. (2012). Conceptualizing feedback literacy: Knowing, being, and acting. *Innovations in Education and Teaching International, 49*(1), 31–40. https://doi.org/10.1080/14703297.2012.647781

Tan, J. P.-L., Yang, S., Koh, E., & Jonathan, C. (2016). *Fostering 21st century literacies through a collaborative critical reading and learning analytics environment: user-perceived benefits and problematics*. In Paper presented at the Proceedings of the Sixth International Conference on Learning Analytics &; Knowledge, Edinburgh, UK. doi:https://doi.org/10.1145/2883851.2883965.

Teasley, S. D. (2017). Student facing dashboards: One size fits all? *Technology*. *Knowledge and Learning, 22*(3), 377–384. https://doi.org/10.1007/s10758-017-9314-3

Tett, L. (2014). Learning, literacy and identity: 'I don't think I'm a failure any more'. *British Journal of Sociology of Education, 37*(3), 427–444. https://doi.org/10.1080/01425692.2014.939265

Thorley, C. (2017). *Not by degrees improving student mental health in the UK's Universities*. Retrieved from https://www.ippr.org/files/2017-09/1504645674_not-by-degrees-170905.pdf

Trautwein, U., Lüdtke, O., Marsh, H. W., & Nagy, G. (2009). Within-school social comparison: How students perceive the standing of their class predicts academic self-concept. *Journal of Educational Psychology, 101*(4), 853–866. https://doi.org/10.1037/a0016306

Turner, L., & Tobbell, J. (2018). Learner identity and transition: An ethnographic exploration of undergraduate trajectories. *Journal of Further and Higher Education, 42*(5), 708–720. https://doi.org/10.1080/0309877X.2017.1311993

Universities UK (Producer). (2020). *UK stepchange: Mentally healthy universities*. Retrieved from https://www.universitiesuk.ac.uk/stepchange-mhu

Wenger, E. (1998). *Communities of practice: Learning, meaning, and identity*. Cambridge University Press.

Wilson, A., Watson, C., Thompson, T. L., Drew, V., & Doyle, S. (2017). Learning analytics: Challenges and limitations. *Teaching in Higher Education*, 1–17. https://doi.org/10.1080/13562517.2017.1332026

Winstone, N. E., Nash, R. A., Rowntree, J., & Parker, M. (2017). It'd be useful, but I wouldn't use it': Barriers to university students' feedback seeking and recipience. *Studies in Higher Education, 42*(11), 2026–2041. https://doi.org/10.1080/03075079.2015.1130032

Wise, A., Zhao, Y., & Hausknecht, S. (2013). *Learning analytics for online discussions: a pedagogical model for intervention with embedded and extracted analytics*.

Wood, J. V. (1996). What is social comparison and how should we study it? *Personality & Social Psychology Bulletin, 22*(5), 520–537. https://doi.org/10.1177/0146167296225009

You, J. W., & Kang, M. (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers & Education, 77*, 125–133. https://doi.org/10.1016/j.compedu.2014.04.018

Chapter 12
Navigational Behavior Patterns of Learners on Dashboards Based on Assessment Analytics

Fatma Bayrak, Furkan Aydın, and Halil Yurdugül

1 Introduction

Learning analytics (LA) focuses on educational data such as assessment, collaboration, and communication data (Nouira et al., 2019) and provides meaningful information for the improvement of learning and environments. Considering the metrics and data, it is noteworthy that performance and assessment data hold significant value in LA studies (Ellis, 2017). From this perspective, studies about assessment data are recently referred to as assessment analytics (Cooper, 2015; Ellis, 2013, 2017; Nouira et al., 2019; Papamitsiou & Economides, 2016). Assessment analytics examines assessment data to decide on adaptations, make recommendations, provide feedback, and guide learners (Cooper, 2015; Nouira et al., 2019; Papamitsiou & Economides, 2016). Ellis (2013) also stated that assessment data produces valid, reliable, and meaningful feedback and, consequently, highlighted that "assessment analytics has the potential to make a valuable contribution to the field of learning analytics." With the memory capacity, high speed, and cost reduction of today's computers (Hamilton et al., 2000), various e-assessment practices, from self-testing to summative exams, have increased (Gikandi et al., 2011; Thelwall, 2000). While assessment analytics are considered a subdimension of learning analytics (Ellis, 2017), they are essential elements in these e-assessment systems.

Assessment is classified according to their purpose as diagnostic, formative, and summative, and the assessment systems developed are shaped according to these

F. Bayrak (✉) · H. Yurdugül
Hacettepe University, Ankara, Turkey
e-mail: fbayrak@hacettepe.edu.tr; yurdugul@hacettepe.edu.tr

F. Aydın
Kahramanmaraş Sütçü İmam University, Kahramanmaraş, Turkey
e-mail: furkanaydin@ksu.edu.tr

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_12

purposes. Feedback is provided in each assessment process. However, the information provided with feedback differs according to the purpose of the assessment. Feedback is the most important element of formative assessment. Formative feedback helps the learner identify their weaknesses and strengths, construct their own learning goals, take more responsibility for their learning, and increase their learning awareness. In student-facing dashboards, indicators presented as feedback can serve these purposes.

Carless (2007) introduced the term learning-oriented assessment (LOA) by examining formative assessment processes in detail. He defined (Carless, 2015) LOA as "assessment where the primary focus is on the potential to develop productive student learning processes." Additionally, Mok (2013) claimed that such assessments support students' self-directed learning and, furthermore, introduced self-directed learning-oriented assessment (SLOA). In these processes, learners' interaction with feedback also has emerged as an essential element.

In definitions of assessment analytics, assessment data is emphasized (Cooper, 2015; Ellis, 2013, 2017; Nouira et al., 2019; Papamitsiou & Economides, 2016). However, for formative assessment processes, the interaction of the student with the provided feedback is imperative. For this reason, in this study, assessment analytics were handled as the data obtained from assessment tasks and students' interactions with feedback. While it is easy to track students' interaction with feedback through technological developments, few studies examined this situation (Kia et al., 2020; Yera et al., 2018). It is noteworthy that in these studies, the role of examinations was not the focus of any indicators. In this respect, this study aims to investigate students' transitions between feedback types presented via student-facing dashboards. According to the aim, a Self-Directed Learning-Oriented Assessment System was developed for students to test themselves. In the developed system, the students' interaction behaviors with feedback were subsequently modeled statistically.

One of the data mining methods used for behavior modeling is the lag sequential analysis (LSA). With LSA, it is possible to examine student behaviors in online learning systems according to learner characteristics (Şahin et al., 2020) or different system designs (Hwang et al., 2021). Findings in this study are based on the data obtained from the student interaction with feedback in anticipation that their navigation behaviors between the indicators would shed light on making dashboard designs more efficient. At the same time, feedback preferences of the learners can be modeled.

1.1 Dashboards Based on Assessment Analytics

Assessment is an inevitable element in learning, and various assessment tasks can be designed in accordance with the learning output. For each assessment task, tracked data and feedback presented to the learner may vary. Carless (2015) stated that a wide variety of assessment tasks could come together within the scope of the LOA. One of these assessment tasks is tests. Tests consisting of multiple-choice questions are extensively used so that students can get immediate feedback to monitor their learning processes, and tests can be used together with other assessment tasks. Accordingly, feedback can be classified based on item and test in these self-testing processes and feedback is presented through student-facing dashboards.

Schwendimann et al. (2016) define dashboards as "single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations." Learners can see indicators based on item and test such as (a) how many correct and incorrect answers they had, (b) what subjects were these incorrect answers related to, (c) whether they have improved compared to their previous performance, or (d) how their development compares to their group. In terms of feedback types, these examples are classified respectively as (a) criteria-referenced feedback (CRF), (b) elaborated feedback (EF), (c) self-referenced feedback (SRF), and (d) norm-referenced feedback (NRF) (Brookhart, 2008; Hattie & Gan, 2011; Shute, 2008). In dashboards, it is crucial to visualize indicators according to their purpose. Accordingly, pie charts can be used to show criteria-referenced feedback, and line graphs can be used to show both self- and norm-referenced feedback. A variety of visualizations can be used for these indicators, but the effects of different visualizations will not be examined within the scope of the study.

The test score is one of the test-based feedbacks, and the grade can be compared according to criterion (criterion-referenced), previous performance (self-referenced), and group performance (norm-referenced). Wise (2014) stated that reference frames are useful for students in dashboard design. Through criteria-referenced feedback, learners are able to recognize their deficiencies and take action to overcome them (Wilbert et al., 2010). However, in the study conducted by Mensink and King (2020), it was reported that learners exit without looking at another feedback when they access the grade. Considering that criterion-referenced feedback can be given in student-facing dashboards, it is necessary to examine whether students switch to other tabs to see the other indicators. While learners can focus on their learning processes by following their development through self-referenced feedback (Aguilar, 2018; Wilbert et al., 2010), they can see their position within the group through norm-referenced feedback (Wilbert et al., 2010; Zhang et al., 2018). In addition, according to Festinger's (1954) social comparison theory, group comparison can positively affect learners' intrinsic motivation.

Norm-referenced feedback has been continually discussed as part of assessment feedback and LA studies (Aguilar, 2018; Guerra et al., 2016; Jivet et al., 2018; Mumm & Mutlu, 2011; Shute, 2008; Teasley, 2017). In the systematic review study by Jivet et al. (2018), it was concluded that norm-referenced comparison does not always have a positive effect. When the learner fails, they may avoid comparison with the group (Chan & Lam, 2010). Conversely, the learner who sees that he/she is more successful than the group may stop trying harder. Alternatively, if the learner is successful, he/she might prefer this type of feedback over other types, or there might be situations where learners resemble each other. Park and Jo (2015) also state that comparison affects motivation. Additionally, in learning analytics dashboard studies, it was reported that students preferred comparative information (Bodily et al., 2018; Schumacher & Ifenthaler, 2018).

The test-based feedback expressed so far provides information about the student's general situation. However, the learner is able to see his/her gap and close it more efficiently if they are presented with result information about each item and guiding learners back to the relevant topics to questions with incorrect answers. This type of feedback is defined as elaborated feedback (Shute, 2008). However, the question was raised about whether the students would examine the item based information or not.

Various studies have been carried out on dashboard design, the majority of which are based on student views and self-report data (Jivet et al., 2020; Silius et al., 2010; Santos et al., 2012; Charleer et al., 2013; Park & Jo, 2015; Vigentini et al., 2017). In these studies, it was discovered that some students found dashboards helpful and used them to control their learning processes, while other students felt bombarded with over-information (Bodily et al., 2018). Few studies have examined which dashboard components students prefer (Jivet et al., 2020; Kokoç & Altun, 2021; Sansom et al., 2020; Schumacher, & Ifenthaler, 2018), and in these studies, assessment analytics were not handled separately.

This study aims to examine transitions between feedback types presented via student-facing dashboards using the navigation data. By examining learners' interactions with feedback, input can be provided to adaptive systems to design personalized learning dashboards. In this study, firstly, the transitions of all students between (a) criteria-referenced feedback (CRF), (b) elaboration feedback (EF), (c) self-referenced feedback (SRF), and (d) norm-referenced feedback (NRF) were examined. In addition, the success of the learners at the end of the process was handled to examine feedback interaction behavior during the process. Accordingly, a comparison was made in navigation behavior within dashboards according to students' master and non-master status, and inferences were made for the dashboard design.

2 Method

2.1 Design of SLOAS (Self-Directed Learning-Oriented Assessment System)

A web-based system for learners to test themselves has been developed by the researchers using HTML, PHP, JavaScript, and MySQL. Multiple-choice questions about word processor software were selected from the item pool for five tests for the system. The item pool was created according to European Computer Driving Licence Curriculum by subject-matter experts. For elaborated feedback, each item-relevant topic was entered into the system as metadata.

After the learners' interactions with the tests, four various feedbacks were presented in different tabs to the learners: (a) criteria-referenced feedback (CRF), (b) elaboration feedback (EF), (c) self-referenced feedback (SFR), and (d) norm-referenced feedback (NRF). A dashboard may contain one or more indicators. Depending on the purpose of the study, each dashboard is designed to include an indicator (feedback) so that students' transitions between indicators can be tracked. In addition, learning dashboards are learning analytics tools, and learning dashboards can be classified according to analytics type (e.g., descriptive, predictive, and prescriptive). Descriptive analytics focus on the question "what happened?" and descriptive dashboards were created accordingly in this study.

Menus as shown in Fig. 12.1 were created to display the specified dashboards. Students are able to make the learning dashboard they want to see visible by clicking the icons in the menu. In this way, learners could switch between dashboards, and the system would track these transitions (interaction streams, the click from one dashboard to another) (Fig. 12.2).

General Result According to the test's total number of questions, the percentage of correct and incorrect answers was shown as a pie chart in this tab (as seen in Fig. 12.3). From the pie chart, students could see a visual representation of their results as a whole. The information provided here was within the scope of criterion-referenced feedback.

Fig. 12.1 The menu to display the dashboards

Fig. 12.2 For video you can scan the QR code

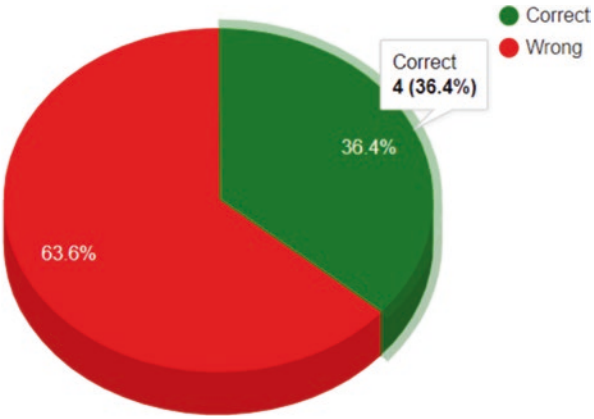


Fig. 12.3 Pie chart for general result

Questions The students were able to see in this tab whether the answer he/she gave to each question was correct or incorrect, as well as the topic title of the question. The information provided here was within the scope of elaborated feedback.

Progress In this tab, the student was able to see his/her previous and last results in a line graph. Through the line graph, the student was able to see the increase or decrease of their results with respect to time (as seen in Fig. 12.4). The information provided here was within the scope of self-referenced feedback.

Situation Within the Group

In this tab, the student could see his/her results in a line graph and compare their performance with the group's performance. The information provided here was within the scope of norm-referenced feedback. Students were grouped for each test performance as low, medium, and high for norm-referenced feedback. Cumulative percent was employed in the separation of the groups. Those below 24.5% were defined as the lower group, 24.5–74.5% as the middle, and those above 74.5% as the upper group. These calculations were made according to each quiz and presented to students. In addition, low, medium, and high groups changed instantly according to

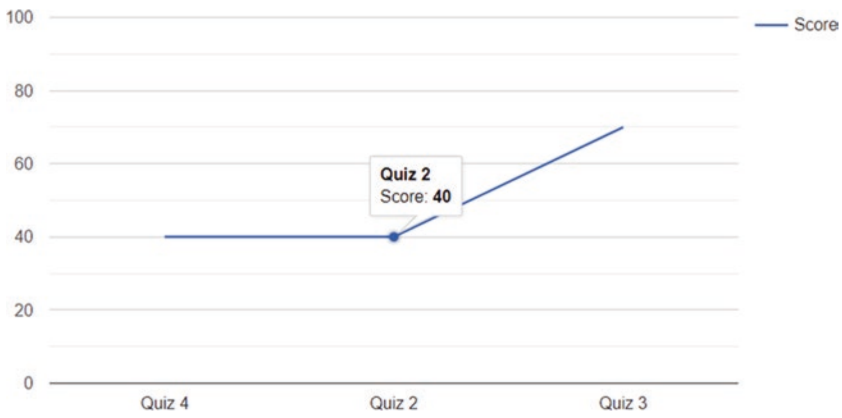


Fig. 12.4 Line graph for progress

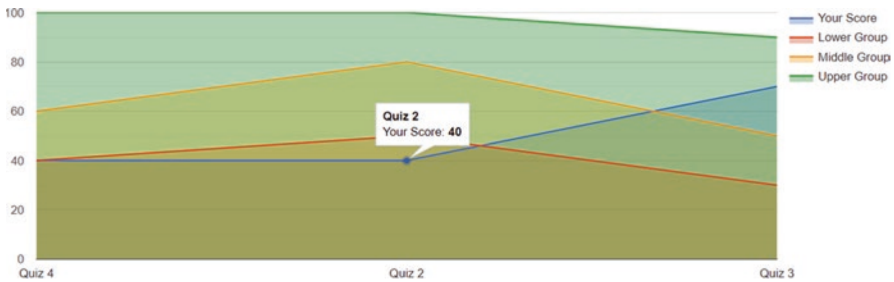


Fig. 12.5 Line graph for progress

real-time data, and students were able to see in which group they were in the line graph (as seen in Fig. 12.5).

2.2 Participants and Implementation Process

The research was conducted at a state university in Turkey. One hundred associate degree students who took the Basic Information Technologies course at the Medicine and Technical Services department participated in the research. Seventy-two of the participants were women (72%), and 28 of them were men (28%).

Usernames and passwords were sent to the e-mail addresses of the participants to log into the system. The participants took tests in the system within 4 weeks and reached the feedback module. All interaction data of the participants between login and logout were tracked and saved in the database (Table 12.1).

In the study, only navigation data on the feedback module were used. As seen in Fig. 12.6, the student in the first line visited dashboards in the order of General result, Questions, Progress, and then Situation according to the group.

Table 12.1 Field names in database table

login_id	Account name of the participant
cnumber	Number of correct answers
wnumber	Number of wrong answers
score	Total score (number of correct answer * 10)
transitions	Clicks among the indicators of the participants were recorded using (D, M, P, G) abbreviations
exam_ date	Time when student took the test

login_id	cnumber	wnumber	score	transitions	exam_date
19060312012	6	4	60	D,M,P,G,	2019-12-06 14:34:09
19060312012	9	1	90	D,M,P,G,	2019-12-06 14:41:21
19060312012	6	4	60	D,M,P,G,	2019-12-06 15:00:16
19060312012	4	6	40	D,M,	2019-12-06 15:15:04
19060312012	9	1	90	D,M,P,G,	2019-12-06 15:23:14

Fig. 12.6 User's example navigation data in database
Transitions' code: *D* **General result,** *M* **Questions,** *P* **Progress,** *G* **Situation according to the group**

2.3 Analysis

Quantitative data was collected from 100 freshmen students and consisted of learners' interactions with the system. Lag sequential analysis (LSA) was utilized to determine which dashboards (feedback type) the learners visited following different feedback types.

Lag sequence analysis (LSA) is a statistical technique to analyze a sequenced series of dichotomous codes such as event-based sequential data (Allen, 2017; Pohl et al., 2016). According to Allen (2017), the analysis does not assume equal time intervals between events. LSA, also referred to as behavior sequence analysis (BSA), is a proper method for understanding the dynamic relationship between behavioral progressions (Marono et al., 2018). This method first calculates the frequency of each behavior connected to the next by calculating each sequence's z-value to confirm whether each sequence's connectedness has a significant difference. After significant transitions are determined according to the z-score, the behavioral transition diagram is created (Hwang et al., 2021).

In the study, z-scores were computed as follows (Bakeman & Gottman, 1997):

$$Z_{GT} = \left(x_{GT} - m_{GT}\right) / \surd\left(m_{GT}\left(1-p_G\right)\left(1-p_T\right)\right.$$

Assume that the behavioral event of interest is called the "target" event, and that we want to relate that to another event, called the "given" event, *G*.

…

m_{GT} is an estimate of the expected frequency, x_{GT} is the sum of the observed frequencies in the Gth or given row, $X + T$ is the sum of the observed frequencies in the Tth or target column, and x_{++} is the total number of tallies in the table.

…

$$\text{where } p_{G+} \text{ is } x_{G+} \div x_{++} \text{ and } p_{+T} \text{ is } x_{+T} \div x_{++}.\text{"}$$

In this study, the lag sequential analysis was used to make sense of behavioral differences between master and non-master students when interacting with the presented learning dashboard. In the first stage, the frequency of navigation between the four feedback categories presented to students in the learning dashboard was coded. For each transition, to determine if the transitional probabilities deviated significantly from their expected value, z-values were calculated. The z-value was also combined with Yule's Q to indicate the strength of the relationship between transitions (Pohl et al., 2016). According to Bakeman et al. (1996), "Yule's Q is a transformation of the odds ratio designed to vary, not from zero to infinity with 1 indicating no effect, but from 1 to −1 with zero indicating no effect, just like the Pearson correlation. For that reason, many investigators find it more descriptively useful than the odds ratio." Thus, transitions from one feedback screen to another were accepted as significant if the calculated z-value was above 1.96 and the Yule's Q value was at least 0.30 (Bakeman & Gottman, 1997).

After examining LSA results, ten students were randomly selected from master (n = 5) and non-master (n = 5) students. A form containing one question was sent to them: "Which feedback type(s) did you prefer after the test? Can you explain in detail?"

3 Results

First, the navigation of all participants between the dashboards was coded. Frequencies for each transition, transition rates, z-values, and Yule's Q values were calculated and presented in Tables 12.2 and 12.3 and Fig. 12.6. Data generated from the users' interactions with dashboards was analyzed using a package program (Spreadsheets).

Table 12.2 Z-values of participants' transitions between indicators

Z-values	CRF	EF	SRF	NRF
CRF	−7,07	**9,11**	−1,31	−3,61
EF	**5,49**	−9,06	**7,66**	−1,51
SRF	−0,57	−2,88	−7,03	**10,22**
NRF	**4,56**	1,21	1,09	−5,40

Table 12.3 Yule's Q value of participants' transitions between indicators

Transitions	Q value
CRF→EF	0,702
EF→CRF	0,639
EF→SRF	0,674
SRF→NRF	0,803
NRF→KR	0,609

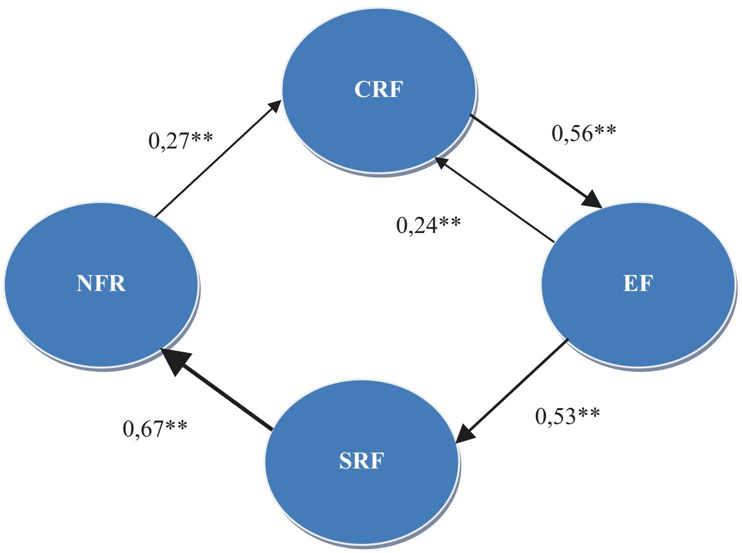


Fig. 12.7 State transition diagram occurring in the log file data (all participants)

As humans only have a limited working memory, an individual can focus more easily on the information optimized by visualization (Yiğitbaşıoğlu & Velcu, 2012). The fundamental purpose of visualization is to create a graphical representation of quantitative data for a more straightforward interpretation (Ahokas, 2008). Visualization of the obtained results helps users interpret results more easily (Chatti et al., 2012). Consequently, LSA outputs were visualized to better understand student interaction behavior with feedback. As LSA reveals user behaviors and sequential situations, statistically significant transitions emerge. Accordingly, when looking at the LSA visualizations, it was discovered that transition diagrams are used in relevant studies (Hwang et al., 2021; Pohl et al., 2016; Şahin et al., 2020). Based on this, transition diagrams were presented, and the arrows were thickened according to the transition probabilities.

According to the results (Fig. 12.7), students participating in the research followed the order given by the researchers in the design (CRF-EF-SRF-NRF). It was determined that the highest transition probability occurred between self-referenced feedback to norm-referenced feedback (z = 10,22, Q = 0,803). The second transition probability occurred between criterion-referenced feedback to elaborated feedback (z = 9,11, Q = 0,702). Additionally, there was a bidirectional transition between criteria-referenced feedback and elaboration feedback (z = 5,49, Q = 0,639).

To reveal the behavior of students who need more help, the group was divided into two categories, master and non-master. Separation into these two groups was made according to the student's test scores. The students' scores over five tests were summed up, and their geometric mean was obtained. As a result of the calculation, if the student's average score was 70 and above, it was considered master. If not, they were considered non-master. Then, the behaviors of master and non-master students were examined separately. The results obtained from the analysis are given in Tables 12.4, 12.5, 12.6, and 12.7. Transition possibilities are given in Figs. 12.8 and 12.9.

According to the results, it was seen that there is a difference in transition between the types of feedback in master and non-master students' transitions. Master students tend to follow the existing design linearly. Non-master students also tend to follow the existing design linearly; and besides, there was a transition between SRF and NRF (z = 2.52, Q = 0.447) in non-master students' transitions.

Table 12.4 Z-values of participants' transitions between indicators

Z-values	CRF	EF	SRF	NRF
CRF	−7,07	**9,11**	−1,31	−3,61
EF	**5,49**	−9,06	**7,66**	−1,51
SRF	−0,57	−2,88	−7,03	**10,22**
NFR	**4,56**	1,21	1,09	−5,40

Table 12.5 Z-values of participants' transitions between indicators

Z-values	CRF	EF	SRF	NRF
CRF	−5,12	**8,21**	−1,49	−3,93
EF	**3,59**	−7,58	**6,55**	−0,64
SRF	−0,33	−3,012	−5,23	**8,72**
NRF	**3,40**	1,41	0,16	−4,03

Table 12.6 Yule's Q value of transitional probabilities (non-master)

Transitions	Q value
CRF→EF	0,745
EF→CRF	0,703
EF→SRF	0,662
SRF→NRF	0,810
NRF→SRF	0,447
NRF→KR	0,583

Table 12.7 Yule's Q value of transitional probabilities (master)

Transitions	Q value
CRF→ EF	0,782
EF→ CRF	0,575
EF→ SRF	0,721
SRF→ NRF	0,854
NRF→ KR	0,598

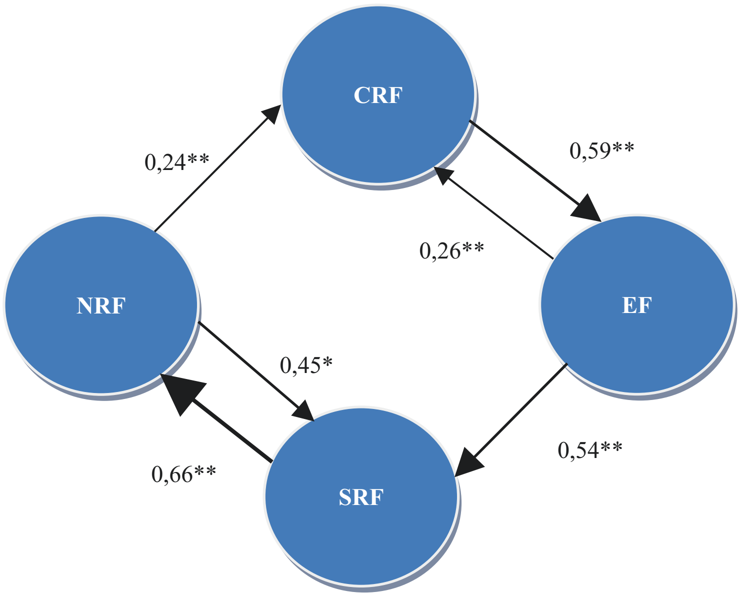


Fig. 12.8 State transition diagram occurring in the log file data (non-master)

Ten students (five master and five non-master) answered two questions: "Which feedback type(s) did you prefer after the test? Can you explain in detail?" and "If you had a single feedback choice, which would it be?". Upon questioning which feedback(s) the students preferred, it was concluded that five master students preferred all the feedbacks and three non-master students preferred all, too. However, one non-master student stated that if he/she had deficiencies, he/she would not prefer norm-referenced feedback.

Master students' views are as follows:

> I tried to see my progress by looking at all types of feedback. Among the types of feedback, I tried to look more at the general result and progress. (S70)
>
> First, I used the general result feedback. I then used the questions to see the answers to the questions I got wrong. Finally, I evaluated my position according to the group. I seldom preferred my progress feedback because I assessed myself by examining my right and wrong answers.(S73)

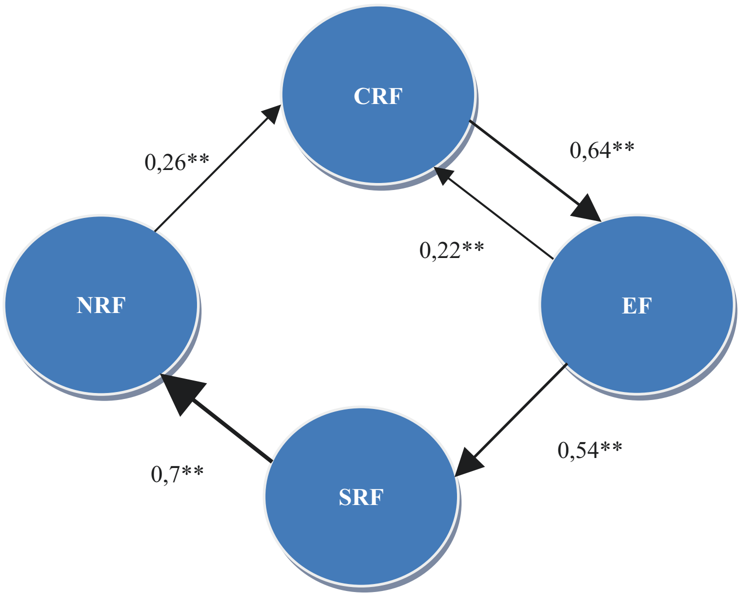


Fig. 12.9 State transition diagram occurring in the log file data (master)

> I generally preferred all of them. Because I was curious about both my own progress and my average situation compared to my group. I used the questions feedback to see what I did wrong and what my mistake was. Of course, when I got right, I did not examine the process and the position within the group module. (S20)
>
> Overall, the general result was more important to me. Comparing myself with the rest and seeing my position within the group affected me more positively. Questions feedback was of course an important factor. The Progress section helped me see how far I have progressed and where I have come. seeing where I stand within the group was the best factor in comparison. (S5)
>
> In my test results, I used general result, the questions and situation within the group feedback because the general result indicated the grade I got from 10 questions. Questions feedback revealed what I did wrong in which sub-topic and what I should work on. If I were to choose between the two, I would prefer questions feedback. The situation within the group enabled me to act on the average of the class. Generally, it made me happy that I was above the class average. (S4)

Non-master students' views are as follows:

> Generally, I used all types of feedback because they are all useful and informative content. (S98)
>
> When I first took the test, I looked at my correct and wrong answers, then the class average. In the next tests, I have used the development part and analyzed my progress. (S27)
>
> Frankly, I looked at them all. But in general, examining the questions and the situation within the group was more important to me because I wonder about my situation in the classroom. When I examined the questions, I looked back at my notes regarding the wrong answers. But since I do not know much about computers, I can say that I looked for the questions solution. By questions feedback, I could see which subject I had to go on. (S7)

> In order to learn the Test Result, I mostly used the General Results, Questions and Progress feedback. After solving the questions, I used the feedbacks in the order given above, and mostly paid attention to the Questions feedback because it was a very important point, thanks to this feedback, I could work on which subjects more. (S77)
>
> I preferred Questions and the General result feedback type.
>
> …
>
> My reason for not choosing the situation within the group; more precisely, the reason why I prefer it primarily; I cannot compete with a group without completing my shortcomings; so if I have too many weaknesses, my position in the group may be distracting me from the subject. (S49)

Another question in the form is “If you had only one feedback choice, which would it be?”. When the answers given to this question were examined, it was seen that three master students preferred the general result (criterion-referenced) feedback, two master students preferred questions feedback (elaborated feedback), and five non-master students preferred the questions (elaborated) feedback.

4 Discussion and Conclusion

Feedback is an essential part of the formative assessment. In meta-analysis studies on learning, it was discovered that feedback has a significant effect on learning (Hattie & Timperley, 2007; Wisniewski et al., 2020). Therefore, effective feedback design has been studied extensively. While research on how to produce effective feedback is a common focus, it is also necessary to examine learners’ interaction with feedback. In this way, further suggestions for feedback design can be obtained.

With recent developments in technology, patterns can be found in learners’ interactions with the system, as well as through the examination of learners’ interaction with student-facing dashboards that present these patterns. In this study, the learners’ navigation sequences in dashboards based on assessment analytics were examined. The first finding was that the students participating in the research followed the order given by the researchers in design (CRF-EF-SRF-NRF). Learners visited all types of feedback. In the study conducted by Mensink and King (2020), it was reported that if grades could be seen in a system module, most of the students looked at the grade but did not open the elaborated feedback file. A similar situation was reported in the study by Winstone et al. (2020). Assessment tasks in these studies were performance-based, and this might be the reason for the difference in transition behavior. In this respect, it can be said that there is a need to examine learner behaviors in terms of various assessment tasks, feedback types, and dashboard design. In this study, the test-based assessment feedback order was created as CRF-EF-SRF-NRF. In general, students followed this existing order. It is possible that learners’ transitions may differ in systems where the indicators were shown in an alternate order. Moreover, students may even be allowed to make their own dashboard designs, and their transitions could also be investigated.

Within the system’s scope, descriptive analytics level feedback was presented, and pie charts and line graphs were used in this context. Information designers have experimented with variations on these graphics (Skau & Kosara, 2016) that have been in use for 200 years. Accordingly, learner behaviors can be compared in dashboards where different types of graphics are used.

The second research finding was that there was a difference in transition between the types of feedback in master and non-master students. Both master and non-master students tended to follow the existing design linearly. However, there was a significant transition between NRF and SRF in non-master students' transitions. Non-master students' transitions between NRF and SRF might be an indicator of avoiding seeing their position in the group. However, in the study conducted by Kia et al. (2020), it was found that low-achieving students visited NRF more. From this point, it can be said non-master students' behavior should be examined in detail. It can also be stated that when it comes to developing a standard learning panel, CRF-EF and NRF-SRF should exist together.

When the learners' statements were examined, it became apparent that they visited each type of feedback in a way that supports LSA results. Depending on the literature (Chan & Lam, 2010; Guerra et al., 2016; Jivet et al., 2018; Shute, 2008; Teasley, 2017), it was expected that non-master students in particular would not visit/would rarely visit norm-referenced feedback. However, according to the results of the research, both master and non-master students visited the norm-referenced feedback. That said, visiting norm-referenced feedback does not mean that the student is positively influenced by this comparison. One of the non-master student's statements showed that he/she avoided visiting the group-comparison panel. As stated before, there was a significant transition from NRF to SRF. This situation may be related to learners' goal orientation. Recently, in studies on feedback, it is stated that learners' interactions with feedback can be shaped according to their goal orientation (VandeWalle, 2003; Janssen & Prins, 2007; Runhaar et al., 2010; Winstone et al., 2019). Based on this, behavior modeling studies regarding the goal orientation characteristics of learners are needed.

There are some limitations in the research. First, the participants of the research included those in a single associate degree program. Second, students' computer and internet knowledge and skills were not assessed. Therefore, the results should be carefully interpreted while keeping these limitations in mind. Moreover, e-test applications are a type of e-assessment, and, in general terms, e-assessment can be considered within the scope of preparing, displaying, applying, and scoring an assessment task in technologically supported environments. Accordingly, e-assessment can be handled with various applications such as synchronous-asynchronous, cooperative-individual, etc. (Bayrak & Yurdugül, 2015). Assessment analytics were limited with test and item results within the scope of this study. In addition, Ellis (2017) examined the e-portfolio process and Misiejuk et al. (2021) examined the peer feedback process. In this respect, other dimensions should also be examined within the scope of assessment analytics.

Integrating visuals related to the student feedback and interaction patterns into the teacher and student systems would assist teachers in making decisions about the feedback and how to further guide students. However, it should be emphasized that the users must have the necessary literacy (data and graph literacy; Sansom et al., 2020) to make sense of visuals.

References

Aguilar, S. J. (2018). Examining the relationship between comparative and self-focused academic data visualizations in at-risk college students' academic motivation. *Journal of Research on Technology in Education, 50*(1), 84–103. https://doi.org/10.1080/15391523.2017.1401498

Ahokas, T. (2008). *Information visualization in a business decision support system*. Master thesis, University of Helsinki, Finland.

Allen, M. (Ed.). (2017). *The Sage encyclopedia of communication research methods*. Sage.

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis*. Cambridge University Press.

Bakeman, R., Mcarthur, D., & Quera, V. (1996). Detecting group differences in sequential association using sampled permutations: Log odds, kappa, and phi compared. *Behavior Research Methods, Instruments, & Computers, 28*(3), 446–457. https://doi.org/10.3758/BF03200524

Bayrak, F., & Yurdugül, H. (2015). E-assessment and E-feedback [E-değerlendirme ve E-dönüt]. In B. Akkoyunlu, A. İşman & F. Odabaşı (Eds.), *Technology readings in education* [Eğitim Teknolojileri Okumaları] (pp. 448–467) TOJET – Sakarya University.

Bodily, R., Ikahihifo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598. https://doi.org/10.1007/s12528-018-9186-0

Brookhart, S. M. (2008). *How to give effective feedback to your students*. ASCD.

Carless, D. (2007). Learning-oriented assessment: Conceptual bases and practical implications. *Innovations in Education and Teaching International, 44*(1), 57–66. https://doi.org/10.1080/14703290601081332

Carless, D. (2015). Exploring learning-oriented assessment processes. *Higher Education, 69*(6), 963–976. https://doi.org/10.1007/s10734-014-9816-z

Chan, J. C., & Lam, S. F. (2010). Effects of different evaluative feedback on students' self-efficacy in learning. *Instructional Science, 38*(1), 37–58. https://doi.org/10.1007/s11251-008-9077-2

Charleer, S., Klerkx, J., Santos, J. L., & Duval, E. (2013). *Improving awareness and reflection through collaborative, interactive visualizations of badges*. In ARTEL@ EC-TEL Proceedings of the 3rd workshop on awareness and reflection in technology-enhanced learning, 1103, pp. 69–81.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5–6), 318–331.

Cooper, A. (2015). *Assessment analytics*. In Eunis Elearning task force workshop. Retrieved from https://dspacecris.eurocris.org/bitstream/11366/559/1/12%20Adam%20Cooper%20EUNIS%202015%20ELTF%20Workshop.pdf

Ellis, C. (2013). Broadening the scope and increasing the usefulness of learning analytics: The case for assessment analytics. *British Journal of Educational Technology, 44*(4), 662–664. https://doi.org/10.1111/bjet.12028

Ellis, C. (2017). The importance of E-portfolios for effective student-facing learning analytics. In T. Chaudhuri & B. Cabau (Eds.), *E-portfolios in higher education, a multidisciplinary approach* (pp. 35–49). Springer.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117–140.

Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers & Education, 57*(4), 2333–2351. https://doi.org/10.1016/j.compedu.2011.06.004

Guerra, J., Hosseini, R., Somyurek, S., & Brusilovsky, P. (2016, March). *An intelligent interface for learning content: Combining an open learner model and social comparison to support self-regulated learning and engagement*. In Proceedings of the 21st international conference on intelligent user interfaces, pp. 152–163.

Hamilton, L. S., Klein, S. P., & Lorie, W. (2000). *Using web-based testing for large-scale assessments*. RAND.

Hattie, J., & Gan, M. (2011). Instruction based on feedback. In R. E. Mayer & P. A. Alexander (Eds.), *Handbook of research on learning* (pp. 249–271). Routledge.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*, 81–112. https://doi.org/10.3102/003465430298487

Hwang, G. J., Wang, S. Y., & Lai, C. L. (2021). Effects of a social regulation-based online learning framework on students' learning achievements and behaviors in mathematics. *Computers & Education, 160*, 104031. https://doi.org/10.1016/j.compedu.2020.104031

Janssen, O., & Prins, J. (2007). Goal orientations and the seeking of different types of feedback information. *Journal of Occupational and Organizational Psychology, 80*(2), 235–249. https://doi.org/10.1348/096317906X103410

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). *License to evaluate: Preparing learning analytics dashboards for educational practice*. In Proceedings of the 8th international conference on learning analytics and knowledge, pp. 31–40.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Kia, F. S., Teasley, S. D., Hatala, M., Karabenick, S. A., & Kay, M. (2020). *How patterns of students dashboard use are related to their achievement and self-regulatory engagement*. In Proceedings of the tenth international conference on learning analytics & knowledge, pp. 340–349.

Kokoç, M., & Altun, A. (2021). Effects of learner interaction with learning dashboards on academic performance in an e-learning environment. *Behaviour & Information Technology, 40*(2), 161–175. https://doi.org/10.1080/0144929X.2019.1680731

Marono, A., Clarke, D. D., Navarro, J., & Keatley, D. A. (2018). A sequence analysis of nonverbal behaviour and deception. *Journal of Police and Criminal Psychology, 33*(2), 109–117. https://doi.org/10.1007/s11896-017-9238-9

Mensink, P. J., & King, K. (2020). Student access of online feedback is modified by the availability of assessment marks, gender and academic performance. *British Journal of Educational Technology, 51*(1), 10–22. https://doi.org/10.1111/bjet.12752

Misiejuk, K., Wasson, B., & Egelandsdal, K. (2021). Using learning analytics to understand student perceptions of peer feedback. *Computers in Human Behavior, 117*, 106658. https://doi.org/10.1016/j.chb.2020.106658

Mok, M. M. C. (Ed.). (2013). *Self-directed learning oriented assessments in the Asia-pacific*. Routledge.

Mumm, J., & Mutlu, B. (2011). Designing motivational agents: The role of praise, social comparison, and embodiment in computer feedback. *Computers in Human Behavior, 27*(5), 1643–1650. https://doi.org/10.1016/j.chb.2011.02.002

Nouira, A., Cheniti-Belcadhi, L., & Braham, R. (2019). An ontology-based framework of assessment analytics for massive learning. *Computer Applications in Engineering Education, 27*(6), 1343–1360. https://doi.org/10.1002/cae.22155

Papamitsiou, Z., & Economides, A. A. (2016). An Assessment Analytics Framework (AAF) for enhancing students' progress. In S. Caballé & R. Clarisó (Eds.), *Formative assessment, learning data analytics and gamification* (pp. 117–133). Academic Press.

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110. http://www.jucs.org/doi?doi=10.3217/jucs-021-01-0110

Pohl, M., Wallner, G., & Kriglstein, S. (2016). Using lag-sequential analysis for understanding interaction sequences in visualizations. *International Journal of Human-Computer Studies, 96*, 54–66. https://doi.org/10.1016/j.ijhcs.2016.07.006

Runhaar, P., Sanders, K., & Yang, H. (2010). Stimulating teachers' reflection and feedback asking: An interplay of self-efficacy, learning goal orientation, and transformational leadership. *Teaching and Teacher Education, 26*(5), 1154–1161. https://doi.org/10.1016/j.tate.2010.02.011

Şahin, M., Keskin, S., & Yurdugül, H. (2020). Sequential analysis of online learning behaviors according to E-learning readiness. In P. Isaias, D. G. Sampson, & D. Ifenthaler (Eds.), *Online teaching and learning in higher education* (pp. 117–131). Springer.

Sansom, R. L., Bodily, R., Bates, C. O., & Leary, H. (2020). Increasing student use of a learner dashboard. *Journal of Science and Educational Technology, 29*, 386–398. https://doi.org/10.1007/s10956-020-09824-w

Santos, J. L., Verbert, K., & Duval, E. (2012, September). Empowering students to reflect on their activity with StepUp!: Two case studies with engineering students. In *ARTEL@ EC-TEL* (pp. 73–86).

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189. https://doi.org/10.3102/0034654307313795

Silius, K., Miilumäki, T., Huhtamäki, J., Tebest, T., Meriläinen, J., & Pohjolainen, S. (2010). Students' motivations for social media enhanced studying and learning. *Knowledge Management & E-Learning: An International Journal, 2*(1), 51–67.

Skau, D., & Kosara, R. (2016, June). Arcs, angles, or areas: Individual data encodings in pie and donut charts. *Computer Graphics Forum, 35*(3), 121–130.

Teasley, S. D. (2017). Student facing dashboards: One size fits all? *Technology, Knowledge and Learning, 22*(3), 377–384. https://doi.org/10.1007/s10758-017-9314-3

Thelwall, M. (2000). Computer-based assessment: A versatile educational tool. *Computers & Education, 34*(1), 37–49. https://doi.org/10.1016/S0360-1315(99)00037-8

VandeWalle, D. (2003). A goal orientation model of feedback-seeking behavior. *Human Resource Management Review, 13*(4), 581–604.

Vigentini, L., Clayphan, A., Zhang, X., & Chitsaz, M. (2017). Overcoming the MOOC data deluge with learning analytic dashboards. In A. Peña-Ayala (Ed.), *Learning analytics: Fundaments, applications, and trends* (pp. 171–198). Springer.

Wilbert, J., Grosche, M., & Gerdes, H. (2010). Effects of evaluative feedback on rate of learning and task motivation: An analogue experiment. *Learning Disabilities: A Contemporary Journal, 8*(2), 43–52.

Winstone, N. E., Hepper, E. G., & Nash, R. A. (2019). Individual differences in self-reported use of assessment feedback: The mediating role of feedback beliefs. *Educational Psychology*, 1–19. https://doi.org/10.1080/01443410.2019.1693510

Winstone, N., Bourne, J., Medland, E., Niculescu, I., & Rees, R. (2020). "Check the grade, log out": Students' engagement with feedback in learning management systems. *Assessment & Evaluation in Higher Education*, 1–13. https://doi.org/10.1080/02602938.2020.1787331

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In Proceedings of the fourth international conference on learning analytics and knowledge (pp. 203–211).

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology, 10*, 3087. https://doi.org/10.3389/fpsyg.2019.03087

Yera, A., Muguerza, J., Arbelaitz, O., Perona, I., Keers, R., Ashcroft, D., ... & Vigo, M. (2018, April). *Inferring visual behaviour from user interaction data on a medical dashboard*. In Proceedings of the 2018 international conference on digital health, pp. 55–59.

Yiğitbasıoğlu, O. M., & Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems, 13*(1), 41–59. https://doi.org/10.1016/j.accinf.2011.08.002

Zhang, J. H., Zhang, Y. X., Zou, Q., & Huang, S. (2018). What learning analytics tells us: Group behavior analysis and individual learning diagnosis based on long-term and large-scale data. *Journal of Educational Technology & Society, 21*(2), 245–258. https://www.jstor.org/stable/26388404

Chapter 13
Development and Evaluation of a Student-Facing Gamified Learning Analytics Dashboard

Gökhan Akçapınar and Mohammad Nehal Hasnine

1 Introduction

In learning analytics, a dashboard is an important element for sense-making. According to Schwendimann et al. (2016), a learning analytics dashboard is *a single display that aggregates multiple visualizations of different indicators about learner(s), learning process(es), and/or learning context(s).* A learning analytics dashboard, often addressed as LAD, provides a visual representation of the valuable information required to achieve learning goals, consolidated and arranged on a single screen so the information can be monitored at a glance (Teasley, 2017). Most of the dashboards are built in a combination of educational data mining techniques and information visualization techniques (Verbert et al., 2014). So far, it has been used as the most common learning analytics intervention for the stakeholders (i.e., students, teachers, policy-makers). The objectives of developing LADs in the educational contexts include offering students with a tangible reference to their learning process which could support in self-regulated learning (Molenaar et al., 2020; Roll & Winne, 2015; Winne & Baker, 2013); presenting data through various visualizations techniques, such as graphs, gauges, dials, and maps (Baker, 2007; Schwendimann et al., 2016); making data actionable by analyzing and representing it in meaningful ways to various stakeholders (Sutherland et al., 2012); connecting various data sources including resource use, social interactions, and time spent in one place (Broos et al., 2018; Verbert et al., 2014); empowering students and

G. Akçapınar (✉)
Hacettepe University, Ankara, Turkey
e-mail: gokhana@hacettepe.edu.tr

M. N. Hasnine
Hosei University, Tokyo, Japan
e-mail: nehal.hasnine.79@hosei.ac.jp

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_13

educators in making informed decisions about the learning process (Jivet et al., 2018); improving students' engagement during face-to-face lectures (Barr & Gunawardena, 2012); improving balance in group work (Martinez Maldonado et al., 2012); supporting students about the awareness of time and resource while using blended or online learning environments (Govaerts et al., 2012); and supporting the dialogue between teachers and students (Carless & Boud, 2018).

Although the benefits of using LADs are proved (Bodily et al., 2018; Verbert et al., 2013), the low usage of these systems is one of the critical problems addressed in literature (Bodily et al., 2018; Bodily & Verbert, 2017). In a recent literature review of student-facing LADs, the researchers reviewed 93 articles and found that the articles reported around 30% of students access to LAD on average (Bodily & Verbert, 2017). Lack of motivation is one of the reasons behind the low use of LADs (Kim et al., 2016). Therefore, new methods should be examined to keep students motivated to engage with LADs (Bodily et al., 2018).

Gamification is an effective method to increase student success, motivation, and engagement in learning environments. Therefore, in this chapter, it is aimed to design a LAD that includes gamification elements to increase students' motivation towards using LAD. The focus of this chapter is to explain the design and development process of a gamified LAD and, furthermore, to evaluate students' perceptions related to developed LAD from the Gamification Acceptance Model's aspects. Students' LAD interactions were also analyzed to get an insight into their actual usage behaviors.

The rest of the chapter is organized as follows: The second section includes studies on the student-facing dashboard, current problems related to LADs, and studies on gamification in education. In the third section, the design and development process of LAD is explained. In the fourth section, the method of the evaluation study is explained. In the fifth section, the results of the evaluation study are presented. In the last section, a comprehensive discussion and conclusion are articulated.

2 Background

2.1 Student-Facing LADs

The LADs developed for students often refer to the student-facing dashboards. The purpose of developing student-facing dashboards is to represent data about the learning process to students and allow them to be actionable decision-makers. In recent years, student-facing dashboards have gained an increasing amount of attention (Teasley, 2017), and therefore, the development of student-facing dashboards that address the needs and issues of the students (Bodily et al., 2018) has become mainstream research for learning analytics. REX (Results of EXaminations) is student-facing dashboard capable of providing feedback on academic achievement (Broos et al., 2017). This dashboard is meant to be supporting freshman year students in a STEM program. In designing the REX dashboard, the key principle followed was actionable feedback to the students. Moreover, the designing principles were to have a consistent and simple design. Students found the earlier edition of the REX dashboard useful (71% out of 167 respondents) and clear (89%). Also, 81% of 1406 students who used the dashboard achieved higher scores on average for each of the LASSI (Learning and Study Strategies Inventory) scales. As for the REX dashboard usage, students kept using it as the dashboard provides students with feedback on their academic achievement after each examination period, although some freshman year students found it difficult to interpret their results on the REX dashboard (Broos et al., 2020). NoteMyProgress (Pérez-Álvarez et al., 2017) is a student-facing dashboard that helps students in tracking how they spend time in a course. StepUp (Santos et al., 2013) is another addition to the student-facing dashboard that promotes students' reflection by comparing their learning activities with the peers in open learning environments. E2Coach (McKay et al., 2012), a student-facing dashboard, assists students in passing difficult courses by acquainting them with the feedback and study habits/strategies of previously successful students. Degree Compass (Denley, 2013) is a dashboard for assisting students in enrolling courses where they are more likely to succeed by studying the demographics, academic preparation, final grades, and course registration choices of past students. LAView is another example of a student-facing dashboard developed especially for e-book-based learning (Majumdar et al., 2019).

In the last decade, many LADs are built and tested in educational contexts. However, there are many issues related to these dashboards that are yet to tackle. Not all LADs developed so far are useful for learning (Tan et al., 2017). Another issue that suppresses the impact of LADs is low student access. Bodily and Verbert (2017) reported 30% as the average students' access rate to LADs based on their review study. In a recent large-scale study with the participation of 860 students, it was stated that 48% of the students did not access the dashboard even once (Kia et al., 2020). Robert Bodily et al. (2018) reported that only 25% of students used the dashboard multiple times, despite the majority of students found it user-friendly, engaging, informative, and useful.

This chapter addresses the low usage problem related to the conventional LADs. To address the issue, a LAD is developed using gamification mechanics to increase students' motivation towards using LAD. Students' perceptions about LAD were analyzed according to the Gamification Acceptance Model components. The LAD's usage data were also analyzed to observe the actual usage by the students.

2.2 Gamification in Education

Gamification is defined as using game elements in non-game environments to motivate people in engaging with non-game contexts (Deterding et al., 2011). Although it is not a new term (Simões et al., 2013), recent studies show its advantages of using in different settings, including educational environments (Akçapınar & Uz Bilgin, 2020; da Rocha Seixas et al., 2016; Özhan & Kocadere, 2020; Uz Bilgin & Gul, 2020), corporate settings (Armstrong & Landers, 2017), and health settings (Janssen et al., 2016).

Bunchball (2010) proposed a framework for gamification and its mechanics. Game mechanics include points, levels, leaderboards, or gifts found in typical computer games. Game mechanics trigger players' emotions that motivate them to play, which are labeled as game dynamics. Game dynamics include status, achievement, competition, etc. (Bunchball, 2010). As gamification became popular in different settings, misconceptions about this approach increased too. Kapp (2012) claimed that badges, points, or levels are not the essential elements of gamification – the most important features of the gamification approach are problem-solving, engagement, and challenge. Simões et al. (2013) suggested the following gamification guidelines to create engaging experiences in learning environments: break tasks into sub-tasks, give different ways to accomplish tasks, and change the complexity of tasks according to learners' skill levels. Czikszentmihalyi's (1990) flow theory also claims that there should be a balance between skills and challenge. This balance makes individuals to be in the state of flow or immersed in the game. Using these gamification elements in learning environments led to promising results in terms of engagement (Çakıroğlu et al., 2017; da Rocha Seixas et al., 2016), motivation (Leaning, 2015), and academic achievement (de Marcos et al., 2014).

In this regard, recent studies combined gamification with learning analytics to promote academic achievement, engagement, and motivation (Cassano et al., 2019; Jen-Wei & Hung-Yu, 2016; Klemke et al., 2018; Şahin & Yurdugül, 2019). Our previous study also compared a non-gamified LAD versus a gamified LAD (Akçapınar & Uz Bilgin, 2020). We found that adding game elements to the student-facing LAD significantly increased students' overall interactions inside a learning management system. Klemke et al. (2018) combined the motivation aspect of gamification elements and data-driven learning analytics solutions to propose a new model. This model suggests that there should be a shift from extrinsic motivation elements (badges, points, and levels) to intrinsic motivation elements (engagement, community-building, and personalization) of gamification, and they used learner-generated data in order to promote these intrinsic motivation elements. In the study of Cassano et al. (2019), points, levels, and badges were used to motivate students to participate in activities including reading a wiki page, publishing post, liking posts, commenting on posts, and creating and editing wiki pages. Researchers found promising results in terms of usability and acceptance of this gamified system.

3 Design and Implementation

This section explains the system architecture and the elements of the LAD developed using game mechanics. Student-facing LADs typically present data related to students' activity with online tools (e.g., overall LMS activity, forum usage, etc.) and performance data such as grades shown in comparison to their peers (Teasley, 2017). LADs are expected to improve students' performance by supporting their awareness, self-reflection, and sense-making (Verbert et al., 2013). Therefore, self-regulation (Butler & Winne, 1995) and social comparison (Festinger, 1954) theories are commonly used while designing dashboard elements (Teasley, 2017). In addition to these theories, motivational factors and gamification mechanics were also considered while designing dashboard elements.

3.1 System Architecture

The architecture of the developed system is shown in Fig. 13.1. The system works with Moodle learning management system. Moodle records all types of student interaction in the database. The developed system captures learners' data from Moodle's database. Based on the Moodle logs, metrics and analytics are calculated. In this step, the developed analytics engine analyzes the data it receives from the Moodle database with machine learning methods and saves the results back to the Moodle's database. The dashboard is designed as the intervention of the system. It can be accessed from Moodle course. The main objective of the dashboard is to share analytics results with students and instructors. The dashboard is mainly developed for students, but instructors can also see class-level metrics and analytics through the dashboard.

The dashboard was developed using the ASP.Net Core MVC framework and deployed on the same server as Moodle learning management system. Thus, it can get the data directly from the Moodle database. The server-side, which is responsible for creating, reading, updating, and deleting data from the database, has been

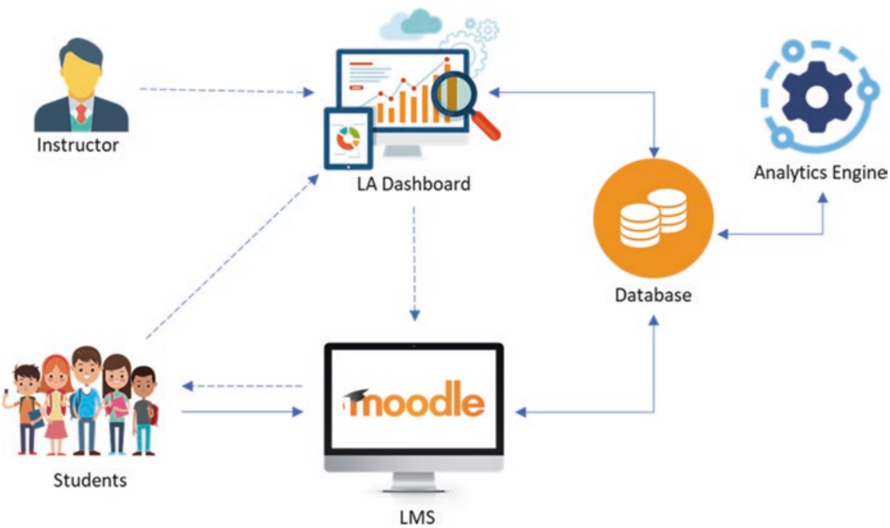


Fig. 13.1 Overview of the system

developed as a Web API. Machine learning analyses were carried out using the R statistical programming language.

The analytics engine runs once a week and updates related tables in the database. Other information is accessed directly from the Moodle logs. The system uses regression models for score prediction. Because of the "one size does not fit all" problem in machine learning, regression models were generated for each course. The steps followed in the process of producing course-specific prediction models are summarized as follows: (1) Students' midterm scores are used as a target variable; features extracted from Moodle logs are used as a predictor. (2) Regression models are trained by using Random Forest (RF), Gradient Boosting Machine (GBM), and k-Nearest Neighbors (kNN) algorithms. (3) Tenfold cross-validation is used as a sampling method. (4) Best performed model is selected based on the R-squared and Root Mean Square Error (RMSE) metrics and saved for further use.

3.2 Elements of the Dashboard

The current version of the dashboard has six elements to give feedback to students about their learning performance. The following course components were considered while designing the dashboard: Assignment, Discussion, Quiz, Session, and Activity. For the gamification purpose, students' learning logs related to those components were converted into standard scores using the percentile ranking method. Percentile ranking was used for the following reasons: first, to normalize scores between 0 and 100 and, second, to generate comparable scores. For example, if a student gets 70 points from the activity metric, it can be interpreted as she/he performed more activities on the system than 70% of his or her classmates. A list of calculated scores and their descriptions is presented in Table 13.1.

Table 13.1 Calculated scores used in the dashboard elements and descriptions

Name	Description	Used dashboard elements	Calculation method	Range
Assignment	Whether a student submits his/her assignments or not	Notification panel, activity radar	Percentile rank	0–100
Discussion	Number of times that a student posts a question or an answer to the weekly forum	Notification panel, activity radar	Percentile rank	0–100
Quiz	The score obtained from the weekly quiz	Notification panel, activity radar	Percentile rank	0–100
Session	Number of days that student logs in to the system	Notification panel, activity radar	Percentile rank	0–100
Activity	Total number of interactions done by the student	Notification panel, activity radar	Percentile rank	0–100
Overall	Arithmetic means of assignment, discussion, quiz, session, and activity scores	Notification panel, leaderboard	Percentile rank	0–100

The dashboard includes the following game mechanics: (1) point, (2) progress bar, and (3) leaderboard. Calculated scores were used to feed the notification panel, activity radar, and leaderboard. The scores are updated once a week and calculated by considering the interactions of students in the last 7 days. By limiting the data to the last 7 days, students are given a chance to get high scores each week. In this way, it is aimed to minimize the negative effects that gamification can cause on low-performing students. Daily activity chart and forum activity panel show real-time data related to students' activities in the last 7 days. The prediction panel is updated once a week and shows students' end-of-year grade predictions. Therefore it counts all the accumulated data. Details of the dashboard elements are as follows:

3.2.1 Notification Panel

The notification panel is designed to inform students about their weekly performance. When students click on Notifications, they encounter the panel shown in Fig 13.2a. Students' standardized scores for their interactions in the past week are presented under six different categories on this panel. These categories are Assignment, Discussion, Quiz, Session, Activity, and Overall Score (see Table 13.1 for details). At the same time, students can see their rank among their classmates in

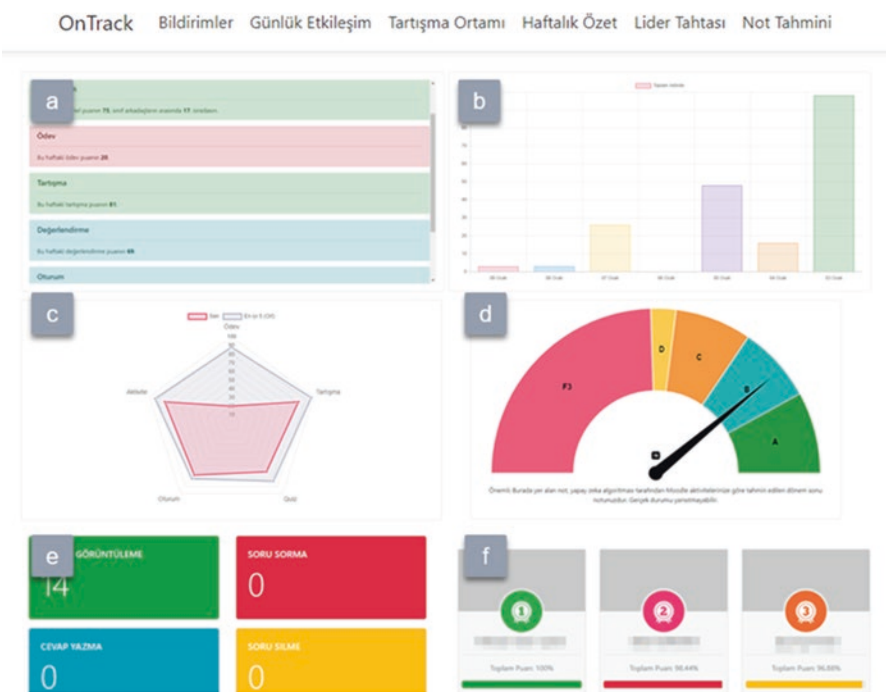


Fig. 13.2 OnTrack: gamified learning analytics dashboard

the Overall Score category. Since the percentile rank method is used to calculate the scores, the scores here also provide information about the rank of the students in the classroom. For example, if the student scores 80 in the Discussion category, this means that the student's rank is higher than 80% of his/her classmates. By looking at the notifications, the student can see the categories with which his/her score being low.

3.2.2 Daily Activity Chart

In the daily activity graph presented in Fig. 13.2b, the number of interactions the student has performed in Moodle in the last 7 days is shown daily. In this way, the student can see how active she/he is in the learning environment during the week. This graph gets data directly from Moodle's log table. Therefore, it shows up-to-date data all the time.

3.2.3 Activity Radar

Similar to the notification panel, in activity radar, students can also see their calculated scores for each category. Differently, they can also see average scores of the top five students in the class for the week. The graph is organized as a radar chart (as shown in Fig. 13.2c) so students can easily compare their scores with the best-performing students.

3.2.4 Prediction Panel

The dashboard contains a prediction panel where students can see their end-of-year *grade predictions*. When the student opens the Grade Prediction panel, a similar visualization as Fig. 13.2d is displayed. In this visualization, the numerical value of the student's final grade and the letter equivalent of this value are shown. The grade predictions are updated weekly by considering all previous activities on the learning management system. Using the Grade Prediction panel, students can receive feedback on their long-term performance in the course. Pre-developed regression models are used to support this panel. An informative text was added to the students stating that the predictions given on this panel are for informative purposes and may not reflect the real situation.

3.2.5 Forum Activity

On the forum activity page (refer to Fig. 13.2e), information about the activities in the discussion environment over the last 7 days is presented. This information is as follows: the number of post views in the discussion environment, the number of posts created, the number of answers written, and the number of deletions. In this way, the student can track how active she/he is in the discussion environment. The data is getting directly from Moodle's log table. Therefore, it shows up-to-date data all the time.

3.2.6 Leaderboard

Here, the names and scores of the first three students who got the highest score according to the overall score are listed (see Fig. 13.2f).

4 Evaluation Study

4.1 Learning Design and Data Collection Process

An evaluation study was carried out to understand students' perceptions of the developed LAD. The study was carried out in the Computer Hardware course designed for sophomores (N = 64) enrolled at a public university in Turkey. The course, which is normally carried out face-to-face, was carried out over the Moodle learning management system with the distance education method due to the COVID-19 pandemic. During the 15-week course, a live session was held with the students once a week. All activities other than this were carried out asynchronously. Asynchronous activities are planned weekly and consist of assignments, forums, course resources, and quizzes. The dashboard was introduced to students in the sixth week of the course and they were allowed access until the end of the term. At the end of 9 weeks of use, students' views on the dashboard were collected and analyzed together with the usage data. Guidelines on the interpretation of the scores, dashboard elements, and how to get scores were explained beforehand to the students.

4.2 Data Collection Tools

To measure students' perceptions related to the gamified dashboard, the Gamification Acceptance Model (GAM) survey developed by Ab. Rahman et al. (2018) was used. The GAM survey consists of 18 items. The survey measures students' engagement (seven items), perceived usefulness (four items), perceived ease of use (four items), and attitude towards using gamification technology (three items). All items used a 5-point Likert scale option ranging from 1 (strongly disagree) to 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree). Sample items from the survey can be seen in Table 13.2. In addition to the GAM survey,

Table 13.2 Sample items from the Gamification Acceptance Model (GAM) survey (Ab. Rahman et al., 2018)

Category	Survey item
Perceived usefulness	Using the gamified dashboard improves my learning performance
	Using the online gamification system is useful in my learning
Perceived ease of use items	The online gamification functionality and interface is clear and understandable
	Overall, I believe that the online gamification system is easy to use
Attitude	I think that using online gamification system is a good idea
	I like learning with online gamification system
Skill engagement	Online gamification system encourages me in taking good notes in classroom
	Online gamification system encourages me in making sure to study on regular basis
Interaction engagement	Online gamification system contributes to me in having fun in the classroom
	Online gamification system contributes to me in asking questions when I did not understand the lecturer

students' perceptions regarding the usefulness of each dashboard element were collected.

Dashboard usage data of the students were taken from the database of the system. Click-stream data were aggregated to analyze students' daily activities in the system. Analysis of the data was carried out using R (R Core Team, 2017) software.

5 Results and Discussion

Three out of 64 students never logged in to the Moodle environment where the lessons were conducted. Fifty-nine out of the remaining 61 students participated in the course activities and took the final exam. Fifty-six students answered the questionnaire. In this section, the results of the data analysis are explained.

5.1 Analysis of the Self-Report Data

Students were asked how often they visited the dashboard. Only 1 of the 56 students answered the questionnaire stating that she/he never used the dashboard. 16% of the students stated that they visited the dashboard at least once a day, whereas 75% said they accessed the dashboard several times a week. 7% of the students mentioned that they visited a few times a semester. The distribution of students' responses for each sub-scale of GAM can be seen in Table 13.3 and Fig. 13.3.

Table 13.3 Distribution of students' responses for each sub-scale

Sub-scale	Mean (SD)	Strongly disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly agree (%)
Perceived ease of use	4.82 (0.43)	0.0	0.0	1.8	14.3	83.9
Attitude	4.61 (0.62)	0.0	0.0	7.1	25.0	67.9
Perceived usefulness	4.21 (0.73)	0.0	0.0	17.9	42.9	39.3
Engagement	3.88 (0.76)	0.0	3.6	25.0	51.8	19.6

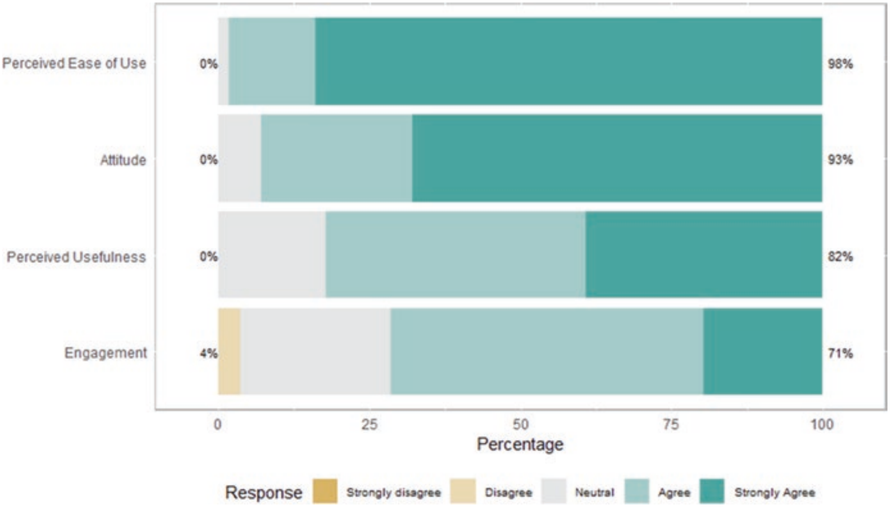


Fig. 13.3 Analysis of students' responses

5.1.1 Perceived Ease of Use

Analysis on the perceived ease of use variable presented in Table 13.3 suggests that, overall, the students strongly agree on the ease of use of the gamified LAD used in this study. Students' mean score for the perceived ease of use is 4.82. Table 13.3 and Fig. 13.3 show the distribution of students' responses for each category. 1.8% of the students are neutral on the ease of use of the gamified LAD, whereas 98.2% of the students agreed and strongly agreed that the gamified LAD was easy to use.

5.1.2 Attitude Towards Using the Gamified LAD

Table 13.3 shows the analysis of students' attitudes towards using gamified LAD. The mean value of 4.61 depicted in Table 13.3 points to the overall students' attitude towards using a gamified LAD between agree and strongly agree.

Table 13.3 and Fig. 13.3 revealed that 7.1% of the students were neutral on their attitude towards using gamified LAD while the other 92.9% of students agreed or strongly agreed on their attitude towards using gamified LAD. Students showed a very positive attitude towards the use of gamified LAD in their online classes.

5.1.3 Perceived Usefulness

Analysis on the perceived usefulness variable is shown in Table 13.3. The analysis indicates that the students agree on the ease of use of the gamified LAD used in this study. The mean score for the perceived usefulness is 4.21. Table 13.3 and Fig. 13.3 show the distribution of the students' answers for each option. 17.9% of the students are neutral on the usefulness of the gamified LAD, whereas 82.2% of the students agreed and strongly agreed that the gamified LAD was useful.

Students were also asked how useful they found each element presented on the dashboard using the Likert scale between 1 and 10 (1, not very useful; 10, very useful). Interpreting the results from Fig. 13.4, it was found that 88% of the students rated 6 and above for the forum activity and notification panel. These are respectively followed by grade prediction, activity radar (summary chart), daily activity, and leaderboard. The element found to be less useful was the leaderboard. Regarding the leaderboard, it is seen that 28% of the students rated 5 or less. When average scores are taken into consideration, the grade prediction obtained the highest score.

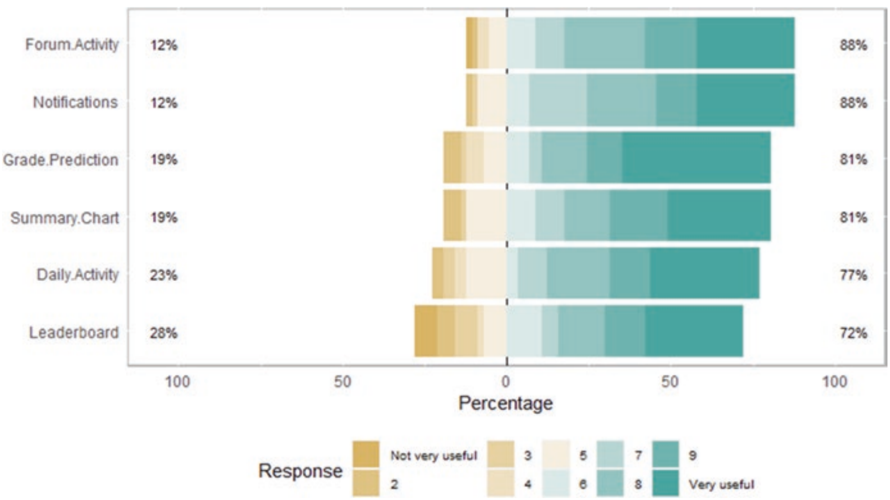


Fig. 13.4 Students' perceptions regarding the usefulness of the dashboard elements

5.1.4 Student Engagement

Table 13.3 shows the analysis of students' engagement with the gamified LAD. The mean value of 3.88 depicted in Table 13.3 points to the overall students who agreed on the engagement when using the gamified LAD. According to Table 13.3 and Fig. 13.3, 3.6% of the students disagree in regard to their engagement when using the gamified LAD, while 25.0% of the students were neutral, 51.8% of students agreed, and 19.6% strongly agreed on their engagement in learning when using the gamified LAD.

5.2 Analysis of the Students' Dashboard Usage Data

In addition to the self-report data, the dashboard usage data of the students were analyzed. The data presented visually in Fig. 13.5 show the number of students visiting the dashboard daily. It is observed that the number of students visiting the dashboard increased on the days when the data was updated (peaks in the graphs). Interaction data indicated that students perform an average of 240 daily activities on the dashboard. This number changed between 800 and 1000 on the days the data was updated.

According to the students' access data, the highest number of unique access (n = 55) was recorded on the first day when the dashboard was introduced. While it is observed that an average of 20 students visit the dashboard on the other days, this number changes between 40 and 50 on the days when updates are available.

Figure 13.6 shows the total number of days that students visited the dashboard. The dashboard was available to the students 9 weeks (64 days) out of the 15-week-long course. Students' access range has changed from 1 day to 57 days. Apart from two students, all students accessed the dashboard at least 1 day (97%). 82% of the students accessed more than 10 days, and 60% accessed more than 20 days.

Relationships between self-report and behavioral data were analyzed with Pearson's correlation analysis. The number of days that students accessed the

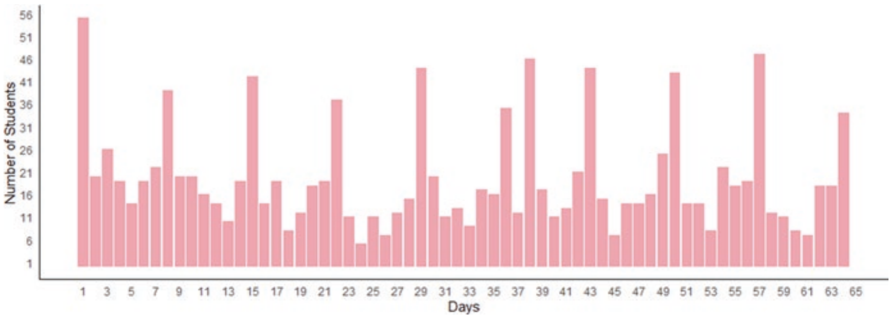


Fig. 13.5 Number of students' access to the LAD daily

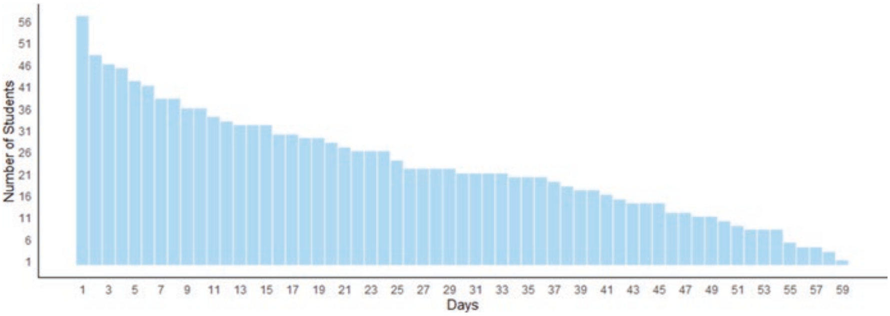


Fig. 13.6 Number of days that students access to the LAD

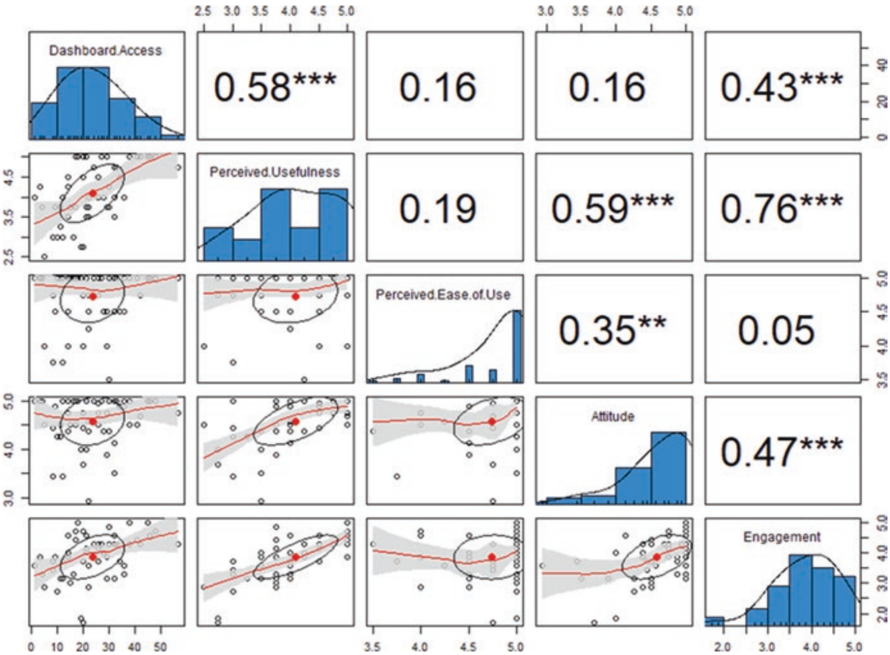


Fig. 13.7 Associations between self-report and behavioral data

dashboard was taken as behavioral data. As self-report data, students' average scores from each sub-scale of the GAM were taken into account. When interpreting the results presented in Fig. 13.7, statistically significant and moderate positive associations were found between the number of different days students accessed the dashboard and the variables perceived usefulness ($r = 0.58$, $p < 0.001$) and engagement ($r = 0.47$, $p < 0.001$). In other words, students who visited the dashboard more stated that they found it more useful and increased their engagement. There was no significant association between behavior data and perceived ease of use and attitude variables. Regardless of their access to the dashboard, this situation can be interpreted as that students find the dashboard easy to use and want to use it in other courses.

When statistically significant associations were examined between other variables, it was seen that a moderate positive association between perceived usefulness and attitude ($r = 0.59$, $p < 0.001$) and a strong positive association between perceived usefulness and engagement ($r = 0.76$, $p < 0.001$) variables were also found. Besides, a weak positive association was found between perceived ease of use and attitude ($r = 0.35$, $p < 0.05$), and a moderate positive association was noticed between attitude and engagement (0.47, $p < 0.001$) variables.

6 Conclusion and Future Directions

In this chapter, we used gamification to address low usage problem associated with LADs. Specifically, game mechanics such as point, progress bar, leaderboard, etc. were used while designing the LAD to motivate students towards using it. Results of the evaluation study showed that 95% of the students visited the dashboard multiple times throughout the semester. This is 65% higher than the average LAD access rate reported by R. Bodily and Verbert (2017). Moreover, 98% of the students agreed or strongly agreed that they found the dashboard useful, 93% of the students agreed or strongly agreed that they found the dashboard easy to use, 82% of the students agreed or strongly agreed that the dashboard helped them to have a positive attitude towards using the dashboard, and 71% of the students agreed or strongly agreed that the dashboard increased their engagement in the course.

Our correlation analysis results showed that students' self-report data might not associate with their actual usage behaviors. This finding was well in line with the results obtained in other studies (Robert Bodily et al., 2018; Kim et al., 2016). It also shows the importance of the analysis of students' usage data while evaluating the effectiveness of the LADs. However, a limited number of LAD studies were reported on usage data. R. Bodily and Verbert (2017) found that 13% of the articles they reviewed reported on tracking student use of their system.

Gamification should be used with caution since its elements such as leaderboard may have a negative effect, especially on low-performing students (Teasley, 2017). To overcome this issue, the life cycles of the developed dashboard elements were limited to 1 week. In this way, students had the chance to rank at the top every week regardless of their performance in the previous week. Moreover, in the leaderboard instead of listing all students' names and ranks, only the top three students were listed. Even so, the dashboard element that students found less useful was the leaderboard. This finding can be interpreted as some of the students are not happy to see the leaderboard. However, further studies are needed to understand which students are dissatisfied.

Interventions are critical for successfully completing the learning analytics cycle and achieving beneficial results (Clow, 2012). One of the most preferred methods for delivering interventions to students is LADs (Wong & Li, 2020). A recent study conducted by Ifenthaler and Yau (2020) demonstrated empirical evidence of how learning analytics have successfully facilitated study success in the continuation and completion of students' learning. The authors found that prediction and visualization through dashboards are two main factors that contribute to study success. For this reason, it is necessary to design dashboards that are easy to interpret by students and would motivate students to use them regularly.

Although gamification has been found to increase students' use of dashboards, this evaluation study was limited to one course and a small number of students participating in the study. For this reason, there is a need for large-scale studies in which the effects of the developed gamified LAD on different courses and different students are tested. In this study, students' views on gamified LAD are examined without considering individual differences among students. In future studies, the perceptions of students with similar characteristics in terms of different variables (academic performance, learning strategy, etc.) can be evaluated. Gamification mechanics used in the designed dashboard were also limited. In future studies, different gamification mechanics can be added such as badges and their effects can be tested. The effects of gamified LAD on students' self-regulating processes and academic success also need to be tested in future studies.

Acknowledgments This study was partly supported by TÜBİTAK (The Scientific and Technological Research Council of Turkey) with project number 120K188.

References

Ab. Rahman, R., Ahmad, S., & Hashim, U. R. (2018). The effectiveness of gamification technique for higher education students engagement in polytechnic Muadzam Shah Pahang, Malaysia. *International Journal of Educational Technology in Higher Education, 15*(1), 41. https://doi.org/10.1186/s41239-018-0123-0

Akçapınar, G., & Uz Bilgin, Ç. (2020). The effect of Gamified learning analytics dashboard on students' engagement in an online learning environment. *Kastamonu Education Journal, 28*(4), 1892–1901. https://doi.org/10.24106/kefdergi.740489

Armstrong, M. B., & Landers, R. N. (2017). An evaluation of Gamified training: Using narrative to improve reactions and learning. *Simulation & Gaming, 48*(4), 513–538. https://doi.org/10.1177/1046878117703749

Baker, B. M. (2007). *A conceptual framework for making knowledge actionable through capital formation.* (D.M.). University of Maryland University College, Ann Arbor. ProQuest Dissertations & Theses Global database. (3254328).

Barr, J., & Gunawardena, A. (2012). *Classroom salon: A tool for social collaboration*. Paper presented at the Proceedings of the 43rd ACM technical symposium on computer science education, Raleigh, North Carolina, USA. https://doi.org/10.1145/2157136.2157196.

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418. https://doi.org/10.1109/TLT.2017.2740172

Bodily, R., Ikahihifo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598. https://doi.org/10.1007/s12528-018-9186-0

Broos, T., Verbert, K., Langie, G., Van Soom, C., & De Laet, T. (2017). Small data as a conversation starter for learning analytics: Exam results dashboard for first-year students in higher education. *Journal of Research in Innovative Teaching & Learning, 10*(2), 94–106. https://doi.org/10.1108/JRIT-05-2017-0010

Broos, T., Verbert, K., Langie, G., Soom, C. V., & Laet, T. D. (2018). *Multi-institutional positioning test feedback dashboard for aspiring students: Lessons learnt from a case study in flanders*. Paper presented at the Proceedings of the 8th international conference on learning analytics and knowledge, Sydney, New South Wales, Australia. https://doi.org/10.1145/3170358.3170419.

Broos, T., Pinxten, M., Delporte, M., Verbert, K., & De Laet, T. (2020). Learning dashboards at scale: Early warning and overall first year experience. *Assessment & Evaluation in Higher Education, 45*(6), 855–874. https://doi.org/10.1080/02602938.2019.1689546

Bunchball, I. (2010). *Gamification 101: An introduction to the use of game dynamics to influence behavior*. White paper, 9.

Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of Educational Research, 65*(3), 245–281. https://doi.org/10.3102/00346543065003245

Çakıroğlu, Ü., Başıbüyük, B., Güler, M., Atabay, M., & Yılmaz Memiş, B. (2017). Gamifying an ICT course: Influences on engagement and academic performance. *Computers in Human Behavior, 69*, 98–107. https://doi.org/10.1016/j.chb.2016.12.018

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Cassano, F., Piccinno, A., Roselli, T., & Rossano, V. (2019). *Gamification and learning analytics to improve engagement in university courses.* Paper presented at the Methodologies and intelligent systems for technology enhanced learning, 8th international conference, Cham.

Clow, D. (2012). *The learning analytics cycle: Closing the loop effectively.* Paper presented at the Proceedings of the 2nd international conference on learning analytics and knowledge.

Czikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. Harper & Row.

da Rocha Seixas, L., Gomes, A. S., & de Melo Filho, I. J. (2016). Effectiveness of gamification in the engagement of students. *Computers in Human Behavior, 58*, 48–63. https://doi.org/10.1016/j.chb.2015.11.021

de Marcos, L., Domínguez, A., Saenz-de-Navarrete, J., & Pagés, C. (2014). An empirical study comparing gamification and social networking on e-learning. *Computers & Education, 75*, 82–91. https://doi.org/10.1016/j.compedu.2014.01.012

Denley, T. (2013). Degree Compass: A course recommendation system. EDUCAUSE Review Online.Retrieved from http://er.educause.edu/articles/2013/9/degree-compass-a-course-recommendation-system. Accessed 15 March 2020.

Deterding, S., Sicart, M., Nacke, L., O'Hara, K., & Dixon, D. (2011). *Gamification. Using game-design elements in non-gaming contexts*. Paper presented at the CHI'11 extended abstracts on human factors in computing systems, Vancouver, BC, Canada. https://doi.org/10.1145/1979742.1979575.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Govaerts, S., Verbert, K., Duval, E., & Pardo, A. (2012). *The student activity meter for awareness and self-reflection*. Paper presented at the CHI'12 extended abstracts on human factors in computing systems, Austin, Texas, USA. https://doi.org/10.1145/2212776.2212860.

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Janssen, A., Shaw, T., Bradbury, L., Moujaber, T., Nørrelykke, A. M., Zerillo, J. A., … Harnett, P. (2016). A mixed methods approach to developing and evaluating oncology trainee education around minimization of adverse events and improved patient quality and safety. *BMC Medical Education, 16*, 91. https://doi.org/10.1186/s12909-016-0609-1

Jen-Wei, C., & Hung-Yu, W. (2016). Exploring engaging gamification mechanics in massive online open courses. *Journal of Educational Technology & Society, 19*(2), 177–203. Retrieved from http://www.jstor.org/stable/jeductechsoci.19.2.177

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). *License to evaluate: Preparing learning analytics dashboards for educational practice*. Paper presented at the Proceedings of the 8th international conference on learning analytics and knowledge, Sydney, New South Wales, Australia. https://doi.org/10.1145/3170358.3170421.

Kapp, K. M. (2012). *The gamification of learning and instruction: Game-based methods and strategies for training and education*. Wiley.

Kia, F. S., Teasley, S. D., Hatala, M., Karabenick, S. A., & Kay, M. (2020). *How patterns of students dashboard use are related to their achievement and self-regulatory engagement*. Paper presented at the proceedings of the tenth international conference on learning analytics & knowledge, Frankfurt, Germany. https://doi.org/10.1145/3375462.3375472.

Kim, J., Jo, I.-H., & Park, Y. (2016). Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(1), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Klemke, R., Eradze, M., & Antonaci, A. (2018). The flipped MOOC: Using gamification and learning analytics in MOOC design – A conceptual approach. *Education Sciences, 8*(1), 25. Retrieved from https://www.mdpi.com/2227-7102/8/1/25

Leaning, M. (2015). A study of the use of games and gamification to enhance student engagement, experience and achievement on a theory-based course of an undergraduate media degree. *Journal of Media Practice, 16*(2), 155–170. https://doi.org/10.1080/14682753.2015.1041807

Majumdar, R., Akçapınar, A., Akçapınar, G., Flanagan, B., & Ogata, H. (2019). *LAView: Learning analytics dashboard towards evidence-based education.* Paper presented at the 9th International Learning Analytics & Knowledge Conference (LAK'19), Tempe, Arizona.

Martinez Maldonado, R., Kay, J., Yacef, K., & Schwendimann, B. (2012). An interactive teacher's dashboard for monitoring groups in a multi-tabletop learning environment, .

McKay, T., Miller, K., & Tritz, J. (2012). What to do with actionable intelligence: E2Coach as an intervention engine. Paper presented at the Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, Vancouver, British Columbia, Canada. https://doi.org/10.1145/2330601.2330627

Molenaar, I., Horvers, A., Dijkstra, R., & Baker, R. S. (2020). *Personalized visualizations to promote young learners' SRL: The learning path app*. Paper presented at the Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, Frankfurt, Germany. https://doi.org/10.1145/3375462.3375465.

Özhan, Ş. Ç., & Kocadere, S. A. (2020). The effects of flow, emotional engagement, and motivation on success in a Gamified online learning environment. *Journal of Educational Computing Research, 57*(8), 2006–2031. https://doi.org/10.1177/0735633118823159

Pérez-Álvarez, R., Pérez-Sanagustín, M., & Maldonado-Mahauad, J. J. (2017). *NoteMyProgress: Supporting learners' self-regulated strategies in MOOCs.* Paper presented at the Data Driven Approaches in Digital Education, Cham.

R Core Team. (2017). *R: A language and environment for statistical computing: R Foundation for statistical computing*. Retrieved from https://www.R-project.org/

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics, 2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Şahin, M., & Yurdugül, H. (2019). An intervention engine design and development based on learning analytics: The intelligent intervention system (In2S). *Smart Learning Environments, 6*(1), 18. https://doi.org/10.1186/s40561-019-0100-7

Santos, J. L., Verbert, K., Govaerts, S., & Duval, E. (2013). *Addressing learner issues with StepUp! An evaluation*. Paper presented at the Proceedings of the Third International Conference on Learning Analytics and Knowledge, Leuven, Belgium. https://doi.org/10.1145/2460296.2460301.

Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., . . ., Dillenbourg, P. (2016). *Understanding learning at a glance: An overview of learning dashboard studies*. Paper presented at the Proceedings of the sixth international conference on learning analytics & knowledge. Edinburgh, United Kingdom. https://doi.org/10.1145/2883851.2883930.

Simões, J., Redondo, R. D., & Vilas, A. F. (2013). A social gamification framework for a K-6 learning platform. *Computers in Human Behavior, 29*(2), 345–353. https://doi.org/10.1016/j.chb.2012.06.007

Sutherland, R. J., Joubert, M. V., & Eagle, S. M. (2012). *A vision and strategy for technology enhanced learning: EFC*. European Commission.

Tan, J. P.-L., Koh, E., Jonathan, C. R., & Yang, S. (2017). Learner dashboards a double-edged sword? Students' sense-making of a collaborative critical Reading and learning analytics environment for fostering 21st century literacies. *Journal of Learning Analytics, 4*(1), 117–140. https://doi.org/10.18608/jla.2017.41.7

Teasley, S. D. (2017). Student facing dashboards: One size fits all? *Technology, Knowledge and Learning, 22*(3), 377–384. https://doi.org/10.1007/s10758-017-9314-3

Uz Bilgin, C., & Gul, A. (2020). Investigating the effectiveness of gamification on group cohesion, attitude, and academic achievement in collaborative learning environments. *TechTrends, 64*(1), 124–136. https://doi.org/10.1007/s11528-019-00442-x

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509. https://doi.org/10.1177/0002764213479363

Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal and Ubiquitous Computing, 18*(6), 1499–1514. https://doi.org/10.1007/s00779-013-0751-2

Winne, P. H., & Baker, R. S. (2013). The potentials of educational data Mining for researching metacognition, motivation and self-regulated learning. *Journal of Educational Data Mining, 5*(1), 1–8. https://doi.org/10.5281/zenodo.3554619

Wong, B. T.-M., & Li, K. C. (2020). A review of learning analytics intervention in higher education (2011–2018). *Journal of Computers in Education, 7*(1), 7–28. https://doi.org/10.1007/s40692-019-00143-7

Chapter 14
Evaluating LA Dashboard in Secondary School and Higher Education: Fostering Goal Setting and Students' Self-Regulation

Lorenzo Vigentini, Brad Swibel, and Garth Hasler

1 Introduction

Datafication is a contemporary phenomenon which refers to the quantification of human life through digital information (Mejias & Couldry, 2019). However, data is generated through a process of explicit tracking and the abstraction from data streams requiring selection and transformation, which is not objective in itself (Kitchin, 2014). Fourcade and Healy argued that 'Contemporary organizations are both culturally impelled by the data imperative and powerfully equipped with the tools to enact it' (2013, p. 13). As a consequence, *what* organisations and people do with the data at their disposal is the most important aspect, especially because the proliferation of data and the ability to join up bits of information make it possible to better understand individuals and their behaviours.

Data has also become essential in driving education at all levels, with the datafication of student learning, with the fields of learning analytics and educational data mining steadily growing over the past two decades (Baker, 2016; Siemens, 2013; Siemens & Baker, 2012).

There is a limited amount of systematic evaluation of the range of data-driven interventions leading to success (Rienties et al., 2016; Wise, 2014), and critical accounts of policies promoting datafication have become more apparent. For example, England is an example where datafication seems to have led to a narrowing of the scope of early years formative experiences (Bradbury, 2019). This forced teachers' work to be increasingly constrained by performativity demands, with high-stakes

L. Vigentini (✉)
UNSW Sydney, Sydney, Australia
e-mail: l.vigentini@unsw.edu.au

B. Swibel · G. Hasler
St. Andrew's Cathedral School, Sydney, Australia

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_14

assessment driving teaching and pedagogy and therefore resembling schooling of later years, very much geared toward successful performance in a statutory curriculum, ability grouping and targeted teaching (Bradbury, 2019; Roberts-Holmes, 2015).

At the other end of the schooling years, in higher education, much research has emerged on the use and effectiveness of *learning analytics* to improve student performance, retention and engagement (Herodotou et al., 2020; Rienties et al., 2016). According to Tempelaar, Rienties and Giesbers, 'a broad goal of learning analytics is to apply the outcomes of analysing data gathered by monitoring and measuring the learning process' (Tempelaar et al., 2015, p. 158). In effect this is the core of datafication in higher education, and while there is good evidence that LA methods and techniques enable to model and predict progression and performance, the biggest challenge is how to put the power of LA into the hands of teachers, administrators (Clow et al., 2014; Papamitsiou & Economides, 2014; Rienties et al., 2016) and the students themselves (Dollinger & Lodge, 2019; Ifenthaler & Schumacher, 2016).

The work presented in this book provides a wide-ranging set of accounts which investigate the uses and effects of dashboards and cases of good practice. This chapter presents an original contribution from two streams of related activities around the use of LAD and self-regulation. On one hand we have a practitioner perspective, with the implementation of LADS in school which shows the effectiveness of a strategic implementation of LADs through a systematic engagement with stakeholders. On the other hand, a research study in higher education focusing on students' perceptions of the effectiveness of the building blocks of a LAD makes it possible to compare the observations from the two contexts to generate recommendations about implementation and use of LAD which may have a broader applicability. Two key questions drive both streams of work: (1) are there general 'building blocks' for LADs which are seen as helpful for students to gauge their progress and help them self-regulate their learning? and (2) are there specific individual characteristics grounded in goal orientation and motivation, which make certain designs/implementations more effective?

2 Background

A considerable amount of work has been published about the use of information visualisation in learning analytics. Already back in 2011, Duval talked about 'goal-oriented visualisations' which were not just visually appealing, but led the end-user to take action (2011). The inspiration was the 'quantified self' movement (Wolf, 2009) and the realisation that commercial apps for running or fitness did a very good job in keeping end-users to maintain their goals and be more effective. This also reflected the growing number of implementations of Thaler's 'nudge theory' which demonstrates how clever and interesting visual design and targeted messages implicitly lead to behavioural changes (Hooker, 2017; Lawton, 2013; Thaler & Sunstein, 2009). LADs enable a process model moving through awareness, reflection, sense-making and impact (Suthers & Verbert, 2013; Mor et al., 2015) which can support self-regulatory processes.

From the initial strides, research explored general principles and applications (Charleer et al., 2014; Greller & Drachsler, 2012; Verbert et al., 2013, 2014), implementations of dashboard in learning platforms like Moodle (Einhardt et al., 2016; Hu et al., 2017; Kennedy et al., 2014; Leony et al., 2012; Podgorelec & Kuhar, 2011) and Blackboard (Aljohani et al., 2019; Arnold & Pistilli, 2012; Tempelaar et al., 2013) as well as very large projects conducted at The Open University, UK (Herodotou et al., 2020; Rienties et al., 2018), and in the realm of MOOCs (Cobos et al., 2016; Dipace et al., 2019; Ruipérez-Valiente et al., 2017; Vigentini et al., 2017b). All these raise several key issues from what should be displayed in dashboards (Jivet et al., 2017, 2018, 2020; Lim et al., 2019; Rienties et al., 2018; Vigentini et al., 2017a), the evaluation of what information is relevant and useful to students and teachers, how to involve stakeholders in the design (Dollinger et al., 2019; Herodotou et al., 2019) and, more broadly, a reflection on the modalities of implementation, adoption and scale (Liu et al., 2017; Vigentini et al., 2020).

It is acknowledged that dashboards are important to aid the sense-making process (Charleer et al., 2014; Duval, 2011) and make the data actionable (Liu et al., 2017; Pardo, 2018). However, there are several implicit design decisions made by dashboard designers and implementers that are neither obvious nor theoretically driven, and are not always grounded in pedagogical principles (Jivet et al., 2017, 2018; Matcha et al., 2020; Teasley, 2017). While the literature suggests that student success (Arnold & Pistilli, 2012; Ifenthaler & Yau, 2020), self-monitoring of activity and progress (Carless, 2019; Pardo, 2018; Schwendimann et al., 2017) and personalisation (Bienkowski et al., 2012; Gašević et al., 2015) are all essential for effective learning, it has been observed that LADs design are rarely grounded in self-regulation research (Jivet et al., 2018; Matcha et al., 2020).

2.1 Motivation, Metacognition and Self-Regulation for Success

To clarify the premises of the work presented in this chapter, we focus on four key theoretical drivers in relation to goal setting and self-regulation in student learning: (1) growth mindset (Dweck, 2012); (2) self-regulation (Greene & Azevedo, 2007; Winne & Hadwin, 1998); (3) feedback for learning (Boud, 2012; Boud & Molloy, 2013; Carless, 2019; Hattie & Timperley, 2007); and (4) coaching models in schools (Allison & Harbour, 2009; Stober & Grant, 2010).

2.1.1 'Growth Mindset' and Goal Setting

Goal setting is a central construct in personalised learning (Bray & McClaskey, 2015). It is often studied as a form of self-regulation (Carver & Scheier, 2012), the success of which is mediated by learner beliefs and various regulatory processes. Additionally, implicit theories of learning influence self-regulation (Dweck &

Leggett, 1988), with strong evidence that an incremental theory of growth (i.e. growth mindset) contributes to successful self-regulatory processes (Nussbaum & Dweck, 2008). When self-regulatory processes such as goal setting occur in contexts that are supportive, and emphasise mastery rather than performance or competition, goal achievement is more likely to occur (Burnette et al., 2013), and perceptions by teachers and students have been positive when deployed in the school assessment portfolio (Cruz & Zambo, 2013). Small-scale qualitative studies have found that goal-setting processes have positive effects on adolescent learners in middle-level settings, and action research studies suggest that academic goal setting may increase student engagement and achievement (Catlin et al., 1999) while a highly structured approach that includes personal, social and academic goals may produce positive outcomes for at-risk students (Pincham, 2006).

2.1.2 Goal Orientation

Over the past three decades, despite the proliferation of models, instruments and labels (Pintrich et al., 2003; Hulleman et al., 2010), goal orientation (GO) researchers across the disciplinary spectrum have developed two broad perspectives.

One uses a two-factor dispositional model (Dweck, 1986; Dweck & Leggett, 1988), which describes goal orientations on a bipolar continuum *learning* and *performance*. In this framework, a *learning goal orientation* (LGO) reflects one's belief that abilities are malleable and can be developed; therefore they hold an incremental perspective on ability: individuals seek to develop their skills and master tasks for their own sake. LGO is also referred to as mastery goal orientation (MGO) (Ames & Archer, 1988), or task involvement (Nicholls, 1984). When adopting a learning goal orientation, individuals tend to judge their competence based on their improvement and use a self-referent standard, and feelings of competence are associated with effortful improvement (Jagacinski & Nicholls, 1984). A *performance goal orientation* (PGO) reflects one's general belief that ability is fixed and cannot be changed. When focused on performance goal orientation (Ames & Archer, 1988; Dweck, 1986), ability goal (Midgley et al., 1996; Carol Midgley et al., 1998) or ego involvement (Nicholls, 1984), individuals seek to demonstrate superior competence at the task. Perception of success or failure of learning and performance is strongly influenced by contextual factors, such as task complexity, uncertainty or broad achievement norms, rather than individuals' ability.

The second perspective uses a three-factor, domain-specific model in which performance goal orientation (PGO) is subdivided based on the valence or focus of the performance-related standards as a tendency to prove or avoid, also referred to as performance-prove goal orientation (PPGO) or performance-avoidance goal orientation (PAGO) (Elliot & Harackiewicz, 1994; Vandewalle, 1997). Elliott and Church built upon this partitioning, focusing on the value of achievement goals (as positive or negative) as empirically different moderators between higher-order motivational constructs and performance, therefore different from LGO and PGO, which in their views provided an integrative hierarchical model of achievement motivation which kept into account both classic motivation theory and achievement goal theories (Elliot & Church, 1997).

2.1.3 Self-Regulation and Goal Setting

The theory about motivation and self-regulation spans across several decades, and several models have been suggested which can be classified according to three broad theoretical lenses: socio-cognitive (Zimmerman, 1990), emotional regulation (Boekaerts, 1997) and information processing (Hadwin et al., 2018; Winne & Perry, 2000). The latter has seen a broad consensus, particularly in relation to computer-supported and adaptive learning. The key element across all models is the involvement of cognitive, meta-cognitive and emotional (or motivational loops) components with a goal driving the interaction between components. Interestingly, 'good intentions' don't have a great reputation as people tend not to stick to their intentions, but also that simple plans go a long way in furthering the attainment of goals (Gollwitzer, 1999). Therefore, providing students with self-regulatory tools and data to engage with attracted further research. Panadero et al. (2016) found that *measurement* and *intervention* are deeply intertwined. The point of the intervention is to get students to stop, reflect on their progress and change their strategy in some way or another (in Gollwitzer's words adjusting goal intentions versus implementation intentions (1999)). External interventions focusing on the *impact* of feedback, albeit targeting higher education students (Henderson et al., 2019; Panadero et al., 2016), targeted student self-regulatory learning as a means of improving their development and thus their learning outcomes. Hattie and Timperley highlighted the power of feedback that encourages self-monitoring, provides direction and guides or regulates action (2007).

2.1.4 Feedback for Learning

Hattie's research on over 1200 meta-studies is particularly relevant to understand impactful strategies for learning and self-regulation (Hattie, 2009). In his analysis, 'providing formative evaluation' is classed as high impact with an effect size of 0.90 and the potential for embedding data-driven feedback, such as the information presented in dashboards is apparent. Hattie encourages teachers to consult various sources to examine the impact of interventions over time on student learning. This comes from where the teacher uses data to improve the instructional process. Formative evaluation is where the learner provides feedback to the teacher helping the teacher to modify their instruction.

In the higher education space, the issue of feedback for learning and the scalability of both assessment and feedback provision has become a growing problem, but good-quality feedback is essential to aid students to improve their learning, and therefore finding the best ways to encourage autonomy and self-regulation is essential (Boud & Molloy, 2013; Henderson et al., 2019). Yet, scaling up good assessment practices is a challenge that may be mitigated with the effective use of data (Arthars et al., 2019; Liu et al., 2017; Pardo, 2018).

2.1.5 Coaching for Success

The 'Growth Learning Plans' at the centre of coaching sessions with students implemented at St Andrew's Cathedral School (SACS) are grounded in (1) a strong support for Dweck's theoretical basis for the growth mindset (Dweck, 2012; Dweck & Leggett, 1988) and (2) growth coaching (https://www.growthcoaching.com.au/). At the core, the belief in the executive team at SACS is that enhancing the quality of conversations with teachers and students can drive improvement of the educational experience for both students and teachers (Allison & Harbour, 2009).

3 An Overview of the Two Cases

Within the broad context presented above, there are several questions emerging which led the work in the two cases presented.

On one hand, understanding what the most effective building blocks for LADs are steered the research study in higher education. The key hypothesis is whether certain design choices are implicitly enabling students with particular motivational premises more than others, in this sense, understanding the focus on the types of visualisation and how the information relates to students' goals.

The second set of questions, with a very pragmatic view on how to implement and adopt the use of LADs in a school setting, focuses on how to leverage on the opportunity, provide training and resources for stakeholders to maximise impact and ultimately improve students' success and their ability to self-regulate.

3.1 A Study of LAD in Higher Education

The research study in higher education tested the relations between routine preferences for learning and studying, goal orientation and the students' reaction to two scenarios with mock-up dashboard designs.

3.1.1 Methodology

Students from a large, public university in Australia across the full spectrum of disciplines were invited to take part in the study and complete an online questionnaire.

The instrument had five sections: (1) questions about their patterns of learning and studying using Barnard's (Barnard et al., 2009) Online Self-Regulated Learning

Questionnaire (OSLQ), (2) a goal orientation (GO) survey (Vigentini & Bucic, *under review*) based on three well-established GO scales (details in Appendix 1), (3) two sets of scenarios and dashboard mock-ups (Appendix 2), (4) goals to be set by the students from the scenarios and (5) a rating of the usefulness of dashboard elements.

3.1.2 Instrumentation and Survey Protocols

The OSLQ was originally designed to measure students' ability to self-regulate their learning in online or blended contexts. The instrument has six subscales including environmental structuring, goal setting, time management, help seeking, task strategies and self-evaluation; all items are available in the original source (Barnard et al., 2009). While the 'online' method of delivery provides a great deal of flexibility in what and how to study (Cunningham & Billingsley, 2002; Mcmanus, 2000), both locus of control and learning styles are key mediators to patterns of learning (Bowen, 1996; Vigentini, 2009, 2010). Barnard suggested that with autonomy, students must be able to display self-regulatory processes in order to be successful. The OSLQ seems to be a reliable tool to identify students' ability to self-regulate across multiple dimensions.

The goal orientation (GO) survey was developed based on the goal orientation scales by Vandewalle (1997), Elliot and Church (1997) and Barron and Harackiewicz (2003). These three GO scales all consist of three similar dimensions of goal orientation including mastery (MGO – describing the degree to which one desires to fully comprehend or master any undertaking in academic), performance-approach (PPO – how much one strives to outperform others) and performance-avoidance orientation (PAO – describes how much one does not want to fail in their undertaking). In the survey a fourth dimension was included which specifically measures fears of performing (FGO), which was found to be qualitatively different from performance-avoidance; the latter is maladaptive, in the sense that it represents behaviours which prevent the student from engaging with activities perceived to be difficult, while the fear of performing seems to be an anxiety-driven response.

The scenarios are based on a fictitious course with three assessment components proposed with typical distributions of weights (Fig. 14.1), which includes weekly

Imagine that you are part of this course which has weekly assessments (worth 50%) and a final assessment (worth 40%). Weekly participation is also marked at 10%.
Please carefully look at the following design for a student-facing dashboard.
We encourage you to consider the whole image as well as individual components.

In this scenario your performance is **lower than your set goals at the start of the term**; based on the information provided, what would you do to adjust your behaviours?

Fig. 14.1 Course scenario example: the wording in bold changes based on the conditions assessment (expecting constant engagement throughout the course, a final assessment and participation to weekly sessions).

A 2 × 2 design was used in which performance (high/low) was combined with the focus of the dashboard design (benchmarking against self/others). Students were randomly exposed to the high and low performance condition and one of the two benchmarking conditions in such a way that if in scenario 1 they were assigned to the high performance, in the second scenario, they were assigned to the low performance condition. Dashboard panels are shown in Appendix 2.

The individual panels were designed based on previous work like Kennedy et al. (2014) and Vigentini et al. (2017a) and represent (1) a set of summary boxes at the top with key figures, (2) a recommendation box, (3) performance in assessment tasks, (4) engagement with course learning activities, (5) completion of content activities and (6) interaction in discussion forums.

After seeing the scenarios, students were asked to indicate what goals they would set in response to the data presented in the scenarios by choosing between (1) amount of effort, (2) participation, (3) peer interaction and help seeking, (4) setting performance targets, (5) setting work plans and (6) focusing/prioritising and then ranking their choices.

The final section asked the students to rate the importance of each element of the dashboard on a scale of 1–5. The aim was to be able to explore what students focus on based on different scenarios. The full list of items is included in appendix for reference. Each statement was generated based on previous research and listed the majority of features under five main areas: (1) performance report and benchmarks, (2) explanations for the information presented, (3) tracking of activity/completion, (4) tracking of engagement and (5) goal settings and recommendations.

Data was analysed using R (R Core Team, 2020) and jamovi (The jamovi project, 2020) performing standard psychometric validations (Nunnally, 1962; Revelle, 2019).

3.1.3 Results

A total of 489 students took part in the study, with a similar split between males (44%) and females (56%) and an equal distribution across the scenarios. The majority of students are undertaking undergraduate studies (95%) in their second (63%) or third year (26%) of a 4-year degree and a representation across disciplines with the majority in Business, Engineering and Sciences (Table 14.1). The vast majority (>90%) declared that they are proficient in using the web in general.

When asked to indicate their current level of performance, students reported similar patterns to university-wide distributions of grades (11% high distinction; 45% distinction; 36% credit and 8% pass; no students with fail grades took part in the study).

The great majority indicated that university is very important (49%) or extremely important (35%) and mentioned that they access the university learning

Table 14.1 Distribution of participants according to study areas

Area of study	%
Arts and Design	2.43%
Business and Management	40.28%
Engineering and Built Environment	30.21%
Law	3.47%
Medicine and Medical Science	2.43%
Music and Performing Arts	0.00%
Psychology	3.82%
Sciences	14.24%
Social Sciences	3.13%

Table 14.2 Importance attributed to different activities in the LMS

Course components	Mean	Std deviation
Do and/or submit quizzes/assessments	3.74	0.52
Access course content	3.72	0.53
View lecture material or recordings	3.69	0.56
Check grades	3.55	0.66
Find course information	3.52	0.65
Check and/or contribute to the forum	2.72	0.91
Others (please specify)	2.61	1.25
Collaborate with others	2.42	0.94

management system frequently (46% between one and three times per day and 41% more than three times per day).

When asked to rate the importance (1 (not important) to 4 (essential)) of each course component, the responses are somewhat predictable with a focus on assessment, course content and lecture recordings (Table 14.2).

Online Self-Regulated Learning Questionnaire (OSLQ)

Analysis of the OSLQ was largely similar to the results reported in Barnard et al. (2009). The factor structure was replicated via confirmatory factor analysis, but using Kline's (2016) recommendations, the model parameters were not a satisfactory model fit ($X^2 = 689$, df = 430, $p < 0.001$, CFI = 0.851, TLI = 0.827, SRMR = 0.087, RMSEA = 0.727).

The chi-square goodness-of-fit statistic was significant, indicating that the model may fit the data, $\chi 2(430) = 689$, $p = 0.05$. As the chi-square statistic is sensitive to sample size, a discrepancy-based fit index may be used as the ratio of chi-square to degrees of freedom ($\chi2$/df). A $\chi2$/df ratio value less than 5 has been suggested as indicating an acceptable fit between the hypothesised model and the sample data (MacCallum et al., 1996). With a $\chi2$/df ratio value of 1.6, the proposed model has an acceptable fit. The root mean square error of approximation (RMSEA) is 0.727, which is considered not acceptable model fit (L. Hu & Bentler, 1999; Steiger, 2007). The value of Tucker-Lewis Index (TLI), also known as the Non-normed Fit Index (NNFI), was 0.83, and the value of the Comparative Fit Index (CFI) was 0.85; neither of these is higher than 0.95, which also indicates a poor fit of the model (L. Hu & Bentler, 1999; Steiger, 2007).

The reliability of the scales was also weaker than the original study, with coefficients ranging in the weak to moderate range (DeVellis, 2003; Nunnally, 1962). While it could be questioned whether the instrument should be used as a single measure of self-regulation, the validation of the tool was not our main concern in this study (Table 14.3).

Goal Orientation Scales

The GO survey analysis largely replicated previous findings, with good reliability of Cronbach alpha in the mastery goal orientation scale (MGO, $\alpha = 0.83$) and the performance-avoidance (PAO, $\alpha = 0.81$) and lower than expected reliability for performance orientation (PPO, $\alpha = 0.63$) and weak reliability for fear goal orientation (FGO, $\alpha = 0.45$). While the exploratory factor analysis generated four-factor model, items from the PPO and FGO scales were found to be more in line with MGO and PAO, which suggests that a deeper analysis should be carried out. For the purposes of this study, only FGO will be dropped (Table 14.4).

Table 14.3 Reliability measures of the various OSLQ scales using Cronbach alpha and factor correlations

OSLQ scale	Cronbach alpha	Mean	Std deviation
Goal setting	0.79 *(0.92)*	19.5	3.74
Environmental structuring	0.78 *(0.92)*	16.1	3.05
Task strategies	0.68 *(0.93)*	12.1	3.54
Time management	0.68 *(0.87)*	10.3	2.78
Help seeking	0.64 *(0.96)*	13.1	3.54
Self-evaluation	0.74 *(0.94)*	13.8	3.52
OSLQ total	0.89	84.7	14.6

Table 14.4 Reliability measures of the various GO scales using Cronbach alpha and factor correlations

OSLQ scale	Cronbach alpha	Mean	Std deviation
MGO	0.83	5.45	0.89
PAO	0.81	4.95	1.11
PPO	0.66	4.5	1.04
FGO	0.45	4.13	0.79

A correlation analysis was conducted to better understand the patterns of relations between the OSLQ and GO surveys. Table 14.5 shows several significant correlations between the subscales of the two instruments suggesting that goal orientations and particularly mastery and performance-avoidance may have important role in determining study behaviours.

Goal setting (GS) in the OSLQ is the dimension with the highest correlation ($r = 0.326$) to mastery orientation (MGO) and help seeking (HS) the one with the lowest correlation ($r = 0.190$). Performance-avoidance (PAO) and the same two scales (goal setting and help seeking) have the highest correlations.

Evaluation of LAD Components

For what concerns the LADs, 85% indicated that the visualisations provided were very useful (42%) or extremely useful (43%). Table 14.6 shows the overall ratings of the dashboard elements without accounting for the different scenarios. When these are kept into account, the MANOVA on the ratings in the 2 × 2 (*benchmarking focus of dashboard* – with levels self/other – and *level of performance* with levels over/under benchmarks) did not result in any significant difference or interaction effect; the only exception was the importance attributed to the item 'seeing indicators about how I learn/progress'. In both scenarios, when performance under the benchmark is shown, the variability of importance is inconsistently rated. Other items in which post hoc Tukey tests between pairs had significant differences ($p < 0.05$) are bolded in Table 14.6.

Evaluating Goal Settings After the Scenario

After being exposed to each scenario, students were asked to select and then rank the importance of goals/actions to be taken from their reading of the dashboards. Table 14.7 provides an overview of their choices. The statistical test using a one-way Friedman ANOVA is non-significant, meaning that there were no real differences in the course of actions to be taken in the various conditions; however the lack of a clear winner between these options may indicate a much more subtle difference between individuals and their preferences which should be investigated further. This may be supported by the fact that the total number of goal areas in scenario 2 (focus on self) indicates that students elect an average of three instead of two goals to work on when exposed to the underperforming scenario.

Evaluating Preferences and Personal Characteristics

The question about the relation between mediating personal characteristics and goal setting behaviour/preferences will require further investigation because of the complexity of the relations, which do not follow a 'linear' pattern.

Table 14.5 Correlations of the OSLQ and GO survey subscales

	PAO	MGO	PPO	OSQL_GS	OSQL_ES	OSQL_TS	OSQL_TM	OSQL_HS	OSQL_SE
PAO	–								
MGO	0.928***	–							
PPO	0.882***	0.875***	–						
OSQL_GS	0.269***	0.326***	0.085	–					
OSQL_ES	0.249***	0.313***	0.146**	0.498***	–				
OSQL_TS	0.253***	0.248***	0.130*	0.367***	0.421***	–			
OSQL_TM	0.268***	0.292***	0.128*	0.449***	0.477***	0.615***	–		
OSQL_HS	0.271***	0.190***	0.086	0.308***	0.300***	0.438***	0.357***	–	
OSQL_SE	0.250***	0.244***	0.070	0.377***	0.361***	0.440***	0.373***	0.654***	–

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14.6 Importance attributed to different elements of the dashboard. Note bold elements report significant differences between scenarios in post hoc paired tests

Aspects of the dashboards rated by participants	Mean	SD
Seeing my overall grade	4.5	0.8
Seeing my areas in need of improvement highlighted on the dashboard	4.22	1
Seeing requirements for passing the course	4.21	1.02
Being able to access the content of the course where I have difficulties directly from the dashboard	4.18	0.99
Seeing indicators about the course activities that I completed	4.14	1
Receiving recommendations on what topics I need to cover next or which topics I should redo	4.09	1
Having my information broken down by topics covered by the course	4.06	0.96
Seeing my performance in comparison to my goals	3.98	1.02
Having a standard to compare my information to	3.97	1.06
Being able to contact the teacher through the dashboard	3.96	1.11
Receiving information that helps me plan my learning (e.g. estimated time needed for each lesson)	3.92	1.09
Seeing my performance in comparison to what maximum activities are possible in the course	3.89	1.09
Having an overview over my information from the beginning of the course up to the current week	3.89	0.98
Seeing indicators about how I learn/progress	3.86	1.11
Being able to set goals and edit them	3.84	1.14
Seeing my performance in comparison to my past performance	3.82	1.2
Receiving recommendations on how I could change my learning behaviour to learn more efficiently	3.81	1.14
Having a consistent use of colours	3.77	1.17
Having my goal at the top of the dashboard as a reminder of my motivation and objectives	3.75	1.17
Seeing my performance in comparison to the other students	3.66	1.28
Having explanations of how dashboard elements and information relate to each other	3.64	1.14
Having explanations of how information is calculated	3.61	1.19
Seeing the predictions of my learning behaviour by the end of the course	3.57	1.25
Having explanations of how the information is relevant to my learning	3.57	1.12
Having explanations on the scales according to which this information is displayed	3.57	1.07
Having explanations of how the information is relevant to my goal	3.52	1.11

What is obvious from the analysis in the previous sections is that there is enough variance in choices and self-reported inventories to make it worthwhile, but nothing obvious emerges from the analysis so far; therefore another study will be required to investigate this further.

Table 14.7 Summary of the mean ranks and standard deviations for the stated preferences of learning goals to take after being exposed to the scenarios

	Benchmark				Self			
	Over		Under		Over		Under	
Amount of effort	1.71	*(0.97)*	1.97	*(0.97)*	2.16	*(1.08)*	1.79	*(0.96)*
Participation	3.09	*(1.35)*	2.7	*(1.35)*	2.76	*(1.21)*	2.87	*(1.22)*
Peer interaction and help seeking	3.07	*(1.39)*	3.31	*(1.39)*	2.78	*(1.31)*	3.18	*(1.52)*
Set performance targets	2.56	*(1.28)*	2.5	*(1.28)*	2.43	*(1.26)*	2.5	*(1.16)*
Set work plans	2.39	*(1.31)*	2.31	*(1.31)*	2.24	*(1.08)*	2.29	*(1.25)*
Focus/prioritise	1.83	*(0.84)*	1.86	*(0.84)*	1.82	*(1.03)*	2.18	*(1.09)*

3.1.4 Discussion

Questioning the validity and reliability of the instruments used remains an important aspect of the evaluation process as too often in the fields of LA, EDM and learning technologies, practitioners take the tools for granted based on citations/prevalence and fail to scrutinise the quality and effectiveness of the questionnaires they use. In this case the validation of the tools used was only partial, with weak support for the OSLQ (with over 400 publications associated with it) and the GO inventory (which despite strong theoretical basis seems to require further refinements in the items). This implies that the interpretation should be cautious, and using Schön's words 'when practitioners accept and try to use the academy's esoteric knowledge they are apt to discover that its appropriation alienates then from their own understandings, engendering a loss of their sense of competence and control' (Schön, 1992, p. 120).

From the pragmatic point of view, there are two key findings from this study: (1) there are little differences in preferences via the importance rankings in situations in which the students are placed in different experimental conditions which manipulate the views and focus of the dashboard elements based on comparisons with self or others whether they underperform or not; and (2) there is a reasonable spread in preferences; this supports the idea that one size does not fit all (Gašević et al., 2016; Teasley, 2017) and that therefore a deeper understanding of students' characteristics and preferences is more important than ever if we want to move from statistical models of recommendations to a more effective personalisation of learning.

This highlights a need to study more the interaction between preferences and designs and/or enable the end-users to customise what to focus on. It also suggests that the tools used to classify personal characteristics may not be reliable enough or sensitive enough to be able to identify clear trends.

From the learning progression perspective and the dashboard design, the question of why is grade so important to students remains unchallenged, and using references to performance benchmarks seems to have a complex effect (Carless, 2019; Lipnevich & Smith, 2008). This will be further explored in the study done in the school.

3.2 Adoption of LADs in a Secondary School

St Andrew's Cathedral School (SACS) is a comprehensive coeducational independent day school of 1500 students in the heart of Sydney. It is well known for its innovative approach to education and a vision 'to inspire students to be passionate, creative learners who engage with Christian values and fully develop their gifts and abilities in order to serve in the world' (SACS mission and vision).

Since 2016, the Deputy Head of School began a change process of data-driven school improvement, engaging stakeholders, data analytics development, resourcing and policy development – initially, a rudimental dashboard in MS Excel which used slicers to filter the data and conditional formatting to highlight changes to identify students who were struggling. This partly automated the data extraction from the school's admin systems and enabled to quickly adopt and further develop dashboards that are now used by all stakeholders, including academic and pastoral leaders, teachers and students.

Together with the development of the dashboards, appropriate business processes were put in place to leverage on the product and support users to interpret and reflect on the data as a routine process. While the initial focus was on the education provider for tracking and monitoring, it became apparent that given the strong correlation between a student's behaviour and their achievement, the dashboard should be built primarily for students rather than the teachers. This approach particularly aligns with several examples in the literature (Jivet et al., 2017, 2018, 2020; Lim et al., 2019; Sedrakyan et al., 2020), especially in the way dashboards should be student focused in terms of setting and tracking goal achievement and students should be included in dashboard design to consider their goals and self-regulated learning skills and in doing so scaffold the development of data literacy skills.

This study fits into this agenda and provided a formal opportunity for student to express their preferences and opinions about the current dashboard design.

3.2.1 Methodology

Performance and behavioural data are routinely collected by the school and stored in a data warehouse. These include assessment data, absences, merit scores, number of infringements and some psychometrics, including a socio-emotional scale managed by an external provider (People Diagnostix) based on Seligman's PERMA model (Seligman, 2018).

Data for this study was collected in February 2021 (coinciding with the 'Review Day', which is conducted annually) and focused on the perceived effectiveness of specific dashboard features and students' preferences. For this study the focus was on students in Years 8–11 (ages between 13 and 18). Students are provided access to their dashboards beforehand, and they are asked to reflect on past performance and set some goals for the new academic year. Students select goals for three of their courses, and they are also given stickers to remind themselves of the goals selected. A survey was given to students on the day so that they could also provide some feedback on the features of the dashboards after they accessed the dashboards and worked through their goal setting with their coaches.

The structure of the survey is similar to the section of the survey in the study with higher education students focusing on the aspects of the dashboard that they deemed important, so that a clear parallel could be drawn out.

The current dashboard design is shown in Appendix 2 and contains tracking information about overall performance against both personal goals (for the concept of personal best, see Martin) and compared against class scores.

3.2.2 Results: Evaluating the Characteristics of the Dashboards

After receiving the invitation, 237 students submitted responses in the online survey. There were a proportion of 69% males and 31% females across Years 8 to 11, including the International Baccalaureate courses (Year 8, 31.7%; Year 9, 44%; Year 10, 15.2%; and Year 11, 8.9%).

The distribution of preferences is provided in Table 14.8 according to the year. The detailed view in Table 14.9 provides an overview of the top three ranked items by importance; this highlights a shift of attention from the grades/performance to a more goal-oriented approach focusing on progress and track record of performance.

No statistical difference was observed in ratings between genders, but there is an observable difference in the ratings of importance of different elements of the dashboard across years which has been simplified by converting the ratings into ranks (Table 14.9).

The most interesting aspect of this analysis is a gradual shift of focus of importance from grades to progress, tracking against own goals and focusing on future areas of development.

This pattern is quite interesting as in later years grades are weighted more in the calculation of the ATAR (Australian Tertiary Admission Rank), which is a number (rank) commonly used by universities admissions to select students.

While many students in qualitative comments praised the dashboard for showing current performance and trends, there were several students pointing out the value in helping them to direct their goal setting activity and tracking against those goals: ‘Looking at my attainment for my prior years and goals would be the most useful because I can reflect on my grades, I can see what I have to improve on, you can see the target and the student goal and I find that useful because it shows where I want to be and what level I want to be at’ (male student, Year 9).

Table 14.8 Importance attributed to different elements of the dashboard across different years/forms. Note that IB stands for International Baccalaureate, which is different from the normal year 11

Aspects of the dashboards rated by participants	Form						
	Mean	Std deviation	8	9	10	11	11IB
Seeing my overall grades/marks	4.28	*0.955*	4.27	4.37	4.09	3.79	4.33
Seeing indicators about my progress	4.12	*0.906*	3.88	4.28	4.06	4.07	4.5
Having my goals in the dashboard as a reminder of my motivation and objective:	3.55	*1.2*	3.66	3.56	3.66	2.86	3.17
Seeing my performance in comparison to other students	3	*1.34*	3.01	3.08	2.91	2.64	3
Seeing my performance in comparison to my past performance	4.13	*1.02*	4.14	4.22	3.94	3.57	4.33
Seeing my performance in comparison to my own goals	4	*0.992*	3.84	4.19	4.14	3.5	4.5
Identifying areas for improvement from the dashboard	3.87	*1.06*	3.86	3.87	3.94	3.57	4.67
Seeing predictions of my MYP Grades, IB Diploma Grades or HSC Bands	3.31	*1.19*	3.33	3.3	3.23	3.36	4
Having targets to compare my progress to	3.8	*1.02*	3.78	3.83	3.69	3.43	4.67
Having explanations of how dashboard elements relate to each other	3.2	*1.1*	3.1	3.3	3.34	2.57	3.5
Having explanations of how the dashboard information is calculated	3.13	*1.23*	2.97	3.28	3.06	2.86	3.83
Having explanations of how the dashboard information is relevant to my goals	3.41	*1.08*	3.47	3.48	3.14	3	4.17
Having explanations of how the dashboard information is relevant to my learning;	3.46	*1.06*	3.55	3.51	3.4	2.71	4
Having explanations on the scales according to which this Information is displayed	3.56	*1.1*	3.59	3.64	3.26	3.36	4.17
Having a consistent use of colours	3.15	*1.33*	3.1	3.3	2.77	2.71	3.83
Being able to set goals and change them	3.82	*1.07*	3.96	3.82	3.71	3.43	3.83
Selecting skills on how I could change my learning behaviour to learn more efficiency;	3.86	*1.08*	4.11	3.88	3.6	3.36	3.67

Table 14.9 Focus ranking of importance attributed to different elements of the dashboard across different years/forms

Aspects of the dashboards rated by participants	Mean	8	9	10	11	11IB
Seeing my overall grades/marks	1	1	1	2	2	3
Seeing indicators about my progress	3		2	3	1	2
Seeing my performance in comparison to my past performance	2	2	3		3	3
Seeing my performance in comparison to my own goals				1		2
Identifying areas for improvement from the dashboard					3	1
Selecting skills on how I could change my learning behaviour to learn more efficiently		3				
Having targets to compare my progress to						1

3.2.3 Discussion

This study explored students' preferences for specific dashboard elements in a similar way to what was done with the study in higher education.

The key observation emerging from the qualitative comments was a general appreciation of the dashboard, with the ability provided to track progress over time, against own performance and against class performance. The design of the dashboard enables students to gauge their trajectories at the point in time (usually at the Review Day) and reflect on what they should do next. This is timely and convenient and provides an excellent starting point to work with their coaches to refine the goals for the new starting term, get a reminder or refocus the previously stated goals and provide detailed information about what they should or could do to improve.

One aspect which will require further analysis is the clear sense of changing perspective over time. Students' attribution of importance to different elements of the dashboard could be an indicator of personal growth (which would be a demonstration of achievement of the school mission), but most importantly, it shows the impact of a dashboard design which is flexible enough to accommodate focused analysis/views of the data which reflects on students' needs.

The idea of the dashboard being a tool supporting tracking of progress and enabling students to reflect upon and reformulate their goals over time is a powerful outcome of the implementation.

These, however, raise more questions about the way in which the dashboard design either aids or constrains the goal setting process: is the continuous benchmarking against self and others working as a motivator to achieve better results, or is it becoming a burden? What type and level of goals are set? Those that are 'easier' to achieve or more difficult, 'stretch' targets, which enable to optimise performance?

4 Overall Evaluation and Future Directions

This chapter provided a unique perspective of dashboards evaluations through the lenses of (1) a research study in higher education which focused on the evaluation of what students find important in a dashboard under different scenarios and considering personal characteristics in terms of self-regulation (measured via Barnard's OSLQ) and goal orientation and (2) a practitioner's driven evaluation of a dashboard implementation.

The core common thread is the statements used to evaluate dashboard's features as well as constant conversations occurring between the practitioners and managers in the school setting and the academic providing them with insights from the extant literature on learning analytics and dashboards.

Table 14.10 Comparison of average ranking of importance of dashboard elements across the two studies

statements about the dashboard	rank_HE	rank_School
Seeing my overall grade	1	1
Seeing my areas in need of improvement highlighted on the dashboard	2	7
Seeing requirements for passing the course	3	
Being able to access the content of the course where I have difficulties directly from the dashboard	4	
Seeing indicators about the course activities that I completed	5	
Receiving recommendations on what topics I need to cover next or which topics I should redo	6	
Having my information broken down by topics covered by the course.	7	
Seeing my performance in comparison to my goals	8	6
Having a standard to compare my information to	9	9
Being able to contact the teacher through the dashboard	10	
Receiving information that helps me plan my learning (e.g. estimated time need for each lesson)	11	
Seeing my performance in comparison to what is maximum activities possible in the course	12	
Having an overview over my information from the beginning of the course up to the current week.	13	
Seeing indicators about how I learn/progress	14	2
Being able to set goals and edit them	15	16
Seeing my performance in comparison to my past performance	16	5
Receiving recommendations on how I could change my learning behaviour to learn more efficiently	17	
Having a consistent use of colours.	18	15
Having my goal at the top of the dashboard as a reminder of my motivation and objectives	19	
Seeing my performance in comparison to the other students	20	4
Having explanations of how dashboard elements and information relate to each other	21	10
Having explanations of how information is calculated	22	11
Seeing the predictions of my learning behaviour by the end of the course	23	8
Having explanations of how the information is relevant to my learning	24	13
Having explanations on the scales according to which this information is displayed	25	14
Having explanations of how the information is relevant to my goal	26	12
Having my goals in the dashboard as a reminder of my motivation and objectives		3
Selecting skills on how I could change my learning behaviour to learn more efficiently		17

The parallels between the two streams of work provide several insights. As shown in Table 14.10, ranking of the importance of different dashboard elements by students is quite different suggesting a number of interpretations. Given that the dashboard designs of the scenarios of the HE study and the secondary school study are different, a direct comparison is not possible, but it is possible to abstract to the level of building blocks of the design and how well these have been rendered in the dashboards. As already observed in the focused school table (Table 14.9) with a shift of focus from performance to action, the evaluation of dashboard elements by students in HE, apart from the focus on the grade, seems to be more focused on what the dashboard can help them with in terms of course requirements, expectations and general references to 'how they are doing'. This is not surprising as in the school context students are heavily scaffolded and the dashboard provides an opportunity to have a high-level, coherent view of progression, while students in HE are missing the same level of support and guidance and seek these aspect in the dashboard.

In both studies qualitative comments relayed the importance of a visual aid to make sense of the data available and stressed the value of dashboards in helping them learn; this is well established in the literature (Lim et al., 2019; Pardo et al., 2016).

In line with the co-participation studies, students also welcomed the possibility to have a say in how the dashboards are developed and keenly provided feedback but had less to say about what could be improved in these dashboards. This lends support to the implementation of co-design strategies (Dollinger et al., 2019; Dollinger & Lodge, 2019; Prieto-Alvarez et al., 2018).

There is also little doubt that students perceived the dashboard generally useful in (1) helping them track their progress more explicitly and (2) making them more aware and willing to engage with goal setting. In both cases the information displayed was deemed important to track both performance and targets but also provide an opportunity to reflect on areas of improvement and generate new goals/targets.

There are three areas in which the two studies pointed to:

- More work needed in the selection and evaluation of self-reported measures in relation to goal orientation and self-regulation
- More work needed to understand preferences in relation to design elements
- More work required to personalise the focus of the dashboard but raising the question whether giving students (in school) exactly what they want only helps them to get into confirmation bias and contributing to the overall tracking and improvement agenda

Finally, while the dashboard may display helpful information to tackle goal setting and directed action, we must acknowledge the great added value of students' conversations with coaches, which offer a great pastoral support in the secondary school setting, but also recognise that this approach may not be scalable for HE. As a consequence, more work is needed to better understand what are the key features that may help to partly automate and scale the process. Similar issues have been observed elsewhere in relation to feedback provision and the problems to implement effective data-driven processes (Ferguson & Clow, 2017; Liu et al., 2017; Vigentini et al., 2020).

While the chapter provides some useful insight in the design and evaluation, another aspect to keep in mind is the two-sided coin of experimental studies which have little bearing on real situations and the less-than-systematic approach implemented by practitioners focusing on the evaluation rather than theory. We hope that the comparison of the two contexts provided some balance in this equation and acknowledge that more work is needed to explore the implementation and use of LADs for learning, especially when moving from the lab to the school setting.

Appendixes

Appendix 1

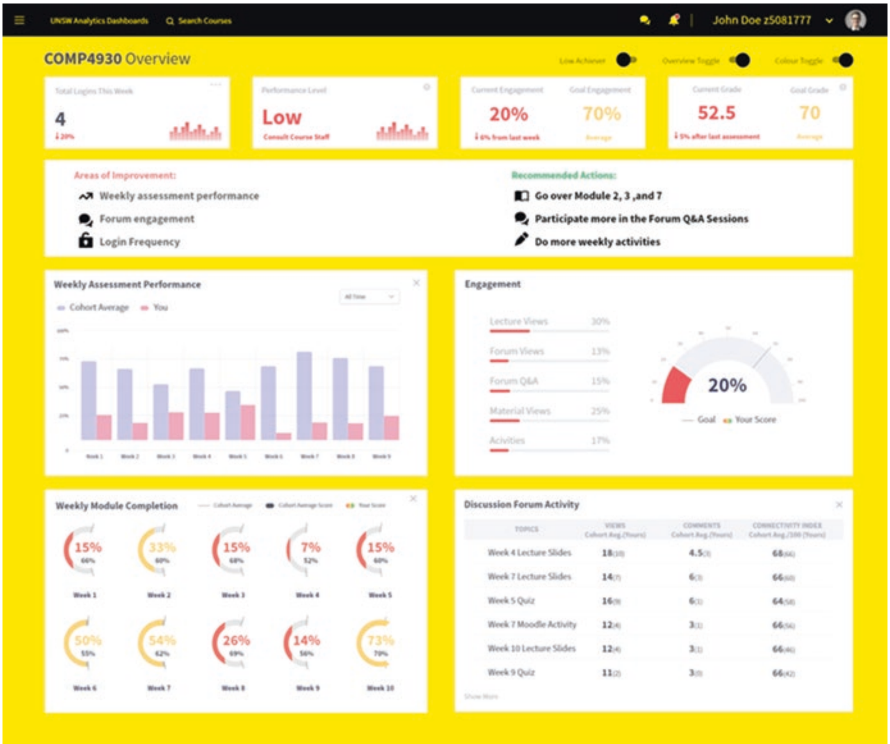
Goal orientation scales.

Scale[a]	Item
MGO	I often read materials related to my courses to improve my abilities
MGO	I work hard in my studies because I really like to learn new things
MGO	I enjoy the challenge of learning new or difficult things
MGO	In my courses, I enjoy challenging tasks where I'll learn new skills
MGO	I want to learn as much as possible from my teachers
MGO	My goal is to learn as much as possible from my courses
PAO	I want to do well in my courses to show my ability to my family, friends, advisors or others
PAO	I enjoy when my classmates look up to me for help in my course
PAO	I enjoy showing my skills to others in my courses
PAO	My goal is to get a better grade than most of the students in my courses
PAO	I am striving to demonstrate my ability relative to others in my courses
PAO	I am motivated by the thought of outperforming my peers in my courses
PPO	I'm afraid that if I ask my instructor a 'dumb' question, they might not think I'm very smart
PPO	I select courses that require the least amount of effort
PPO	Sometimes I wish my courses were not graded
PPO	Avoiding a show of low ability is more important to me than learning a new skill
PPO	I often think to myself, 'what if I do badly in my studies?'
PPO	I just want to avoid doing poorly in my courses
FGO	I am prepared to work hard to achieve my goals
FGO	If I underperform, it is usually because the course is too hard
FGO	I would do anything to get a good grade, even if I have to cheat
FGO	In order to perform well in my courses, I rely on my peers to help me
FGO	I am very self-focused when it comes to preparing for my exams
FGO	I am confident to perform well even if I have not prepared enough for my exams

[a]*MGO* mastery goal orientation, *PAO* performance-avoidance orientation, *PPO* performance orientation, *FGO* fear goal orientation

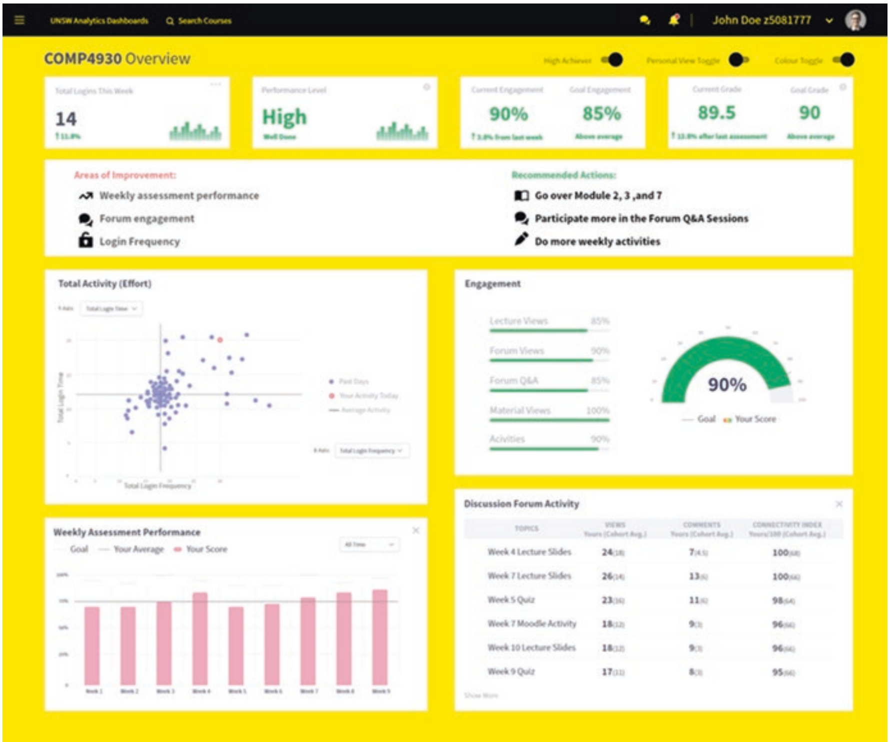
Appendix 2

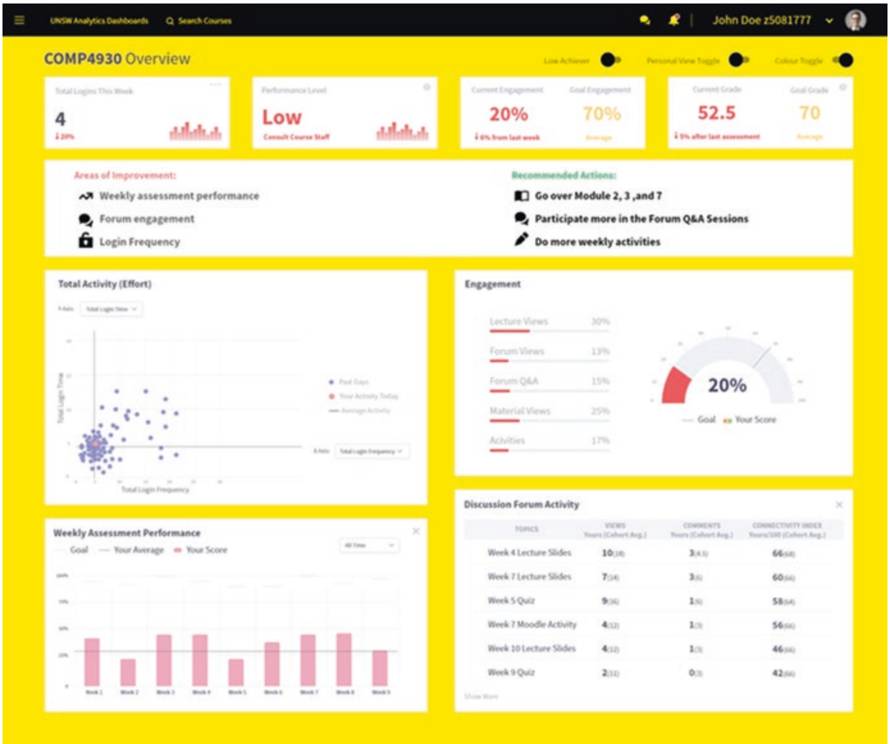
Dashboard designs with focus on comparison of achievement and benchmarking with others' performance over (top panel) or under (bottom) the rest of the class.


UNSW Analytics Dashboards
Search Courses
John Doe z5081777
COMP4930 Overview
4
Low
20%
70%
52.5
70
Areas of Improvement:
Weekly assessment performance
Forum engagement
Login Frequency
Recommended Actions:
Go over Module 2, 3 ,and 7
Participate more in the Forum Q&A Sessions
Do more weekly activities
Weekly Assessment Performance
Cohort Average
You
Engagement
Lecture Views
Forum Views
Forum Q&A
Material Views
Acivities
20%
Goal
Your Score
Weekly Module Completion
15%
33%
15%
7%
15%
50%
54%
26%
14%
73%
Discussion Forum Activity
Week 4 Lecture Slides
Week 7 Lecture Slides
Week 5 Quiz
Week 7 Moodle Activity
Week 10 Lecture Slides
Week 9 Quiz

Appendix 3

Dashboard designs with focus on comparison of achievement and benchmarking with self-performance over (top panel) or under (bottom) the rest of the class.





Appendix 4

Statements about the elements of the dashboard

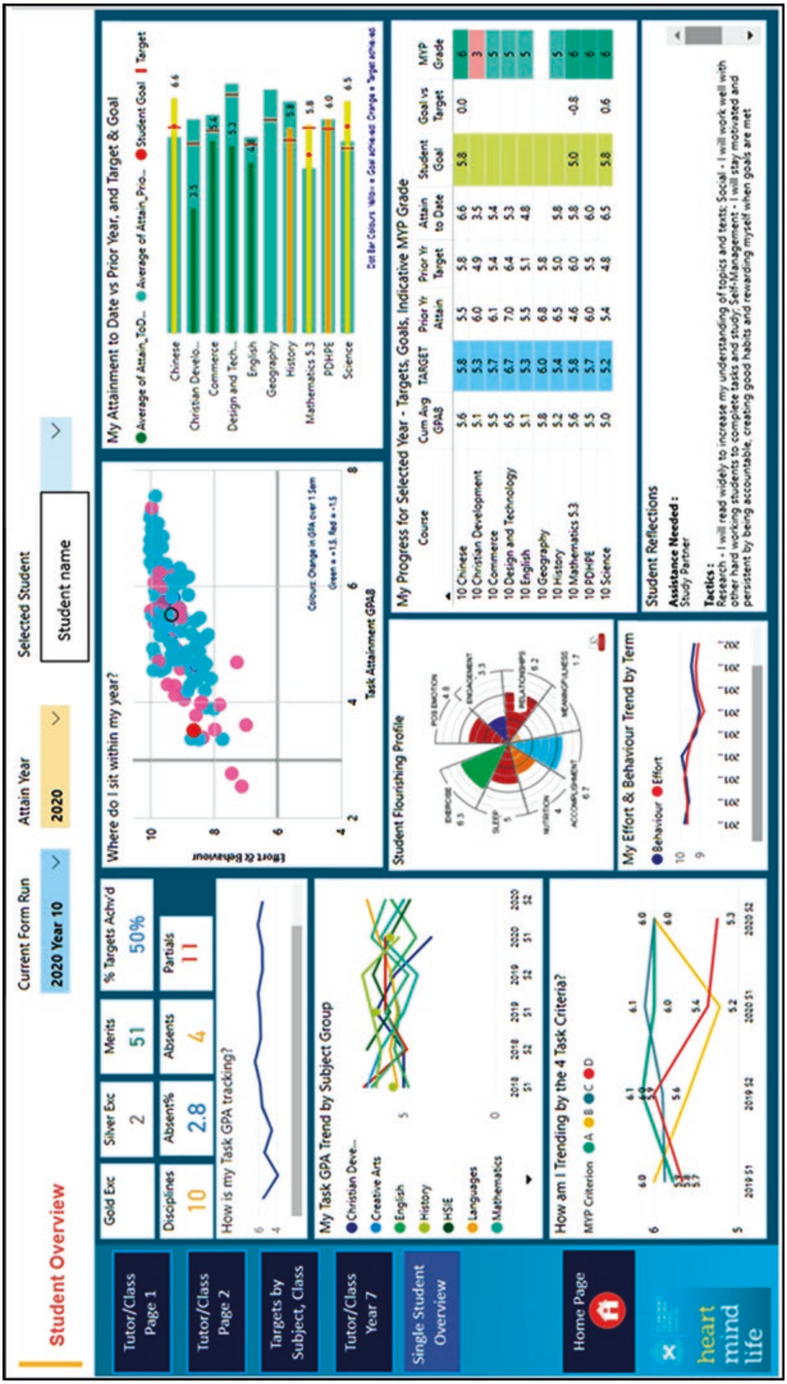
id	Statements for the HE study	id	Statements for the school study
Q5_1	Seeing my overall grade	Q5_1	Seeing my overall grades/marks
Q5_2	Seeing indicators about the course activities that I completed		
Q5_3	Seeing indicators about how I learn/ progress	Q5_3	Seeing indicators about my progress
Q5_4	Seeing requirements for passing the course		
Q5_5	Having my goal at the top of the dashboard as a reminder of my motivation and objectives		
Q5_6	Seeing my performance in comparison to what is maximum activities possible in the course		

id	Statements for the HE study	id	Statements for the school study
Q5_7	Seeing my performance in comparison to the other students	Q5_7	Seeing my performance in comparison to other students
Q5_8	Seeing my performance in comparison to my past performance	Q5_8	Seeing my performance in comparison to my past performance
Q5_9	Seeing my performance in comparison to my goals	Q5_9	Seeing my performance in comparison to my own goals
Q5_10	Seeing my areas in need of improvement highlighted on the dashboard	Q5_10	Identifying areas for improvement from the dashboard
Q5_11	Seeing the predictions of my learning behaviour by the end of the course	Q5_11	Seeing predictions of my MYP Grades, IB Diploma Grades or HSC Bands
Q5_12	Having a standard to compare my information to	Q5_12	Having targets to compare my progress to
Q5_13	Having explanations of how dashboard elements and information relate to each other	Q5_13	Having explanations of how dashboard elements relate to each other
Q5_14	Having explanations of how information is calculated	Q5_14	Having explanations of how the dashboard information is calculated
Q5_15	Having explanations of how the information is relevant to my goal	Q5_15	Having explanations of how the dashboard information is relevant to my goals
Q5_16	Having explanations of how the information is relevant to my learning	Q5_16	Having explanations of how the dashboard information is relevant to my learning
Q5_17	Having explanations on the scales according to which this information is displayed	Q5_17	Having explanations on the scales according to which this information is displayed (eg GPA scales, effort scales, behaviour scales etc)
Q5_18	Having an overview over my information from the beginning of the course up to the current week.		
Q5_19	Having my information broken down by topics covered by the course.		
Q5_20	Having a consistent use of colours.	Q5_20	Having a consistent use of colours
Q5_21	Being able to set goals and edit them	Q5_21	Being able to set goals and change them
Q5_22	Being able to access the content of the course where I have difficulties directly from the dashboard		
Q5_23	Receiving information that helps me plan my learning (e.g. estimated time need for each lesson)		
Q5_24	Receiving recommendations on how I could change my learning behaviour to learn more efficiently		

id	Statements for the HE study	id	Statements for the school study
Q5_25	Receiving recommendations on what topics I need to cover next or which topics I should redo		
Q5_26	Being able to contact the teacher through the dashboard		
		Q5_30	Having my goals in the dashboard as a reminder of my motivation and objectives
		Q5_31	Selecting skills on how I could change my learning behaviour to learn more efficiently
		qual_01	Is there a particular aspect of the dashboard that you find very useful and why?
		qual_02	Points - Is there a particular aspect of the dashboard that you find very useful and why?
		qual_03	Feedback – Is there a particular aspect of the dashboard that you find very useful and why?
		qual_04	Is there anything missing from the dashboard or you would like to see improved?
		qual_05	Points – Is there anything missing from the dashboard or you would like to see improved?
		qual_06	Feedback - Is there anything missing from the dashboard or you would like to see improved?

Appendix 5

SACS 2020 Student Dashboard using Microsoft Power BI


Student Overview
Current Form Run
2020 Year 10
Attain Year
2020
Selected Student
Student name
Tutor/Class Page 1
Tutor/Class Page 2
Targets by Subject, Class
Tutor/Class Year 7
Single Student Overview
Home Page
heart mind life
How is my Task GPA tracking?
My Task GPA Trend by Subject Group
How am I Trending by the 4 Task Criteria?
Where do I sit within my year?
Student Flourishing Profile
My Effort & Behaviour Trend by Term
My Attainment to Date vs Prior Year, and Target & Goal
My Progress for Selected Year - Targets, Goals, Indicative MYP Grade
Student Reflections

References

Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019). An integrated framework for course adapted student learning analytics dashboard. *Computers in Human Behavior, 92*, 679–690. https://doi.org/10/gf7f7p

Allison, S., & Harbour, M. (2009). *The coaching toolkit: A practical guide for your school*. Sage.

Arnold, K. E., & Pistilli, M. D. (2012). *Course signals at Purdue: Using learning analytics to increase student success*. In Proceedings of the 2nd International conference on learning analytics and knowledge, pp. 267–270. https://doi.org/10/ggwgdm

Arthars, N., Dollinger, M., Vigentini, L., Liu, D. Y.-T., Kondo, E., & King, D. M. (2019). Empowering teachers to personalize learning support. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing learning analytics to support study success* (pp. 223–248). Springer. https://doi.org/10.1007/978-3-319-64792-0_13

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80*(3), 260–267. https://doi.org/10.1037/0022-0663.80.3.260

Baker, R. S. (2016). Stupid tutoring systems, intelligent humans. *International Journal of Artificial Intelligence in Education, 26*(2), 600–614. https://doi.org/10.1007/s40593-016-0105-0

Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S.-L. (2009). Measuring self-regulation in online and blended learning environments. *The Internet and Higher Education, 12*(1), 1–6. https://doi.org/10/b6sf5z

Barron, K. E., & Harackiewicz, J. M. (2003). Revisiting the benefits of performance-approach goals in the college classroom: Exploring the role of goals in advanced college courses. *International Journal of Educational Research, 39*(4), 357–374. https://doi.org/10.1016/j.ijer.2004.06.004

Bienkowski, M., Feng, M., & Means, B. (2012). Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. *US Department of Education, Office of Educational Technology, 1*, 1–57.

Boekaerts, M. (1997). Self-regulated learning: A new concept embraced by researchers, policy makers, educators, teachers, and students. *Learning and Instruction, 7*(2), 161–186. https://doi.org/10/djhtk4

Boud, D. (2012). *Developing student autonomy in learning* (2nd ed.). Taylor and Francis.

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: The challenge of design. *Assessment & Evaluation in Higher Education, 38*(6), 698–712. https://doi.org/10.1080/02602938.2012.691462

Bowen, V. S. (1996). *The relationship of locus of control and cognitive style to self-instructional strategies, sequencing, and outcomes in a learner-controlled multimedia environment.* 1.

Bradbury, A. (2019). Datafied at four: The role of data in the 'schoolification' of early childhood education in England. *Learning, Media and Technology, 44*(1), 7–21. https://doi.org/10/ghzv66

Bray, B., & McClaskey, K. (2015). *Making learning personal*. Thousand Oaks, CA.

Burnette, J. L., O'Boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139*(3), 655–701. https://doi.org/10/f4v2f8

Carless, D. (2019). Feedback loops and the longer-term: Towards feedback spirals. *Assessment & Evaluation in Higher Education, 44*(5), 705–714. https://doi.org/10/gf33kc

Carver, C. S., & Scheier, M. F. (2012). *Attention and self-regulation: A control-theory approach to human behavior*. Springer.

Catlin, K. S., Lewan, G. J., & Perignon, B. J. (1999). *Increasing student engagement through goal-setting, Cooperative learning & student choice*.

Charleer, S., Klerkx, J., & Duval, E. (2014). Learning dashboards. *Journal of Learning Analytics, 1*(3), 199–202. https://doi.org/10/ghbgqj

Clow, D., Cross, S., Ferguson, R., & Rienties, B. (2014). *Evidence hub review*. Milton Keynes: LACE Project. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjQ6pXW8f7uAhWL4jgGHbDPC7kQFjAAegQIBhAD&url=https%3A%2F%2F

lace.apps.slate.uib.no%2Fdeliverables%2Fd2-5-evidence-hub.pdf&usg=AOvVaw23hjxhQKrNSvrzXa8yxzGE
Cobos, R., Gil, S., Lareo, A., & Vargas, F. A. (2016). *Open-DLAs: an open dashboard for learning analytics*. In Proceedings of the Third (2016) ACM Conference on Learning @ Scale, 265–268. https://doi.org/10/gh4kfn
Cruz, H. L., & Zambo, D. (2013). Student data portfolios give students the power to see their own learning. *Middle School Journal, 44*(5), 40–47. https://doi.org/10/ghbgqw
Cunningham, C. A., & Billingsley, M. (2002). *Curriculum webs: A practical guide to weaving the web into teaching and learning*. Allyn & Bacon.
DeVellis, R. F. (2003). *Scale development: Theory and applications*. Sage.
Dipace, A., Fazlagic, B., & Minerva, T. (2019). The design of a learning analytics dashboard: EduOpen MOOC platform redefinition procedures. *Journal of E-Learning and Knowledge Society, 15*(3), 29–47. https://doi.org/10/gh4kfq
Dollinger, M., & Lodge, J. (2019). What learning analytics can learn from students as partners. *Educational Media International, 56*(3), 218–232. https://doi.org/10/gh4vrq
Dollinger, M., Liu, D., Arthars, N., & Lodge, J. (2019). Working together in learning analytics towards the co-creation of value. *Journal of Learning Analytics, 6*(2) https://doi.org/10/gf7jrs
Duval, E. (2011). *Attention please! Learning analytics for visualization and recommendation*. In Proceedings of the 1st international conference on learning analytics and knowledge, pp. 9–17. https://doi.org/10/fxvbww
Dweck, C. S. (1986). Motivational Processes Affecting Learning. *American Psychologist, 41*(10), 1040–1048.
Dweck, C. (2012). *Mindset: Changing the way you think to fulfil your potential*. Hachette UK.
Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256–273. https://doi.org/10/g9b
Einhardt, L., Tavares, T. A., & Cechinel, C. (2016). *Moodle analytics dashboard: A learning analytics tool to visualize users interactions in Moodle*. In 2016 XI Latin American Conference on Learning Objects and Technology (LACLO), pp 1–6. https://doi.org/10/gh4kd7
Elliot, A. J., & Harackiewicz, J. M. (1994). Goal setting, achievement orientation, and intrinsic motivation: A mediational analysis. *Journal of Personality and Social Psychology, 66*(5), 968.
Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72*(1), 218.
Ferguson, R., & Clow, D. (2017). *Where is the evidence?: A call to action for learning analytics*. In Proceedings of the seventh international learning analytics & knowledge conference, pp 56–65. https://doi.org/10.1145/3027385.3027396.
Fourcade, M., & Healy, K. (2013). Classification situations: Life-chances in the neoliberal era. *Accounting, Organizations and Society, 38*(8), 559–572. https://doi.org/10/gddxm7
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10/gfxd5s
Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education, 28*, 68–84. https://doi.org/10/gfw7t5
Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist, 54*(7), 493. https://doi.org/10/bv8qnq
Greene, J. A., & Azevedo, R. (2007). A theoretical review of Winne and Hadwin's model of self-regulated learning: New perspectives and directions. *Review of Educational Research, 77*(3), 334–372. https://doi.org/10.3102/003465430303953
Greller, W., & Drachsler, H. (2012). *Translating learning into numbers: A generic framework for learning analytics*. http://dspace.ou.nl/handle/1820/4506
Hadwin, A., Järvelä, S., & Miller, M. (2018). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In *Handbook of self-regulation of learning and performance* (2nd ed., pp. 83–106). Routledge/Taylor & Francis Group.

Hattie, J. (2009). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement (reprinted)*. Routledge.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112. https://doi.org/10.3102/003465430298487

Henderson, M., Ajjawi, R., Boud, D., & Molloy, E. (2019). *The impact of feedback in higher education: Improving assessment outcomes for learners*. Springer.

Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019). Empowering online teachers through predictive learning analytics. *British Journal of Educational Technology, 50*(6), 3064–3079. https://doi.org/10/ghgv72

Herodotou, C., Rienties, B., Hlosta, M., Boroowa, A., Mangafa, C., & Zdrahal, Z. (2020). The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study. *The Internet and Higher Education, 45*, 100725. https://doi.org/10/gh2p5m

Hooker, L. (2017, October 9). Have you been nudged? *BBC News*. https://www.bbc.com/news/business-41549533

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10/dbt

Hulleman, C. S., Schrager, S. M., Bodmann, S. M., & Harackiewicz, J. M. (2010). A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels? *Psychological Bulletin, 136*(3), 422–449. https://doi.org/10.1037/a0018947

Hu, X., Hou, X., Lei, C.-U., Yang, C., & Ng, J. (2017). *An outcome-based dashboard for moodle and Open edX*. In Proceedings of the seventh international learning analytics & knowledge conference, pp 604–605. https://doi.org/10/gh4kd8

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938. https://doi.org/10/f89k7b

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10/ghzv6c

Jagacinski, C. M., & Nicholls, J. G. (1984). Conceptions of Ability and Related Affects in Task Involvement and Ego Involvement. *Journal of Educational Psychology, 76*(5), 909–919. http://doi.org/10.1037/0022-0663.76.5.909

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data driven approaches in digital education* (pp. 82–96). Springer.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018*). License to evaluate: Preparing learning analytics dashboards for educational practice*. In Proceedings of the 8th international conference on learning analytics and knowledge, pp 31–40. https://doi.org/10.1145/3170358.3170421.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758. https://doi.org/10/gg4jzt

Kennedy, G., Corrin, L., Lockyer, L., Dawson, S., Williams, D., Mulder, R., Khamis, S., & Copeland, S. (2014). *Completing the loop: Returning learning analytics to teachers*. ASCILITE.

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*. Sage.

Kline, R. B. (2016). Principles and practice of structural equation modeling. In Principles and practice of structural equation modeling (*4th* ed.) (Chapter xvii, 534 Pages). New York, NY, US: Guilford Press. http://www.proquest.com/docview/1775386879/D41D6069B7FE4F41PQ/1

Lawton, G. (2013). Nudge: You're being manipulated – have you noticed? *New Scientist*. https://www.newscientist.com/article/mg21829221-700-nudge-youre-being-manipulated-have-you-noticed/

Leony, D., Pardo Sánchez, A., Fuente Valentín, L. de la, Quiñones, I., & Delgado Kloos, C. (2012). *Learning Analytics in the LMS: Using Browser Extensions to Embed Visualizations into a Learning Management System*. https://e-archivo.uc3m.es/handle/10016/18720

Lim, L., Dawson, S., Joksimovic, S., & Gašević, D. (2019). *Exploring students' sensemaking of learning analytics dashboards: Does frame of reference make a difference?* In Proceedings of the 9th international conference on learning analytics & knowledge, pp 250–259. https://doi.org/10/ghbgqk

Lipnevich, A. A., & Smith, J. K. (2008). Response to assessment feedback: The Effects of grades, praise, and source of information. *ETS Research Report Series*, *2008*(1), i–57. https://doi.org/10/gf4vbj

Liu, D. Y.-T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student learning support in higher education. In *Learning analytics: Fundaments, applications, and trends* (pp. 143–169). Springer. https://doi.org/10.1007/978-3-319-52977-6_5

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130–149. https://doi.org/10/b89fmw

Matcha, W., Uzir, N. A., Gašević, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 13*(2), 226–245. https://doi.org/10/ghbgqq

Mcmanus, T. F. (2000). Individualizing instruction in a web-based hypermedia learning environment: Nonlinearity, advance organizers, and self-regulated learners. *Journal of Interactive Learning Research, 11*(2), 219–251.

Mejias, U. A., & Couldry, N. (2019). Datafication. *Internet Policy Review*, *8*(4), 4. https://doi.org/10/ghqpmp

Mor, Y., Ferguson, R., & Wasson, B. (2015). Editorial: Learning design, teacher inquiry into student learning and learning analytics: A call for action. *British Journal of Educational Technology, 46*(2), 221–229. https://doi.org/10/f6656d

Midgley, C., Kaplan, A., Middleton, M., Maehr, M. L., Urdan, T., Anderman, L. H., Anderman, E., & Roeser, R. (1998). The Development and Validation of Scales Assessing Students' Achievement Goal Orientations. *Contemporary Educational Psychology, 23*(2), 113–131. https://doi.org/10.1006/ceps.1998.0965

Midgley, C., Maehr, M. L., Hicks, L., Roeser, R., Urdan, T., Anderman, E., Kaplan, A., Arunkumar, R., & Middleton, M. (1996). Patterns of adaptive learning survey (PALS). Ann Arbor, MI: Center for Leadership and Learning.

Nicholls, J. G. (1984). Achievement Motivation: Conceptions of Ability, Subjective Experience, Task Choice, and Performance. *Psychological Review, 91*, 328–346.

Nunnally, J. (1962). The analysis of profile data. *Psychological Bulletin, 59*(4), 311–319. https://doi.org/10.1037/h0041246

Nussbaum, A. D., & Dweck, C. S. (2008). Defensiveness versus remediation: Self-theories and modes of self-esteem maintenance. *Personality and Social Psychology Bulletin, 34*(5), 599–612. https://doi.org/10/dfkrkj

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60*(6), 723–735. https://doi.org/10/ggf2x4

Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society, 17*(4), 49–64.

Pardo, A. (2018). A feedback model for data-rich learning experiences. *Assessment & Evaluation in Higher Education, 43*(3), 428–438. https://doi.org/10.1080/02602938.2017.1356905

Pardo, A., Han, F., & Ellis, R. A. (2016). *Exploring the relation between self-regulation, online activities, and academic performance: A case study*. In Proceedings of the SIXth international conference on learning analytics & knowledge, pp 422–429. https://doi.org/10/ghbgqp
Pincham, L. (2006). Individualized goal setting for at-risk students. In *National Middle School Association (NJ3)* (Vol. 10, Issue 1, pp. 39–40). National Middle School Association.
Podgorelec, V., & Kuhar, S. (2011). Taking advantage of education data: Advanced data analysis and reporting in virtual learning environments. *Elektronika Ir Elektrotechnika, 114*(8), 111–116. https://doi.org/10/dt8qwv
Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Anderson, T. (2018). Co-designing learning analytics tools with learners. *Learning Analytics in the Classroom: Translating Learning Analytics Research for Teachers*, 93–110. https://doi.org/10/ghdg8d
Pintrich, P. R., Conley, A. M., & Kempler, T. M. (2003). Current issues in achievement goal theory and research. *International Journal of Educational Research, 39*(4), 319–337. https://doi.org/10.1016/j.ijer.2004.06.002
R Core Team. (2020). *R: A Language and environment for statistical computing. (Version 4.0)* (4.0) [R]. https://cran.r-project.org
Revelle, W. (2019). *psych: Procedures for Psychological, psychometric, and personality research* [R package]. https://cran.r-project.org/package=psych
Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action evaluation framework: A review of evidence-based learning analytics interventions at the Open University UK. *Journal of Interactive Media in Education, 2016*(1) https://eric.ed.gov/?id=EJ1089327
Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018). Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers. *The International Review of Research in Open and Distance Learning, 19*(5) https://doi.org/10/gh4kf7
Roberts-Holmes, G. (2015). The 'datafication' of early years pedagogy: 'If the teaching is good, the data should be good and if there's bad teaching, there is bad data. *Journal of Education Policy, 30*(3), 302–315. https://doi.org/10/ghzv67
Ruipérez-Valiente, J. A., Muñoz-Merino, P. J., Gascón-Pinedo, J. A., & Kloos, C. D. (2017). Scaling to massiveness with ANALYSE: A learning analytics tool for open edX. *IEEE Transactions on Human-Machine Systems, 47*(6), 909–914. https://doi.org/10/gck34z
Schön, D. A. (1992). The theory of inquiry: Dewey's legacy to education. *Curriculum Inquiry, 22*(2), 119–139. https://doi.org/10/fjsgm8
Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10/f9t33q
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512. https://doi.org/10/ghbgqm
Seligman, M. (2018). PERMA and the building blocks of Well-being. *The Journal of Positive Psychology, 13*(4), 333–335. https://doi.org/10/gdg6tp
Siemens, G. (2013). Learning analytics the emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851
Siemens, G., & Baker, R. S. J. d. (2012). *Learning analytics and educational data mining: Towards communication and collaboration*. In Proceedings of the 2nd International conference on learning analytics and knowledge, pp 252–254. https://doi.org/10.1145/2330601.2330661.
Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences, 42*(5), 893–898. https://doi.org/10/dsxstk
Stober, D. R., & Grant, A. M. (2010). *Evidence based coaching handbook: Putting best practices to work for your clients*. Wiley.

Suthers, D., & Verbert, K. (2013). *Learning analytics as a 'middle space'*. In Proceedings of the third international conference on learning analytics and knowledge, pp 1–4. https://doi.org/10.1145/2460296.2460298.

Teasley, S. D. (2017). Student facing dashboards: One size fits all? *Technology, Knowledge and Learning, 22*(3), 377–384. https://doi.org/10/gf9dz4

Tempelaar, D. T., Heck, A., Cuypers, H., van der Kooij, H., & van de Vrie, E. (2013). *Formative assessment and learning analytics*. In Proceedings of the third international conference on learning analytics and knowledge, pp 205–209. https://doi.org/10/gh4kfj

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior, 47*, 157–167. https://doi.org/10/f67dk9

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

The Jamovi Project. (2020). *Jamovi (version 1.6)* (1.6) [Computer software]. https://www.jamovi.org

Vandewalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement, 57*(6), 995–1015. https://doi.org/10.1177/0013164497057006009

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509. https://doi.org/10/f49sdg

Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal Ubiquitous Comput, 18*(6), 1499–1514. https://doi.org/10/gfj8gh

Vigentini, L. (2009). Using learning technology in university courses: Do styles matter? *Multicultural Education & Technology Journal, 3*(1), 17–32.

Vigentini, L. (2010). *From learning to e-learning: Mining educational data. A novel, data-driven approach to evaluate individual differences in students' interaction with learning technology* [Thesis or Dissertation, University of Edinburgh]. http://www.era.lib.ed.ac.uk/handle/1842/5532

Vigentini, L., Clayphan, A., Zhang, X., & Chitsaz, M. (2017a). Overcoming the MOOC data deluge with learning analytic dashboards. In *Learning analytics: Fundaments, applications, and trends* (pp. 171–198). Springer. https://doi.org/10.1007/978-3-319-52977-6_6

Vigentini, L.., Wang, Y., Paquette, L., & León Urrutia, M.. (2017b). *MOOC analytics: Live dashboards, post-hoc analytics and the long-term effects. Joint MOOCs workshops from the Learning analytics and Knowledge Conference 2017* (online, Vol. 1967). CEUR-WS.org. http://ceur-ws.org/Vol-1967/

Vigentini, L., Liu, D. Y. T., Arthars, N., & Dollinger, M. (2020). Evaluating the scaling of a LA tool through the lens of the SHEILA framework: A comparison of two cases from tinkerers to institutional adoption. *The Internet and Higher Education, 45*, 100728. https://doi.org/10/ggm39d

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. *Metacognition in Educational Theory and Practice*, pp. 277–304.

Winne, P. H., & Perry, N. E. (2000). Chapter 16 – Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531–566). Academic Press. https://doi.org/10.1016/B978-012109890-2/50045-7

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 203–211) https://doi.org/10/ggbn2w

Wolf, G. (2009). Know thyself: Tracking every facet of life, from sleep to mood to pain, 24/7/365 | WIRED. *Wired*. https://www.wired.com/2009/06/lbnp-knowthyself/?currentPage=all

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist, 25*(1), 3–17. https://doi.org/10/fgn62k

Chapter 15
"We Know What You Were Doing"

Understanding Learners' Concerns Regarding Learning Analytics and Visualization Practices in Learning Management Systems

Johanna Velander, Nuno Otero, Teresa Cerratto Pargman, and Marcelo Milrad

1 Introduction

Potential benefits from the use of learning analytics (from now on – LA) in educational settings have been examined in several studies (Viberg et al., 2018), such as improving students' learning outcomes through personalised feedback (Lim et al., 2020) as well as supporting their learning process (Jivet et al., 2020). Although ethical issues of LA systems have been increasingly researched in recent years (Slade & Prinsloo, 2013; Drachsler & Greller, 2016; Slade et al., 2019; Ferguson, 2019; Jones, 2019), little is still known about how such issues play out in educational practice (Cerratto Pargman & McGrath, 2021a). In particular, studies on students' awareness of data collection, data usage at their institution, and how students' awareness impacts the acceptance of the use of student data in LA contexts are not yet commonplace in LA (Cerratto Pargman & McGrath, 2021b).

Most HEIs have adopted LMS to facilitate online learning. As such, students can access their course material, submit and gain feedback on assignments and coursework, and access forums that enable online collaboration. COVID-19 has

J. Velander · M. Milrad (✉)
Linnaeus University, Växjö, Sweden
e-mail: johanna.velander@lnu.se; marcelo.milrad@lnu.se

N. Otero
Linnaeus University, Växjö, Sweden

ITI/LARSyS, Funchal, Portugal
e-mail: nuno.otero@lnu.se

T. C. Pargman
Stockholm University, Stockholm, Sweden
e-mail: tessy@dsv.su

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_15

significantly sped up the uptake of online learning; such a fast-paced move has imposed challenges to educational institutions. As a result of this fast-paced transition, there is a risk that common perceptions regarding online learning as inferior to face-to-face learning are reinforced (Hodges et al., 2020). However, the increased use of LMS in education has facilitated research in the area, which can further inform online learning. LMSs collect data about both student academic performance and student interaction with the system, which can be analyzed and used in the LA system to, for example, inform students on how they are performing, promote reflection, provide personalized learning paths, and enable early intervention when students are at risk of failing. However, LA incorporating predictive analytics (PA) with features such as personalized learning paths is at a very early stage of adoption in Europe. Few HEIs have defined strategies or official policies for using LA (Tsai et al., 2020). A recent publication (Apiola et al., 2019) presenting case studies examining the use of data gathered by existing LMSs has stated concrete benefits of digital learning, such as identifying students at risk of dropping out and providing individual learning paths for students based on their learning styles as well as being helpful for teachers' development of pedagogical models (Apiola et al., p. 631). The accuracy of these outcomes, however, is dependent on rich data sets. The challenge in acquiring the richness of data that is needed for LA to become accurate and valuable and at the same time build and foster trust between the stakeholders is nontrivial. Supporting the building of data richness requires efforts involving the data collecting entity, the institution, and the students since data about learning activities relies on students' active involvement.

It is therefore essential to understand the students' attitudes about their data being collected and used by the HEI before embarking on larger-scale implementations that might (1) not cater to students needs and expectations and (2) might raise concerns about ethical issues including privacy, methods used to analyze the data, and motivations for using the data potentially resulting in damaging the trust that students have in their HEIs. The remainder of the chapter goes as follows; we first give a brief overview of previous research focused on HEI's data collection practices related to LA. We then outline our research questions and explain and motivate the methodology applied. We finish the chapter by presenting the results of our efforts, discussing potential implications for using data in LA dashboards. After highlighting the limitations of our work and suggestions for future research, we conclude by discussing the implications of our findings concerning the design of LA dashboards.

2 Theoretical Background

In this section, we first present relevant research efforts contributing to the understanding of ethical issues/challenges in LA, focusing on students' perceptions and attitudes towards data collection and data usage in LA practices.

2.1 Learning Analytics: Potential Benefits and Hurdles

Previous research in this field has found that both students and staff see potential benefits with LA, such as improving the learning and teaching process and learning outcomes in higher education (Howell et al., 2018; Klein et al., 2019). However, for the potential to be harnessed and translated into tools that are accepted and adopted by its intended users, developers and researchers need to involve stakeholders such as students and teachers in the research contributing to informing and influencing the design and development of LA systems (Knight et al., 2016; Roberts et al., 2017; Klein et al., 2019; Slade et al., 2019). The discussion on ethical issues has highlighted the risk of leaving students vulnerable to unintended LA systems outcomes since the technological advancement is often so fast that it outpaces that of regulatory and institutional frameworks (Prinsloo & Slade, 2015).

Students have expressed concerns about how data presented in LA can potentially lead to self-fulfilling prophecies and preconceptions about students' underperformance (Arnold & Sclater, 2017; Jones, 2019). Similarly, academic advisors have raised concerns that student access to predictive measures should only be allowed with an advisor present to help interpret the predictive scores and mitigate such effects as self-fulfilling prophecies (Jones, 2019).

Several identified hurdles to overcome are related to "lack of trustworthy technological infrastructure, misalignment between LA tool capabilities and user needs, and the existence of ethical concerns about the data, visualizations, and algorithms that underlie LA tools" (Klein et al., 2019, p. 1). Increasing access to data has also triggered a discussion on whether it is morally justifiable not to use this data to provide more effective and relevant support for all students (Prinsloo & Slade, 2015). However, this complex issue requires close attention to benefits and harms related to particular institutional, disciplinary, and geopolitical contexts (Prinsloo & Slade, 2017).

Institutions often adopt a paternalistic approach to justify the data collection and information practices (Connelly, 2000; Prinsloo & Slade, 2015; Rubel & Jones, 2016; Jones, 2019). Students are often unaware of what data is being collected and why, and this could potentially undermine the foundational principles that frame LA systems' development (Beattie et al., 2014; Roberts et al., 2017; Jones, 2019). Although several studies confirm students' willingness to share their data with their HEI (Slade et al., 2019; Tsai et al., 2020; Velander, 2020), the questions formulated to express consent regarding data collection are often asked in general terms not concerning the use in specific contexts. Additionally, the privacy paradox often mentioned in data collection contexts is also true in learning analytics: the phenomenon where users claim to be protective of their data but act contrary to this claim. Students express a willingness to have information regarding data collection and also to have some control over their data (Ifenthaler & Schumacher, 2016); however, they rarely engage in information about institutional data handling policies provided by the institution (Slade et al., 2019; Tsai et al., 2020; Velander, 2020).

Slade et al. (2019) discuss how students can be given more control of their data where transparency of data collection and the data's uses is especially highlighted. This could contribute to students feeling more involved and can move "learning analytics forward from a one-way institutional voice-over on student's learning journeys" (Slade et al., 2019, p. 9).

Learning analytics dashboards (LADs) used in HE has the potential to support both students and teachers in the learning and teaching process (Jivet et al., 2020). This potential is documented in several studies; however, seldom realized in practical implementations of LA (Viberg et al., 2018; Cerratto Pargman & McGrath, 2021).

Through data collected about learners, dashboard visualizations can make learners reflect on their learning and gain an enhanced awareness of their learning performance. Through these dashboards, the data is put into a context to enable students to make sense of the data. In their recent study, Jivet et al. (2020) found that students, through interacting with LA dashboard mock-ups, value features that provide some transparency and allow opening or at least allowing a peek into the *black box*. The provision of information on how indicators are calculated, along with motivations as to why the features are relevant, for example, was especially appreciated when students were trying to master a goal (Jivet et al., 2020, p. 9).

Despite many studies highlighting the absence of empirical research involving stakeholders such as students and teachers, the area remains sparsely investigated. Students' involvement in decisions about LA has been recommended by many (Slade & Prinsloo, 2013; Ifenthaler & Schumacher, 2016; Roberts et al., 2017) as a general ethical principle but is rarely promoted. Not considering students' perceptions in the decision-making process may pose challenges to learning analytics systems (Beattie et al., 2014). Klein et al. (2019) report reasons for the low adoption of LA, such as "lack of reliable technological infrastructure, misalignment between LA tool capabilities and user needs, and the existence of ethical concerns about the data, visualizations, and algorithms that underlie LA tools" (Klein et al., 2019, p. 1). Our study contributes to the area by investigating stakeholders' reflections on the actual use of their data in concrete LA contexts. As such, it increases our understanding of the importance of involving stakeholders early on in the design process of LA. Our results also reveal several benefits and risks that students identify when faced with the data on the LA dashboard. These results are important for understanding stakeholders' expectations of the particular use of their data and revealing tensions that arise when considering the risks and benefits of the uses of their data. Summarizing, these results further highlight the importance of the involvement of stakeholders to avoid unintended consequences from the use of their data.

3 Research Questions

This work aims to investigate students' present understanding and awareness of data collection ongoing at their HEI. More specifically, our efforts were set to answer the following questions:

RQ1: How do students understand emerging learning analytics practices in learning management systems?
RQ2: What are the students' ethical stances when raising awareness of these practices through data visualization?

4 Initial Study: Understanding Students' Awareness and Attitudes of Data Collection at Their HEI

To answer our first research question – *How do students understand emerging learning analytics practices in learning management systems?* – we conducted a survey-based study. Before conducting a deployment study, the rationale was to understand students' attitudes to and awareness of the data collection at their HEI. The questionnaire created for the survey study also asked students to rate values vital to them in data collection practices. The values under consideration in the questionnaire were predetermined and based on values suggested by Friedman et al. (2008). Understanding what values are important to stakeholders can help identify values considered in the technology design. Lastly, we wanted to know how students engage with policy documentation regarding the institution's data collection. More specifically, the questionnaire consisted of 21 questions, including both open-ended and closed questions. The questionnaire opened with questions on demographics, followed by questions regarding online data collection, after which students were asked to rate the importance of different values related to data collection. The questionnaire then explored students' awareness of data collection and data collection practices at their HEI. The questionnaire can be found in its entirety here: https://doi.org/10.6084/m9.figshare.13347695.v1.

In line with previous studies (Slade et al., 2019), we found that a majority, 70%, of students were not at all or just a little bit worried about online data collection. They were even less concerned about the data collection when the HEI is the entity collecting the data; here, as many as 80% were not at all or just a little bit worried. 32.5% were aware of what data is being collected about them by the HEI, and it is of little surprise then that we find that only 22.5% had engaged in privacy policy documentation provided by the HEI. Interestingly, there was a large difference in both students' awareness of data collected by the university and the policy documentation engagement. 57.1% of LNU respondents claimed to be aware of the university's data collection, whereas this figure for SU was only 19.2%. We found a similar pattern examining the proportions of students engaging in policy documentation where 43% from LNU had read these while only 11.5% of respondents from SU had.

4.1 Values Students Appreciate Concerning Online Data Collection

The questionnaire presented students with eight different values to rate according to their importance in a data collection context. This section describes these values and illustrates those that students appreciate most. The values that could be rated by the students were ownership, management and storage, privacy (who has access), privacy (who has control), bias, trust, autonomy, and informed consent. As can be seen in Fig. 15.1, the values of trust and privacy control (who has control of the data) were rated as most important by the students (76.9% rated these values as very important), followed by management and storage, privacy access (who has access), and informed consent (61.5% rated these as very important). The least important value seemed to be autonomy, with only 23.1% rating this as very important, followed by bias with 30.8% rating this as very important. As privacy and trust values that respondents rated very high, these values play an essential role in determining how accepting they are to share their data.

To sum up the results from this survey, we find that students seem very relaxed towards online data collection, mainly if the HEI carries this out. Students value privacy, trust, and informed consent highly regarding online data collection.

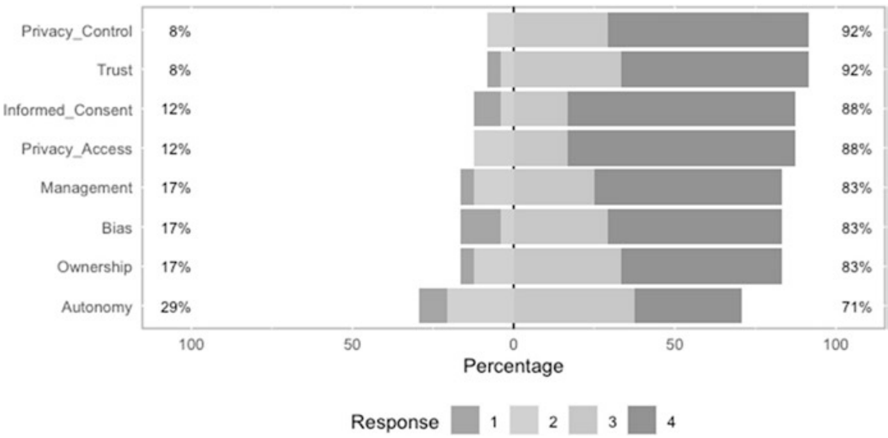


Fig. 15.1 Values stacked bar plot, all responses showing how students rate different values (values, y-axis; percentage, x-axis). Responses according to Likert scale where 1 indicates *not at all important*, 2 *a bit important*, 3 *quite important*, and 4 *very important*

5 Deployment of Analytics Dashboard: Raising Awareness of Data Collection

With the insights from the initial study, we set out to understand how and if students’ attitudes towards data collection practices at their HEI change with an increased awareness of the current data collection taking place. This was done through a deployment study that is described in more detail in this section.

The deployment study carried out involved:

- The development and deployment of a student-facing analytics dashboard illustrating to students the data currently being collected about them by the LMS at their HEI. The LA dashboard for students (hereafter referred to as the analytics dashboard) was developed for the LMS Moodle. This customized analytics dashboard aimed to promote students’ awareness of the LMS data by visualizing data that the LMS collects about them in different graphs on the dashboard.
- A few weeks after deploying the analytics dashboard, we asked participants to answer questions posed in the initial study but also extended the scope addressing issues connected to the actual technological deployment done by asking students to give their thoughts on risks and benefits as well as their attitudes towards the specific LA examples graphing their data on the analytics dashboard.

5.1 Dashboard Visualizations

Initially, an analysis of the data collected by the LMS was conducted. There is a large amount of student data available through Moodle’s APIs and from using custom-made SQL queries. The data is at present unused for analytical purposes. Different stakeholders are exposed to different amounts of data; for example, students can only access their grades on assignments and resources provided by teachers and other staff members. As such, students are often unaware of the data tagged by the LMS they use. The data collected can be broadly categorized into performance data, which details students’ performance on tasks, assignments, and their grades, and events data which details students’ interaction with the system. The events data reveals how active students are by logging, for example, what resources they engage with, from what type of device and IP address they access the system, and timestamps for each of these events. An example of a custom SQL query to retrieve the origin for a student with a particular user id attending a certain course indicated by the course id from the standard-log would look like this:

```
\$DB->get_records_sql('SELECT l.origin, COUNT(*) as count
FROM m_logstore_standard_log
```

WHERE l.courseid = :courseid AND l.userid = :userid
GROUP BY l.origin ORDER BY count DESC',
['courseid' => \$credentials->courseId,
'userid' => \$credentials->userId]);

A more detailed description of the type of data that was chosen to be visualized follows in the following sections; we also provide images of the visualizations that were in the end implemented on the analytics dashboard. Here we present them in three categories, performance, geolocation, and events data.

Student Performance Data Usually, the Moodle course page presents students with their assignment grades feedback page in a grade and written feedback. However, there was no way for students to know how they performed related to other students in the same course. Therefore, we decided to display assignment results on the analytics dashboard presented in two different ways, as can be seen in Fig. 15.2, where all students' results for an assignment were presented in a bar chart (anonymously where the authenticated students' result is highlighted), and another in Fig. 15.3, where the students' result could be compared with the course average.

Student Geolocation Data The likely controversial collection of the IP address was used on the analytics dashboard as in Fig. 15.4. The geographical locations from where the student logged in to the course were plotted on a map together with the time of last access and the number of times the student had logged in from that geographical location.

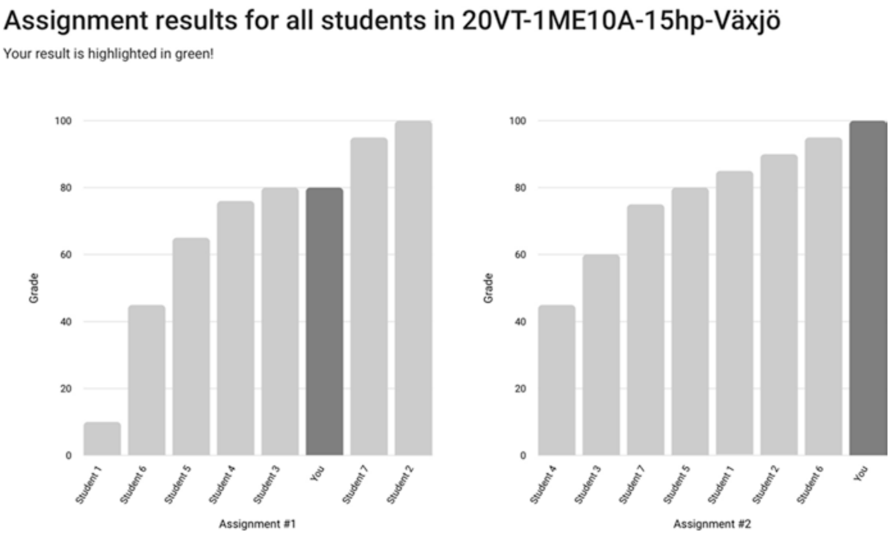


Fig. 15.2 Student performance data comparing the authenticated students' assignment results with all students in the cohort

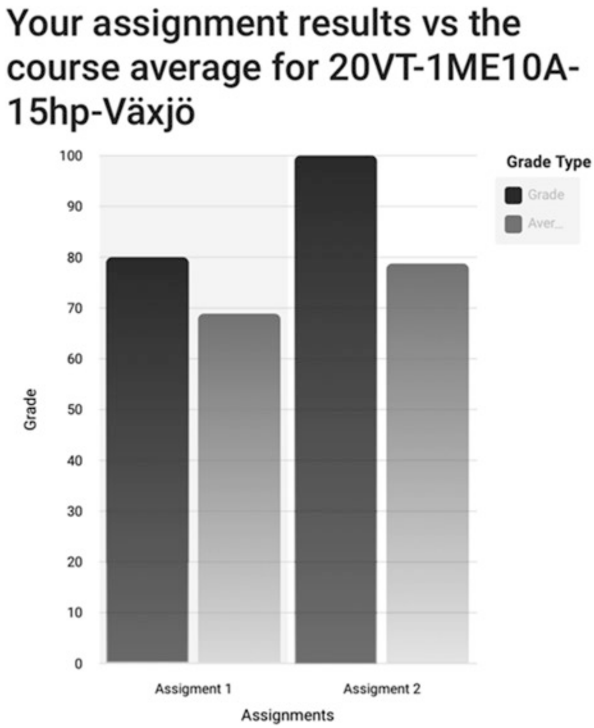


Fig. 15.3 Student performance data comparing the authenticated students' assignment results with the course average

Fig. 15.4 Student geolocation data plotted on Google map and access details, times accessed, and last date of access

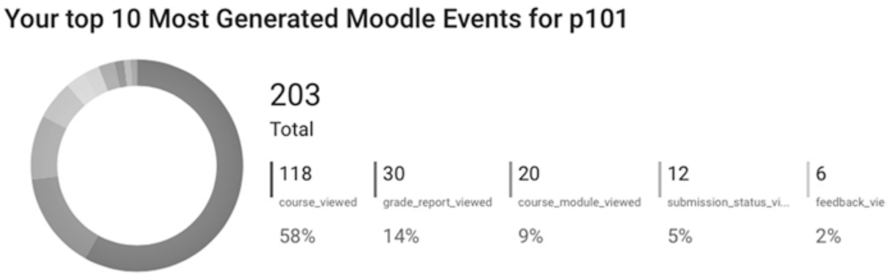


Fig. 15.5 Doughnut chart of the top ten course activities/events accessed by the student

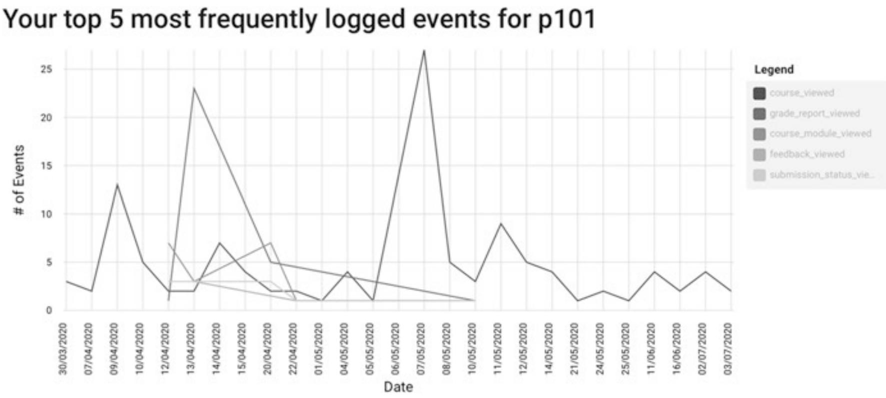


Fig. 15.6 Line chart of the course activities/events accessed by the student over time

Student Engagement Data The data trail of the authenticated student is logged as events in the database. The system logs when a student visits or accesses any events or resources like a breadcrumb trail of their online behavior. The dashboard comprised a doughnut chart showing the ten events the student has visited most frequently to visualize their online behavior for the course, as in Fig. 15.5. It also contained a chart plotting the visited events over time, as in Fig. 15.6.

The dashboard's visualizations were reviewed by an expert in "information visualization and visual analytics." After adjustments based on this heuristic evaluation, the three main areas were followed. It resulted in an analytics dashboard containing the graphs, as can be seen in Figs. 15.2–6; it can also be viewed in more detail by provided screenshots (https://doi.org/10.6084/m9.figshare.13366052.v1).

The data collected by the LMS was in this way presented on the analytics dashboard to raise students' awareness of the data the LMS collects about them. A description of the technical implementation of plugins for the LMS Moodle is required to achieve the dashboard graphs as presented above.

5.2 Technical Implementation

This section describes the technical implementation of the analytics dashboard and details the plugin structure and integration with the Moodle codebase; we also provide access to source code. Moodle[1] is an open-source LMS, and the codebase is provided as open-source software under the GNU General Public License.[2] There was no existing plugin that could satisfy the specific requirements of this study; therefore, to visualize the student data collected by Moodle, it was deemed that a modern web development framework could assist in creating a rich user experience and provide a clear delineation between the various subsystems of the plugin. In practical terms, this meant it was necessary to divide the overall plugin into three separate Moodle plugins.

Each plugin was written in PHP and was installed in the Moodle LMS according to the standard plugin installation workflow. The first of these plugins, the Moodle Web Service Plugin (MWSP), was responsible for handling HTTP requests from the Angular web app, the Angular Dashboard (AD). This plugin created a secure REST API that exposed the student data via HTTP responses containing a JavaScript Object Notation (JSON) response body. The other two plugins (Dashboard Block Plugin and Analytics Dashboard Report) were both responsible for serving the Angular web app in different views within the Moodle course pages.

The sequence diagram depicted in Fig. 15.7 represents the steps required to extract and present the authenticated student with their Moodle data. To simplify the plugin development and deployment, a microservices-like architecture (Fowler & Lewis, 2014) was adopted. By evaluating the plugin's main components, it was determined that three main areas were naturally separate and thus could be modularized.

Moodle APIs and custom SQL queries were implemented in the plugin (web service plugin) to extract the necessary data for use in the plugin that visualized the data (the Angular web app) using the ngx-charts[3] charting library. Authentication is provided to generate an OTP (one-time passcode) token and embed the Angular web app into the Moodle course performing on Moodle's authentication; it is possible to generate the OTP code without having to perform expensive user authentication calls. The code for the Moodle Analytics Dashboard Report plugin has been made available and can be found in https://github.com/jojjovelander/analytics_dashboard, and screenshots from the dashboard are provided in https://doi.org/10.6084/m9.figshare.13366052.v1

[1] https://moodle.org

[2] https://docs.moodle.org/dev/License

[3] https://swimlane.github.io/ngx-charts/#/ngx-charts/bar-vertical

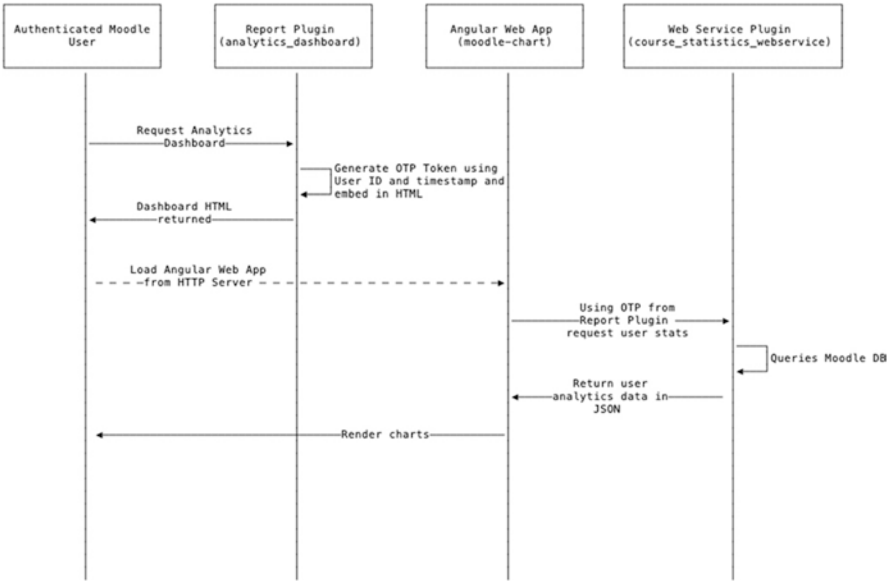


Fig. 15.7 Sequence diagram for the analytics dashboard plugin(s)

5.3 Questionnaire: Understanding the Impact of Awareness

In this section, we describe the design of the questionnaire presented to students following their use of the analytics plugin. The questionnaire was designed to investigate students' perceptions of data collection after having had access to the Moodle analytics course plugin; hence it attempts to answer our second research question – *What are the students' ethical stances when raising awareness of these practices* via *data visualization?* Specifically, students were asked about general attitudes and acceptance to data collection at their HEIs, followed by more detailed questions relating to three examples from the Moodle analytics dashboard, including risk-benefit evaluations of each instance. For example, a question regarding students' general attitude to data collection by the university was posed at the start of the questionnaire. This specific question and a follow-up question to motivate the answer have been reused from Khalil (2018) to allow for further comparison given the different geographical locations: "How comfortable are you with the university collecting data regarding your studies and online engagement to improve the effectiveness of our services and support to you?" and the follow-up question "Why do you feel this way?". To investigate students' attitudes to specific examples of the use of their data as in the analytics dashboard, the following questions were asked: "Would you feel comfortable if this information was made available on your course pages on Moodle?", "Would you be worried about how this data might be used?", and "Would you be worried about who could access this data?". These answers were provided by selecting an option from a Likert scale from "not at all worried

(1)" to "very worried (4)" with a fifth option of "not sure (5)." Open questions then asked students to suggest risks and benefits they could think of in connection with this data being collected and used.

For more details, the post-intervention questionnaire can be found in its entirety here: https://doi.org/10.6084/m9.figshare.13347752.v1. The data analysis included descriptive statistics for quantitative data collection and thematic analysis for the qualitative data.

5.4 Results

What follows are the results from the study. The analytics plugin was tested and ready for deployment relatively late in the spring semester of 2020; therefore, the educational technology department helped identify three summer courses using online learning at LNU. Students registered for these courses had access to the analytics plugin for 2 weeks and were then presented with the post-intervention questionnaire.

5.4.1 General Descriptive Information

Three hundred eighty-one students attending three summer courses at the Faculty of Technology, LNU, had access to the analytics plugin. After nearly 2 weeks of entry, they were presented with the questionnaire. Twenty-one students responded with complete questionnaires (response rate of about 6%), and what follows are the results. A majority of the respondents, 85.0% (17), were undergraduate students, and 15.0% (3) were postgraduate students. 66.7% (14) identified as male and 33.3% (7) as female.

5.4.2 Acceptance and Trust

This questionnaire opens with a general question regarding data collection at the HEI and is taken from a questionnaire (Khalil, 2018) and used in a study by Slade et al. (2019). "How comfortable are you with the university collecting data regarding your studies and online engagement to improve the effectiveness of our services and support to you?" 88.5% of respondents to our survey are either entirely or very comfortable with this. A question asking why the respondents were feeling this way followed, and here 15 out of the 21 respondents mentioned trust as the motivating factor for this. From the respondents' comments, we see that the said trust is placed in both the university and the rules and regulations students assume the university must follow. "... I assume since it is a university that it would have strong policies about not selling my information. But it is just an assumption!!" and "It is often obligatory to consent to be able to complete registration in a system. The context is also of importance. In a studying context, there are often regulations that need to be adhered to. As a private person, I trust there is a certain discipline in a society where laws are followed; therefore, I am quite comfortable with data collection by the university." This latter comment also reveals the feeling that the option of consent is limited and even required. The results are in line with the results from the previous study carried out by Slade et al. (2019); they find 79% of the respondents to be entirely or very comfortable with this data collection, and they also refer to the high number of respondents stating trust is the most important reason for them feeling this way.

5.4.3 Preferred Methods for Information About Data Collection

Students were then asked to indicate how they would like to be informed about the data collection; this question was also adopted from the questionnaire by Khalil (2018).

> How do you think you should be informed about the uses of your data to support your study experience?

As illustrated in Fig. 15.8, 33.3% indicate that they wanted the information as part of the initial registration, 28.6% as part of every (module) registration, and 4.8% as regular posts on a forum in Moodle and 14.3% wanted to receive regular emails, 9.5% after initial registration as part of registration documentation, and 9.5% via existing policy documents. These results are in line with results from the study by Slade et al. (2019) where the authors also mention that this is in "stark contrast with the very low percentage of respondents who had read and engaged with the terms of service of online service providers" (Slade et al., 2019, p. 241).

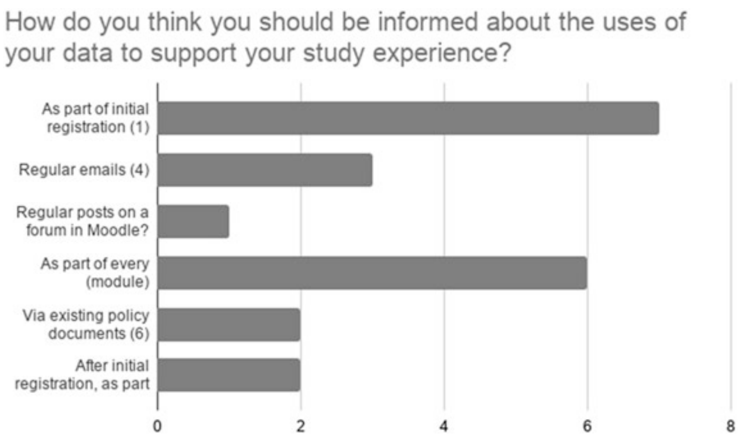


Fig. 15.8 How to be informed illustrates the answers to how students would prefer to be informed about the university's uses of the data collected

5.4.4 Students' Reflections on the Performance Data on the Analytics Dashboard

Presented with questions related to performance data, specifically asking how they felt about having the visualizations as in Fig. 15.2 available on the analytics dashboard, 52.4% were either worried or very worried about who could access this data, and 20% were concerned about how the data was used. This is a notable increase compared to how comfortable they were sharing their data when asked how they felt about data collection by the HEI in general. Somewhat surprisingly, 47.1% of respondents claimed to be unaware of this kind of data being collected about them. A majority (71%) expected to be informed about collecting this data; the rest indicated that they were not sure. Notably, none of the respondents said that they don't want to be informed. A majority also want to be provided with the option of giving consent to this data being collected, stored, and used.

5.4.5 Risk-Benefit Evaluation on the Performance Data on the Analytics Dashboard

Students could see many benefits in this data being used in LA contexts, such as understanding how they perform compared to their peers, assessing the complexity of tasks, and allowing teachers to understand and improve course tasks. One student identified the possibility of early intervention: "In this case, one can follow up on, e.g., students and see a diverging performance, which allows for, at an early stage, one [sic] can catch those students and help them. The data can also be used to evaluate and discuss potential measures for respective courses." Simultaneously, the students voiced concerns about being discouraged if they see that they perform worse than others and the risk of being identified hence their anonymity being compromised. This, in turn, had consequences; one student mentioned the risk of discrimination and polarization of groups, and another captures a concern that several students mention, that of an altered atmosphere in the cohort: "Fundamentally I think that everything concerning academic results should be anonymous, you should, of course, be able to see how a student is performing for a collected end result, but only teachers should have access rights to this. Otherwise, there is a risk of discrimination against those that are not doing so well. Favourisation [sic] of those that are doing well and increased individual stress because of the competition like a situation that will emerge, between students." The increased competitive atmosphere, the risk of compromised anonymity, and the risk of discrimination/favoritism are risks students identify with comparing their results with other students in the cohort. However, no names are provided in the chart.

5.4.6 Students' Reflections on the Geolocation Data on the Analytics Dashboard

66.7% were quite or very worried about who could access this data and 42.9% about how it could be used. Here we observed an even more notable change compared to the result gained when students were asked how comfortable they were with the HEI data collection in general. 85.7% wanted to be informed about this kind of data being collected about them, and also 85.7% expected to be asked to give informed consent for this data to be collected, used, and stored.

5.4.7 Risk-Benefit Evaluation on the Geolocation Data on the Analytics Dashboard

Only seven students chose to comment on the benefits they could identify with using this data in LA; out of these, three say that they can see *no* benefits, their comments being "No clue," "None," and similar. Only one student gave a possible beneficial use of this data: "Only the number of logins could be used to understand how active students are," indicating that the geolocation is superfluous, and the interesting statistics would be the number of times the student authenticates and accesses the course. Six respondents chose to comment on the risks with remarks all in the same vein, "Breakage of privacy since this is an online course it should not matter," "my position should be confidential," "1984!", and "If this data is leaked there are more significant problems, it will be official when I have been away and where."

5.4.8 Students' Reflections on the Events Data on the Analytics Dashboard

None of the respondents indicated that they were very worried about how this data might be used and only 9.5% indicated that they are quite worried. A large majority, 85.7% indicated that they were either a bit worried or not at all worried. Similarly most respondents 81% were either just a bit worried or not at all worried about who might be able to access this data. Only 19% of respondents were aware of this kind of data being collected about them. Although concerns over access and use of this data was low, 66.7% still wanted to be informed about this data being collected and 76.2% wanted to be asked to give informed consent.

5.4.9 Risk-Benefit Evaluation on the Events Data on theAnalytics Dashboard

Seven students offered suggestions as to what potential benefits they identified with this kind of data collection. Five of these mentioned evaluations of either the course events or the functions that are helpful or interesting and not. One respondent suggested that it might be “beneficial for the teachers to see where it is important to invest time.” Two other students mention that it can help “follow levels of engagement” and “It is useful to see if I [sic] am missing anything to get update [sic] on.” Six students commented on the risks of event data, four of which stated “none” or “nothing comes to mind.” Really only two students identified possible risks, which were somewhat ambiguous or difficult to understand; they were “There are certain risk [sic] and could easily be translated for personal behaviors deviation against the others...” and “It is visible which courses you have visited, if you have visited completed courses that you have missed people can see that you have been there a lot.”

6 Discussion

We first observe students’ discrepant views on how their educational institutions should handle student data from the results obtained. This is particularly tangible at the level of students’ perception of data privacy and informed consent. Here we unpack such a general observation by discussing (i) the inherent trust of the students in their institutions, (ii) the impact of the dashboards on the students’ increment of awareness of (and interest in) the transparent institutional management of student data, (ii) the need for transparency in current institutional data management practices, (iv) the reliance in meta information for more transparent algorithmic-based analytics practices on students’ data, and (v) the importance of data in context to assess the acceptance of data usage.

6.1 Students’ Trust, Privacy Paradox, and Informed Consent Dilemma

The students’ responses confirm previous research indicating that student awareness of data collection practices at their HEI is often low. Very few students engage with their HEI’s personal data policy documents (Slade et al., 2019; Tsai et al., 2020; Velander, 2020). We also observe that the participating students appreciate being informed about collecting their data, and they express their needs regarding being in control over their digital traces on institutional LMS. As such, the students’ responses reflect conflicting opinions regarding data ownership that echoes the privacy paradox outlined by Barth and De Jong (2017). Such a paradox explains the dichotomy between privacy attitudes and actual online behavior (Barth & De Jong, 2017). Such a paradox is more concretely reflected in what the students say about data privacy and what they do in practice (Adorjan & Ricciardelli, 2019). In the case studies, the students are, on the one hand, not very worried about the data collection and express their trust in their educational institutions. However, on the other hand, an overwhelming majority of students want to be informed about what LMS data is being collected. The students also expect to be asked for informed consent regarding data capturing and analysis from their digital traces. In this vein, we understand that the students' trust in their educational institutions contributes to the lack of students' engagement in policy documentation and information regarding data collection at the HEI, leading to students' low awareness of current data collection practices at their educational institutions. Furthermore, the privacy paradox mentioned above is reflected in what we call the informed consent dilemma. Such a dilemma underscores the students' expressed interest in asking for permission regarding their digital traces for institutional purposes while saying no need to engage with the institutions' documents and policies about student data.

6.2 Impact of the Dashboard on the Students' Data Awareness and Their Relation with the Institutional Request for Informed Consent

The informed consent dilemma becomes more salient when presenting the students with visualizations of their data in the LMS's dashboards. Here an overwhelming majority of students wanted to be informed about their collected data and said they expected being asked to give informed consent. However, the students expressed their needs to be asked for consent as part of the initial course (module) registration process. As informed consent is a context-sensitive legal practice, asking the students in general terms at the course registration does not play the ethical and legal role expected from the consent forms. Furthermore, other problems with being informed during the registration process have been identified by Tsai et al. (2020). These authors point out that the students' priority to complete course enrollment impacted their interest in engaging with information about student data collection practices (Tsai et al., 2020, p. 237). In this respect, the results obtained may indicate, as previously noted in Velander (2020), "that the information about the data collection would be presented once, hence should the data collected be changed, be aggregated or used for purposes other than those stated in the initial information then students might still be unaware or not informed about this" (Velander, p. 66). This also points out that the data collected would be unclear, and communication regarding the student data collected was challenging to understand. The students need to be informed about time points. The purposes of managing their data without needing to deal with lengthy documentation add complexity to the ethical and legal management of student data in higher education.

6.3 The Need for Transparency in Current Institutional Management Practices

Based on our results, we argue that nurturing trust is an essential responsibility for the institution to handle given the unequal power relationship between students and institutions (Slade & Prinsloo, 2013). Fostering trust requires methods to provide students with clear insights into the *black box* of data management, facilitating students' awareness and understanding of what data and methods have been applied and are behind the outcomes of learning/predictive analytics. Previous studies by Ifenthaler & Schumacher (2016) have discussed this point in terms of dashboard design and contextual integrity, which are extended by our empirical results. Our study emerges that the specific context in which the data is accessed and represented (visualized) is of utmost importance to communicate to ensure transparency in student data management processes. As such, asking general questions regarding data collection that are not adequately situated/linked to the places (i.e., information fields) where the data is captured for further use in LA at HEI is nonsense and potentially does not comply with ethical and legal considerations regarding informed consent. Considering the potential of dashboards for presenting information leading to student awareness, reflection, and action, a future challenge is to identify the relevant methods for involving students in transparent data management practices. This would facilitate student autonomy since a transparent use of data and the inherent analytics would ensure that the algorithmic outcomes complement the user's decision-making processes.

6.4 Towards Transparency and Explainability of Algorithmic-Based Analytics Practices on Student Data

The reliance on relevant and available data that different machine learning algorithms depend on for accuracy is a complex issue considering the different extent of engagement with LMS; hence, the student data's availability depends on, for example, online and blended learning. Students and advisors have already pointed out the risks of unintended effects such as self-fulfilling prophecy and reliance on inaccurate or insufficient data for making predictions. In future efforts to account for effects like these, we see a potential for investigating the feasibility of providing students with an estimated accuracy of predictions based on the amount of data the algorithm had access to and the importance of that data in terms of providing an accurate forecast. Another way to mitigate suspicion of the accuracy of data and methods used to arrive at conclusions by machine learning models is to provide transparency by opening the *black box*. The use of black box machine learning can lead to not justifiable, legitimate decisions (Arrieta et al., 2020). LA especially using PA relies on machine learning models. These models are *black-boxed*, but using different methods, they can be considered transparent if by themselves they are understandable to their users (Arrieta et al., 2020, p. 88). While there are methods to achieve this through simulatability, decomposability, and algorithmic transparency (Arrieta et al., 2020. p. 90), these do not apply to more complex models using deep learning which rely on post hoc analysis where model simplification or feature relevance techniques are often needed to be able to allow transparency (Arrieta et al., 2020, p. 90). Providing transparency and explainability to machine learning models requires careful consideration during the model design and implementation. Although there might be a tradeoff between the performance and the transparency, the fact that humans are reticent to adopt techniques that aren't readily interpretable and trustworthy (Zhu et al., 2018; Arrieta et al., 2020) would make this effort meaningful in LA, where stakeholders rely on interaction with the AI system and hence require these systems to be understandable (Alonso & Casalino, 2019) to feel confident to rely on and be able to interpret and evaluate the information provided.

6.5 Importance of Data in Context for Assessing Acceptance Towards Data Usage

The general questions regarding attitudes towards data collection, specifically by the HEIs, revealed a very accepting attitude both in the initial and deployment studies. However, students seem to be increasingly worried about who can access the data once presented with the data in a learning context on the analytics dashboard. When reflecting on their data used in specific learning contexts, students identify many benefits and risks with using the data. We believe these risks and benefits have to be evaluated based on values that students regard as important.

More than 50% of students participating in our study claim to be worried about who can have access to their performance data. The risk-benefit evaluation indicates that students are concerned about sharing their performance results with others since this could be demotivating for students that are not performing so well. The risk of biases, added stress, and promoting a competitive atmosphere was also mentioned as detrimental. A recent study by Jivet et al. (2020) where students rate features supporting self-regulating learning on a LA dashboard reveals that students prefer performance metrics where their results are related and compared to their past performance and goals rather than with other students' performance (Jivet et al., 2020). Based on these findings, the need for this kind of metric on a student-facing dashboard can therefore be questioned. Our study, however, reveals that students see more benefits when this data is accessible for teachers where it can help evaluate the course and the complexity of tasks. Slade and colleagues also find that "respondents are saying that they care much less about what is collected and more about who sees that information" (Slade et al., 2019).

Students' reflections on the collection of the geolocation data indicate a clear reluctance to both sharing and using this data. Since our study is limited to evaluating the acceptance of data collection and the use of the data, it does not carefully consider how accepting students would be if this data was used to benefit them. Since acceptance seems to be related to the perceived usefulness or motive of using data, this should be further examined. Ifenthaler & Schumacher, for example, find that users are more willing to share data if the LA system provided rich and meaningful information (Ifenthaler & Schumacher, 2016).

6.6 Summarizing the Findings Related to Our Research Questions

To sum up, our findings related to each RQ are presented here. Related to RQ1, results from our initial study reveal that students are largely unaware of the data collection and use of data. They seldom engage with the privacy policy documentation provided by the institution, and when asked in general, they are very accepting towards the institution collecting and using their data. This might be due to their trust in the institution and the laws and regulations that these have to adhere to. When asked, few respondents provide thoughts on how data can be used to improve teaching and learning.

Considering RQ2, we find that students' ethical stance somewhat changes once they have seen the use of their data on the LA dashboard. They are especially concerned about who can access the data. A vast majority want to be informed about this data collection and expect to give informed consent for the data to be collected and used. Students also elaborate on the risks and benefits that they see with the use of the data. This reveals tensions of data use that need to be considered. For example, while students can see the benefits of comparing performance between students to inform them on how they are doing, this can also have a demotivating effect if one doesn't perform well.

7 Limitations and Current and Future Work

We believe that our contribution to this book showed the complexity of addressing ethical issues concerning the implementation and use of LAs in LMS from a learners' perspective. The qualitative results presented enable us to envision the need for larger-scale studies exploring the potential of quantitative approaches. More specifically, soon, we plan to extend the sample sizes to apply more robust statistical analyses and expand the investigations across different HEIs using different teaching methods such as online and blended learning. Nevertheless, the sample used in our studies includes students from two universities studying at both undergraduate and postgraduate levels. It offers a good insight into students' awareness and perceptions of data-driven practices.

We are also limiting the scope to include data-driven practices and students as stakeholders. Given the range of stakeholders affected by learning analytics and data-driven practices, we are also planning to have teachers and staff such as educational technologists in the LA dashboards and supporting systems. As an example of current ongoing work, an initial effort to further our understanding of how the university approaches ethical issues in technologies such as LMS, we presented our findings to the educational technologists at LNU. Ten educational technologists attended the session, and the presentation was followed by a spontaneous discussion where it was mentioned that ethical aspects in technologies and how to approach them were something that they seldom got together to discuss or know enough about. Preliminary findings suggest that the university is collecting the data but is not using it unless there is a need to verify something. At the moment, the stakeholders participating were not sure about the implications of gathering all this data – "who owns this data?" was asked. Nevertheless, suggestions of how the data could be used were made, such as providing teachers with a better overview and understanding of how students perform.

This explorative study included results from a pre-study having different participants than the main deployment study. To properly assess individual changes of attitudes, we see the potential of conducting a pre-post intervention study involving the same participants observing these individual changes in attitudes. We are therefore planning on extending the deployment to include pre and post questionnaires and examining data logs to observe user behavior in terms of the extent to which the dashboard is used and whether the awareness of data collection practices alters user behavior interacting with the LMS.

Finally, we want to mention that our study did not carefully consider how the data visualizations could help the students in their learning; this would be a natural next step in the endeavor to understand and empirically examine the putative benefits of dashboards. Involving stakeholders in designing features to improve the learning process and outcomes will be a necessary step in the overall design cycle. As we noted, providing the expected information and ensuring consent and privacy so that students will engage with systems implemented is a complex process.

8 Conclusions

This chapter reports on student awareness and attitudes of the collection and use of student data in HEI. The findings reveal several aspects of data handling that can be important to consider in designing and planning student-facing dashboards.

Decision-Making Based on Particularized Information

First, we want to draw attention to the unreliability in concluding acceptance of data collection and usage based on generalized questions. When designing and planning dashboards, it is of utmost importance to investigate the acceptance of the data in the intended context to avoid unintended consequences and not overestimate students' acceptance of the data used in particular situations.

Main Identified Challenges

We identify several challenges in providing students with the levels of detail about data collection that they expect. Students' trust in the institutions leads to lower levels of engagement in policies and information regarding data practices, although they express an evident willingness and expectation to be informed and asked for consent concerning their data being collected and used. Combined with our findings that indicate that data collection processes and data usage are highly related to the context of its use and with whom such data is shared, we propose methods resonating with HCLA (Human-Centered Learning Analytics) as proposed by Ochoa and Wise (Ochoa and Wise, 2021) bringing students into (1) design and conceptualization process and (2) transparency in order to facilitate trust in the system.

Recommendations Concerning LA Dashboard Design Based on Identified Challenges

Allow students insight into what data is used, how it is used, and why it is used in different dashboard features. This information presented in connection with the specific use of data should be easily digestible. By presenting the information in the explicit context of its use, the amount of information will be reduced and more easily understood, thus avoiding students to (a) proactively search for policy documents, (b) read long texts that are difficult to digest and relate to a specific use of data, and (c) be suspicious of data, methods, and motives used. Considering methods promoting transparency and explainability in AI methods used in LA dashboards will enable its users to understand, trust, and make informed decisions based on these predictions.

Involve stakeholders in the design process of LA dashboards. Not only is the input from stakeholders valuable at the evaluation stage but of great value throughout from early on in the conceptualization phase. Co-design methods such as VSD can help organize and ensure stakeholders' input is considered throughout.

References

Adorjan, M., & Ricciardelli, R. (2019). A new privacy paradox? Youth agentic practices of privacy management despite "nothing to hide" online. *Canadian Review of Sociology/Revue canadienne de sociologie, 56*(1), 8–29.

Alonso, J. M., & Casalino, G. (2019, June). Explainable artificial intelligence for human-centric data analysis in virtual learning environments. In *International workshop on higher education learning methodologies and technologies online* (pp. 125–138). Cham: Springer.

Apiola, M., Karunaratne, T., Kaila, E., & Laakso, M. J. (2019, May). Experiences from digital learning analytics in Finland and Sweden: A collaborative approach. In *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)* (pp. 627–632). IEEE.

Arnold, K. E., & Sclater, N. (2017, March). Student perceptions of their privacy in learning analytics applications. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 66–69).

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities, and challenges toward responsible AI. *Information Fusion, 58*, 82–115.

Barth, S., & De Jong, M. D. (2017). The privacy paradox–Investigating discrepancies between expressed privacy concerns and actual online behavior–A systematic literature review. *Telematics and Informatics, 34*(7), 1038–1058.

Beattie, S., Woodley, C., & Souter, K. (2014). Creepy analytics and learner data rights. In *Rhetoric and reality: Critical perspectives on educational technology. Proceedings ascilite* (pp. 421–425).

Cerratto Pargman, T. C., & McGrath, C. (2021a). Mapping the terrain of ethics in learning analytics: A systematic literature review of empirical research. *Journal of Learning Analytics*. https://learning-analytics.info/index.php/JLA/article/view/7254

Cerratto Pargman, T. & McGrath, C. (2021b). Be Careful What You Wish For! Learning Analytics and the Emergence of Data-Driven Practices in Higher Education In Petersson, S. (ed.) (2021) Digital Human Sciences: New Objects – New Approaches. Stockholm: Stockholm University Press. https://doi.org/10.16993/bbk

Connelly, R. J. (2000). Intentional learning: The need for explicit informed consent in higher education. *The Journal of General Education, 49*(3), 211–230.

Drachsler, H., & Greller, W. (2016, April). Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 89–98).

Ferguson, R. (2019). Ethical challenges for learning analytics. *Journal of Learning Analytics, 6*(3), 25–30.

Fowler, M., & Lewis, J. (2014) *Microservices*. https://martinfowler.com/articles/microservices.html

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. *Educause Review, 27*, 1–12.

Howell, J. A., Roberts, L. D., Seaman, K., & Gibson, D. C. (2018). Are we on our way to becoming a "helicopter university"? Academics' views on learning analytics. *Technology, Knowledge and Learning, 23*(1), 1–20.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 100758.

Jones, K. M. (2019). Advising the whole student: eAdvising analytics and the contextual suppression of advisor values. *Education and Information Technologies, 24*(1), 437–458.

Khalil, M. (2018). Student privacy questionnaire_anonymized.pdf. figshare. Media. https://doi.org/10.6084/m9.figshare.7150853.v1.

Klein, C., Lester, J., Rangwala, H., & Johri, A. (2019). Technological barriers and incentives to learning analytics adoption in higher education: Insights from users. *Journal of Computing in Higher Education, 31*(3), 604–625.

Knight, D. B., Brozina, C., & Novoselich, B. (2016). An investigation of first-year engineering student and instructor perspectives of learning analytics approaches. *Journal of Learning Analytics, 3*(3), 215–238.

Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Fudge, A., Pardo, A., & Gentili, S. (2020). Students' sense-making of personalised feedback based on learning analytics. *Australasian Journal of Educational Technology, 36*(6), 15–33.

Nissenbaum, H. (2004). Privacy as contextual integrity. *Washington Law Review, 79*, 119.

Ochoa, X., & Wise, A. F. (2021). Supporting the shift to digital with student-centered learning analytics. *Educational Technology Research and Development, 69*(1), 357–361.

Prinsloo, P., & Slade, S. (2015, March). Student privacy self-management: Implications for learning analytics. In *Proceedings of the fifth international conference on learning analytics and knowledge* (pp. 83–92).

Prinsloo, P., & Slade, S. (2017, March). An elephant in the learning analytics room: The obligation to act. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 46–55).

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*(3), 317–333.

Rubel, A., & Jones, K. M. (2016). Student privacy in learning analytics: An information ethics perspective. *The Information Society, 32*(2), 143–159.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.

Slade, S., Prinsloo, P., & Khalil, M. (2019, March). Learning analytics at the intersections of student trust, disclosure and benefit. In *Proceedings of the 9th International Conference on learning analytics & knowledge* (pp. 235–244).

Tsai, Y. S., Whitelock-Wainwright, A., & Gašević, D. (2020, March). The privacy paradox and its implications for learning analytics. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 230–239).

Velander, J. (2020). *Student awareness, perceptions and values in relation to their university data*.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110.

Zhu, J., Liapis, A., Risi, S., Bidarra, R., & Youngblood, G. M. (2018, August). Explainable AI for designers: A human-centered perspective on mixed-initiative co-creation. In *2018 IEEE Conference on Computational Intelligence and Games (CIG)* (pp. 1–8). IEEE.

Part III
Practices and Evidence from the Educator’s Perspective

Chapter 16
Teachers' Perspectives on the Promises, Needs and Challenges of Learning Analytics Dashboards: Insights from Institutions Offering Blended and Distance Learning

Rogers Kaliisa, Anna Gillespie, Christothea Herodotou, Anders Kluge, and Bart Rienties

1 Introduction

In the last 10 years, technological advancements have led to a strong interest in analysing students' learning behaviour data by means of learning analytics (LA), with the aim of supporting teachers and students with informed and timely feedback. LA has been broadly conceptualised as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens & Long, 2011, p. 34). LA is further defined as "the use of static and dynamic information about learners and learning environments, assessing, eliciting and analysing it for real time modelling, prediction and optimization of learning processes, learning environments as well as educational decision making" (Ifenthaler & Gibson, 2020, p. 4).

A key assumption is that learners and teachers will carefully use the information provided by LA to help them monitor, reflect on and regulate the learning process

R. Kaliisa · A. Kluge
Department of Education, University of Oslo, Oslo, Norway
e-mail: rogers.kaliisa@iped.uio.no; anders.kluge@iped.uio.no

A. Gillespie
Faculty of Wellbeing, Education and Languages Studies, The Open University, Milton Keynes, UK
e-mail: anna.gillespie@open.ac.uk

C. Herodotou · B. Rienties (✉)
Institute of Educational Technology, The Open University, Milton Keynes, UK
e-mail: christothea.herodotou@open.ac.uk; bart.rienties@open.ac.uk

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_16

(Bodily & Verbert, 2017). Following these assumptions, part of the research effort in LA has been devoted to developing approaches and tools to present LA feedback to teachers and students. One approach has been the development of dashboards, which are presented in different learning environments (Bodily et al., 2018; Jivet et al., 2018), such as learning management systems (LMS) and personal learning environments (e.g. microblogging tools).

Borrowing from data and web analytics in other domains, LA dashboards aggregate indicators of student activity and learning from one or more sources, using one or more visualisations (Schwendimann et al., 2016; Verbert et al., 2013). If provided in appropriate and timely ways, such visualisations can be used by teachers to inform their current and future teaching practices (e.g. to check how students have used course materials), while students can use them as tools to support self-regulation (e.g. checking their progress against the required course activities) (Sedrakyan et al., 2020). Many dashboards are used to support teachers in terms of obtaining a better overview of course activities, reflecting on their teaching practice and tracking the progress of students and identifying those who require specific attention (Rienties et al., 2018). Using such insights allows formative and summative feedback that can support teachers and students in making data-informed learning and teaching decisions (Ifenthaler et al., 2018).

Despite the substantial number of LA visualisation tools and dashboards proposed so far, their adoption in authentic practice is still limited (Rienties et al., 2018); this represents a yet-unsolved challenge in the field of LA. Moreover, to the best of our knowledge, despite the attention devoted to the issue, a critical analysis of the state of the art of the research on teachers' perspectives regarding the needs for and barriers to using LA dashboards in everyday teaching practice has not yet been carried out. Since LA dashboards are used by teachers (along with other stakeholders, including students and administrators), the acceptance of the tools is key. Thus, there is a need to explore why there is (in some cases) reluctance from teachers to fully adopt LA dashboards as a tool to support teaching (Herodotou et al., 2017, 2019a, b; Herodotou et al., 2020a).

The purpose of this chapter is to contribute to the shortcomings in terms of existing LA dashboards and the literature (e.g. the lack of a clear understanding of teachers' preferences for LA dashboards). We achieve this through discussing relevant literature as well as presenting two unique case studies, The Open University (OU) in the UK and the University of Oslo (UiO) in Norway, which have different approaches and are at different stages of LA dashboard development and implementation. The remainder of the chapter is structured as follows: The next section provides a brief discussion of the current research on dashboards and visualisations for LA. This is followed by a brief description of the two case studies and, thereafter, a discussion of the key lessons and implications for research and practice arising from these two case studies and the existing literature.

1.1 Relevant Research on LA Dashboards

Considerable work has explored the potential use of LA dashboards in educational environments to support teachers, students and other education stakeholders (e.g. Bodily & Verbert, 2017), as also indicated in this book in Chapters 1 and 27 [*to be added by the editor*]. Foundation works on the use of LA dashboards revealed that they have the potential to be used as support tools for teachers to gain a better overview of course activities (Munzner, 2014; Herodotou et al., 2017, 2019b, 2020b) and students' social activities (e.g. student-student interactions) (Bakharia & Dawson, 2011). Teachers can also use LA dashboards to reflect on their teaching practice (Klerkx et al., 2017) and, in some cases, to identify underperforming students, which allows timely interventions by teachers (Verbert et al., 2013; Sun et al., 2019). One initially prominent LA dashboard example is Purdue University's Course Signals, which uses the power of LA to allow teachers to provide real-time feedback to students. By using data collected by the institution and by instructional tools, it identifies students who are falling behind and is able to warn them about any problematic areas. The findings from the implementation of the Course Signals system showed an improvement in the success of first- and second-year students, as well as in the overall university results (Arnold & Pistilli, 2012). More recently, Raclet and Silvestre (2020) introduced Git4School, a dashboard for teachers that offers visualisations based on data extracted from students' online repositories and temporal contextual information. The findings from the evaluation of the LA dashboard revealed that teachers were able to make timely decisions during planned interventions as specified by a learning design.

Meanwhile, some critical voices have raised concern about LA dashboards. According to Sawyer (2014), most research on LA dashboards lacks both theoretical support from recent advancements in the learning sciences and an evidence-informed foundation for choosing the data. He argued that the lack of theoretical orientation is, therefore, not effective in assisting, observing and assessing learning processes to identify the feedback needs of teachers. Consequently, instead of supporting timely and accurate decisions, LA dashboards might result in inaccurate decisions being made by teachers. Similarly, Jivet et al. (2018) conducted a systematic review of 26 papers that described various LA dashboards. The authors concluded that very few LA dashboard designs and evaluations took into account theoretical perspectives (e.g. rooted in the learning sciences), a finding similar to that of Kaliisa et al. (2021a), who also noted that the connection between LA dashboards and pedagogical approaches remains uncertain, which affects teachers' attempts to use dashboards in meaningful ways.

Addressing the lack of uptake by teachers, Holstein et al. (2017) noted that the kind of data illustrated by LA dashboards does not usually align with teachers' needs, since they are often not consulted as part of the design process. In other words, even though using LA dashboards could be intuitively attractive, their effectiveness may depend on the degree to which the intended users (e.g. teachers) are involved in co-designing them (Echeverria et al., 2018). Kaliisa et al. (2021a) recently highlighted the same concern in their review of existing LA frameworks and tools. The authors concluded that if LA adoption by teachers is to be realised, teachers need to be at the centre of the design process since they are the engine of innovation in education. Furthermore, recent research on the effectiveness of LA dashboards highlights that formal validation (i.e. whether the visualisations fulfil their intended purpose, such as improving teachers' decision-making processes) is limited, which makes their adoption challenging (Ferguson et al., 2016). Schwendimann et al. (2016) noted in their systematic review of 55 studies on LA dashboards that 58% of studies contained no evaluation of the LA dashboards regarding efficient teaching. Other concerns have focused on the ethical use of information, with some teachers calling for a more open dialogue regarding the use of students' data (Kollom et al., 2021).

In the following section, we present two case studies of institutions that are using LA dashboards and highlight past and ongoing studies in relation to LA dashboards and teachers' perspectives toward them. The two cases provide examples of how to deal with some of the challenges highlighted in existing LA dashboard research (e.g. the lack of teacher involvement in co-designing dashboards). In line with Yin (2009), a case study is undertaken to examine the characteristics of a single individual unit (recognising its individuality and uniqueness, e.g. a student, a group or an organisation). Aligning with Yin (2009), the two case studies investigate the phenomenon of LA dashboard design and use by teachers in authentic teaching and learning contexts.

2 Case Studies

2.1 *Case Study 1: The Open University, UK – Early Alert Indicators*

The OU is a distance learning university. Most of the OU's students (both full- and part-time) study from home, with some postgraduate research students based in the campus in Milton Keynes. Many students juggle home responsibilities and employment with their studies. The OU is one of the largest universities in the UK with over 170,000 students. Teachers at the OU are predominantly part-time and are responsible for teaching both undergraduate and postgraduate modules across four faculties, and many have professional working roles outside of the university. In 2021, 3880 teachers were employed to lecture on undergraduate modules, and 497 were teaching postgraduate modules.

The distance learning aspect of teaching and learning brings with it several challenges. Unlike face-to-face teaching, distance learning relies on various initiatives to maintain tutor-student contact, such as online tutorials, forums and regular email or telephone tutorials. The graduation rate at the OU is 25%, which is lower than those of full-time face-to-face institutions (Herodotou et al., 2020a). Furthermore, some students choose to study individual modules to access other higher education institutions, rather than completing a full degree programme (this is particularly true for professional degrees, such as social work or nursing). There is no specific estimation of the numbers of students who transfer to other institutions. Therefore, in this respect, the low retention figure is less surprising than might be expected.

The OU is one of many universities around the world that have developed the conceptualisation of LA dashboards (Rienties et al., 2017, 2020). The OU has focused on the benefits of gathering LA data to support students through a pedagogically led LA approach (Rienties et al., 2017; Hlosta et al., 2017). It has seen the university-wide implementation of an LA dashboard with a specific focus on undergraduate modules (Herodotou et al., 2020b). One of the most significant approaches taken by the OU is the critical analysis of its own practice to address what works well and what requires development (Ferguson et al., 2016; Ferguson & Clow, 2017; Rienties et al., 2020). This practice has led to a significant number of studies, the most recent of which are discussed below.

2.1.1 Early Alert Indicators: An LA Dashboard Visualisation Tool

The Early Alert Indicators (EAI) project was set up as a "test-and-learn" project to help the OU to identify how using an LA dashboard could support students on their learning journeys (Hlosta et al., 2017). The EAI LA dashboard is the result of bringing together two systems: OU Analyse (OUA) with short-term or weekly predictions and the Student Probability Model (SPM) with long-term predictions, both of which are discussed below. Two types of data are utilised for calculating predictions: static data demographics, such as age, gender, previous education and geographic location, and dynamic data, such as a student's activities in a virtual learning environment (VLE) (Herodotou et al., 2017) (see Figs. 16.1 and 16.2).

OU Analyse (OUA) is a predictive system, which makes short-term predictions of progress and can be used by teachers to identify those students who might be at risk of not submitting their next assignment, referred to in the OU as a Tutor Marked Assignment (TMA). It provides manageable data in the form of visualisations to interested parties (e.g. teachers and administrators) on a weekly basis throughout the module. As shown in Figs. 16.3 and 16.4, it uses a traffic light system to identify at-risk students as follows:

- Red identifies students at risk of non-submission or of failing the next assignment (TMA).
- Amber identifies those students who are likely to submit their next assignment but with a mark within the grade range of 40–54.
- Green identifies those students who are likely to submit their next assignment and gain a pass of 55 or above.

The Student Probability Model (SPM) produces a longer-term prediction of whether a student will reach specific learning milestones. It provides a percentage

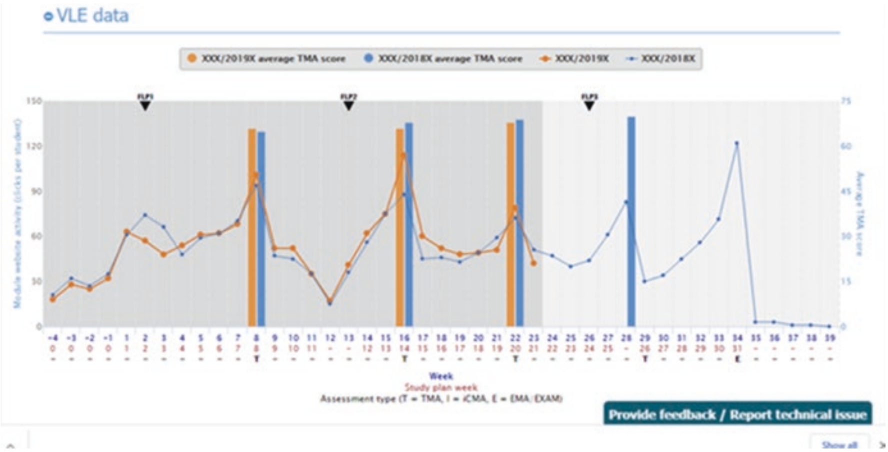


Fig. 16.1 VLE data indicating the average activity in the VLE (brown trend line) of all students on a module compared with the average of students' from the previous year (blue trend line). The columns indicate the average assignment mark (brown) compared with the student average in the previous module year (blue)

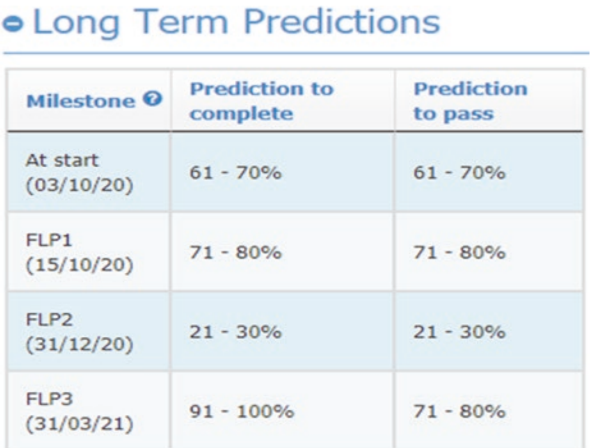
Fig. 16.2 Data specific to an individual student and their activity in the VLE (brown) compared to the average for students on the same module in the same academic year (blue)

Next TMA prediction	Previous TMAs	Future TMAs
Will submit and score 55 or greater	Has submitted and score 55 or greater	The result is not known
Will submit and score between 40 and 54	Has submitted and score between 40 and 54	
Will not submit or score lower than 40	Has not submitted or score lower than 40	
	Has submitted, the score is unavailable	
	Assessment is banked from previous presentation	

Fig. 16.3 Traffic light system for predictions of next assignment submissions

Student Information				Next TMA predictions Generated: 27/01/21 (102 days ago) Week: 17		
	Student PI	Name	TMA (TMA 03)	Submission	Risk of NS	Grade
	AXXXXXXX	Philip Jerde	83 NS	Submit		Pass 2
	AXXXXXXX	Otho Klocko	78 S	Submit		Pass 2
	AXXXXXXX	Queen Fay	85 S	Submit		Pass 2
	AXXXXXXX	Yvonne Brekke	82 NS	Submit		Pass 2
	AXXXXXXX	Minnie Berge	41 NS	Not Submit		Not Submit
	AXXXXXXX	Dennis Klocko	43 NS	Not Submit		Not Submit
	AXXXXXXX	Caitlyn Orn	73 S	Submit		Pass 2
	AXXXXXXX	Susana Armstrong	82 S	Submit		Pass 2
	AXXXXXXX	Esperanza Bartoletti	NS NS	Not Submit		Not Submit
	AXXXXXXX	Chelsie Leuschke	71 S	Submit		Pass 2
	AXXXXXXX	Timothy Rowe	87 S	Submit		Pass 2
	AXXXXXXX	Rowan Schuppe	64 S	Submit		Pass 2
	AXXXXXXX	Christ Senger	73 S	Submit		Pass 2

Fig. 16.4 Anonymised data of a student group predicting whether students will submit their next assignment and its grade outcome



Long Term Predictions

Milestone	Prediction to complete	Prediction to pass
At start (03/10/20)	61 - 70%	61 - 70%
FLP1 (15/10/20)	71 - 80%	71 - 80%
FLP2 (31/12/20)	21 - 30%	21 - 30%
FLP3 (31/03/21)	91 - 100%	71 - 80%

Fig. 16.5 Long-term predictions for an individual student's likelihood of completing and passing the module

prediction of the likelihood of a student completing and passing a course or not (Fig. 16.5). Predictions or probabilities are based on models generated through the logistic regression of a set of 70 explanatory variables. While OUA is updated weekly, student probability data are generated at the start of a module and updated on three other occasions. These points are fixed according to when the next payment of their fees is due (these are variable but usually in weeks 2, 13 and 26).

Because the EAI LA dashboard can identify students who may be struggling with their studies, OU teachers can offer early support to those students most likely to need it. Most OU teachers are highly experienced in working with students who are studying at a distance; however, EAI data provide additional insights and help

OU teachers to support students to progress through the module and allow them to intervene at an earlier stage to offer appropriate support or advice. Once a teacher has identified a student who is at risk of non-submission, they can offer the student help with their studies in several ways, for example, through additional support sessions, granting an extension (where appropriate), supporting a managed withdrawal or the deferral of the module.

The EAI LA dashboard provides an indication of the possibility of a given outcome; it does not supply an absolute prediction but instead works as an indicator. No model can predict outcomes with absolute certainty, and there will always be things that affect students' learning and performance that are beyond the university's control or knowledge, such as a change in personal circumstances (Hlosta et al., 2020). However, the predictive models used combine the effects of multiple factors to create their probabilities and have been shown to provide an acceptable level of accuracy at the individual student level (Hlosta et al., 2017).

2.1.2 What We Know from Previous and Current LA Visualisation Studies at the OU

Ongoing research at the OU contributes to the strategy for improving the use of LA dashboards in distance learning. This section outlines some of the more recent studies that have taken place and how these studies will support the development of LA dashboards moving forward.

In initial studies, the use of OUA was piloted with OU teachers ($n = 240$) and ten modules (Herodotou et al., 2017). Data were collected to investigate whether using short-term predictions could improve (a) the retention and (b) the performance of students who were at risk of non-submission. One reflection gained from this study was that further investigation is required to ascertain how OU teachers engaged with the predictive data and whether low engagement was due to time, resources and organisational constraints. Further research with OU teachers ($n = 251$) and 21 modules indicated that only 22% of them made consistent systematic use of OUA.

More recently, the EAI dashboard has been rolled out to include access for all OU teachers, staff tutors and module teams on all undergraduate modules. Since the roll out, more recent studies have examined the effectiveness of the SPM. One study considered the impact of student support interventions with regard to undergraduate students ($n = 630$) who were considered to be at risk of not completing their studies. Students were randomly assigned to a control group ($n = 312$) or an intervention group ($n = 318$). The intervention group was contacted by the university student support teams using a set of actions, such as text, phone and email, to provide students with prompts to remind them of upcoming deadlines and study activity deadlines. Results showed statistically significant better student retention outcomes for the intervention group, showcasing the usefulness of SPM predictions in identifying students at risk and of student support teams for working alongside teachers to offer additional interventions (Herodotou, Naydenova, et al., 2020a).

In recognising that sometimes predictions are erroneous, Hlosta et al. (2020) carried out a mixed methods study with first-year OU STEM students to identify students who were incorrectly identified as at risk of not submitting their next assignment but did submit (FN), and those who were not identified as at risk of non-submission but did not submit (FP), based on the findings from OUA short-term predictions. Between 2017 and 2019, they identified 38,073 predictions over 17 modules that met the criteria and concentrated on predictions 2 weeks prior to the submission date of the student's first assignment. Using receiver operating characteristic (ROC) and the area under the curve (AUC) analysis, 29,247 students were identified, and the overall prediction was 0.8897. For the confidence regarding not submitting predictions, the decision tree correctly classified 50.91% of the FP errors with 75.29% precision. For the confidence in terms of submitting predictions, the model distinguished 18.73% of the FN errors with 68.73% accuracy. Follow-up semi-structured interviews with students ($n = 12$) indicated that none of the erroneous predictions could be explained by the data alone. Unexpected life events, issues with student finances and computer problems were key factors as to why the data were not accurate. For example, one student who was not predicted to submit but did, reported that she had no internet access and had downloaded her course material to work offline; therefore, she appeared to not be engaging online. Another student who was expected to submit but did not deferred the module to a later date as she had taken on too many modules alongside her workplace commitments. As the OU does not collect data from external resources to explain such events, it is difficult to prevent errors in such predictions moving forward. However, the predictions are only one part of the process and should be used as a tool, along with pedagogical-based strategies and teachers' knowledge of their students, to improve student success and support their learning.

One of the strengths of the OU approach to using visualisations is the ongoing recognition of the importance of involving teachers in its development. Contrary to findings by Holstein et al. (2017) and Kaliisa, Kluge, and Mørch (2021a), who suggest that teachers are rarely consulted about the design of LA, the EAI dashboard has been designed and redesigned following feedback from teachers who use it, and such feedback on what they need has been instrumental in the LA dashboard's development. However, an ongoing issue is the lack of the systematic use of the EAI LA dashboard. Herodotou et al. (2017) and Herodotou et al. (2019a) found that most teachers who used the EAI LA dashboard only tended to log in occasionally, and their usage was not consistent over time. Despite this, follow-up interviews indicated that teachers held positive views of the EAI LA dashboard as it supported their existing teaching skills and helped them to keep abreast of their students' progress. In a follow-up study, it was found that those teachers who did use the EAI dashboard consistently had better outcomes in terms of students' retention and achievement on the module they were studying compared to those who did not use it or used it only occasionally. While it is not possible to prove the retention increase was solely due to the use of the EAI dashboard, it does indicate that there are benefits to using it as an early intervention strategy (Herodotou et al., 2019a).

From these studies, there appears to be significant evidence that the use of LA dashboards in distance learning leads to significant outcomes for students; however, the issue regarding teachers' adoption of the dashboards remains problematic. A study of 95 OU teachers indicated the belief that ongoing training for teachers was essential for incorporating LA visualisations into their teaching practice (Rienties et al., 2018). As part of the teacher training process, a 4-year roll-out programme to train teachers at the OU in the use of the dashboard took place between 2015 and 2019. This included a discussion forum and the option of giving feedback to the development team to share experiences with a view to improving the EAI dashboard interface to make it more intuitive regarding teachers' needs. The training programme has since been replaced by recorded sessions that demonstrate how to use the EAI LA dashboard. Furthermore, ongoing research at the OU is trialling different interventions, such as email triggers from teaching managers and student support teams, as a means to engage teachers with the EAI LA dashboard in a more systematic manner.

In terms of developing an understanding of teacher resistance to using the EAI dashboard, further studies continue to investigate the possible reasons behind it. Resistance to change is a potential reason why teachers might not accept the adoption of new technologies; however, it can also be attributed to organisational culture (Piderit, 2000). Consequently, it is important to look at prevailing organisational factors, such as resource allocation and a lack of communication, which influence teachers' workloads. Technological changes within the OU have created some anxiety amongst OU teachers (particularly when they are mandatory). Use of the EAI LA dashboard is voluntary, and thus, it is often used less by teachers who are having to manage their time effectively. Further concerns included scepticism as to how management might use the data. For example, would a student's lack of engagement be seen as a teacher failure and thus become a form of performance management? Other areas of resistance to use included teachers' concerns about how far using LA dashboards is contrary to traditional teachers' roles. Many OU teachers reported that they had developed their own teaching approaches to support students studying at a distance and that, with this teaching experience, they could intuitively recognise when students were at risk of non-submission. They therefore did not feel they needed to use the EAI LA dashboard (Herodotou et al., 2017).

To date, several studies have addressed to what degree OU teachers are comfortable with the use of technology using models including the technology acceptance model (Davis et al., 1989; Bagozzi, 2007) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). These studies have addressed the perceived usefulness of the EAI LA dashboard and its perceived ease of use. Further studies are being conducted using UTAUT measures to look more closely at how teachers use the EAI LA dashboard by using eye-tracking technology to move beyond self-reports and include observations of the actions taken and retrospective think-aloud protocol interviews to identify which parts of the EAI LA dashboard are used the most and why. Eleven teachers have so far participated in this study, and the following UTAUT indicators were used as indicators to structure and analyse the self-reports:

- Performance expectancy: The degree to which an individual believes that using the system will help them to attain gains in job performance
- Effort expectancy: The degree of ease associated with the use of the system (perceived ease of use, complexity and ease of use)
- Facilitating conditions: The degree to which an individual believes that an organisational and technical infrastructure exists to support his or her use of the system
- Social influence: The degree to which the user perceives others (who are important to the user) believe that they should use the system.

Preliminary eye-tracking findings indicate that teachers (n = 6) do not always understand all parts of the dashboard and use it erroneously; therefore, some of their self-reports were based on misunderstandings. Regarding the self-reports, performance expectancy was based on having only limited awareness of its functionality; however, teachers believed it was helpful in supporting student success. However, their effort expectancy was limited to only those parts of the dashboard that made sense to them or that were considered useful (as identified by the eye tracking). The long-term SPM is seemingly less useful to teachers in terms of focusing on their interventions with students (this was also evident from using the eye tracker). OU Analyse short-term predictions (e.g. encouraging students to get through the next assignment) were more relevant to teachers as they felt more achievable. Reports on facilitating conditions indicated that most teachers do not see management as driving forward the use of the EAI dashboard, and they feel that they are facilitating it by their own volition and in some cases through the support of peers (Gillespie et al., 2021).

2.2 *Case Study 2: The University of Oslo – Canvas LA Visualisations*

The University of Oslo (UiO) is a public university that was established in 1811. It currently has approximately 28,000 students enrolled in its eight faculties and schools and is predominantly an institution with face-to-face learning. However, with the growing advances in the use of technology to support teaching and learning, like many other universities, the UiO has adopted a more blended, rather than a purely face-to-face, approach through providing some online teaching services using the Canvas LMS (e.g. online discussions, peer grading) to supplement the physical classes. In the autumn of 2017, the UiO took a formal decision to use Canvas as the sole system for supporting teaching and learning activities at the university. The decision was motivated by a need to provide teachers and students with better technological support and opportunities for interactivity and connectivity for the purposes of teaching and learning (Sagvik, 2018). Overall, the UiO is in the initial stages of exploring possibilities of implementing LA, with small-scale implementation (i.e. piloting scales by individual researchers at the course level) but without institution-wide uptake. To support the adoption of LA by teachers, efforts are ongoing in terms of designing relevant dashboards to provide timely and easy-to-access informative visualisations to the teachers. One of the LA visualisation tools under development is the Canvas discussion analytics (CADA) application.

2.2.1 The Canvas Discussion Analytics (CADA) Dashboard

CADA is a dashboard that visualises participation, social networks, text/epistemic networks and concepts used by students within the Canvas LMS discussion forum on a need-to-know basis (Fig. 16.6). CADA can help teachers to identify misconceptions quickly and easily in students' discussions and track how well the students are using

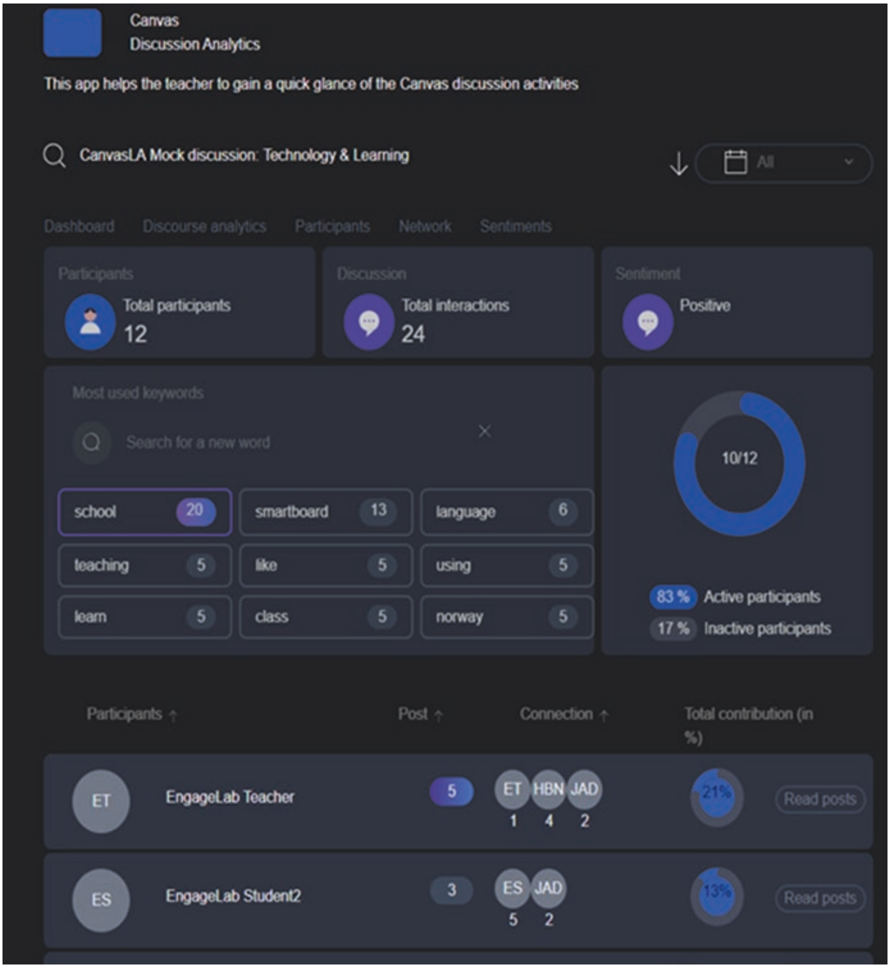


Fig. 16.6 The CADA interface: general participation analytics (top), the summary of key concepts (middle) and views and connections of individual students (bottom)

the course materials or assigned readings in real time. Besides, the visual representations provided by CADA afford teachers to see students' interactions regarding the discussion activity at a glance, and they can potentially make strategic decisions to, for example, notify students to participate or decide on how to follow-up important concepts from the discourse during upcoming lessons. In certain situations, the dashboard may signal that the majority of students possess obvious misconceptions regarding what are considered relevant concepts for the course overall. CADA rests on assumptions and principles from the learning sciences and human-computer interaction (HCI). We understand learning as the participation in, and mastery of, subject-specific discourses and practices mediated by artefacts (such as online discussions), which, together with teachers' needs, lay the foundation for the main learning theoretical constructs (Säljö, 2000). In this regard, CADA provides an example of a theory-driven LA dashboard, an area that has until now received little attention as noted by Kaliisa, Kluge, and Mørch (2021a) with most LA dashboards reported as lacking support from advancements in the learning sciences.

2.2.2 Studies: What We Know from Previous and Current LA Studies at the UiO

Early pilot studies on the use of LA at the UiO included the use of low-fidelity prototypes of LA visualisations generated from students' weekly action logs in the Canvas LMS (page views, participation views) and visualisations from course activities (e.g. social network sociograms and text networks). The paper-based sketches were shared with the four teachers who taught the undergraduate blended learning courses with the intention of identifying their perceptions and assessing the usability of the visualisations for learning design purposes. In this study, Kaliisa et al. (2020) concluded that, overall, teachers explicitly expressed the value of the LA visualisations in several ways. For example, the teachers found the LA visualisations to be informative with regard to the flow of the course and recognised that they could be used to make necessary modifications throughout the process. According to the teachers, the visualisations raised their awareness of the quality of the students' online discourse by identifying the main themes and their connection to the intended pedagogical content. In the same study, teachers found visualisations from LA dashboards to be valuable tools for kick-starting discussions with students during face-to-face seminars and for pointing out concepts that emerged during the online discussions.

More recently, Kaliisa et al. (2021b) conducted a qualitative study with 16 teachers at the UiO to explore the latter's design practices and perspectives on LA as a tool to support their learning designs. Guided by principles of the technology acceptance model, this study identified mixed reactions amongst teachers regarding the awareness, understanding and potential use of LA visualisations to support course design practices. On a positive note, most teachers appreciated the formative and normative value of LA visualisations in providing more objective evidence concerning students' learning patterns and in shaping learning trajectories.

Furthermore, CADA was trialled at the UiO, with six teachers and six different courses during autumn 2020. The teachers worked with CADA throughout the semester, guided by the protocol provided by one of the researchers. At the end of the course or a module where the CADA tool was used, the participating teachers were invited for an interview to discuss their experiences of the tool. Data were collected to investigate whether using visualisations from CADA could support teachers in improving their ongoing course designs. Preliminary findings from the follow-up interviews after the first iteration of the CADA implementation show that teachers appreciate the timely visualisations offered by CADA, which support course adaptations. The teachers also expressed satisfaction with the easy interface provided by CADA and the application's ease of access since it is integrated within the Canvas LMS (Kaliisa and Dolonen, work in progress).

However, studies conducted with teachers at the UiO also highlighted challenges associated with the adoption of LA visualisations. One of the key challenges raised by teachers was the non-timely sharing of aggregated LA visualisations since they were shared outside Canvas and after the courses had ended. The teachers were also concerned about the sophisticated nature of the visualisations, which made their potential use difficult in practice. For example, some teachers felt that the text networks generated from online discussions were so dense and contained so many links that the detail impeded the extraction of meaningful insights, especially for LA novices (Kaliisa et al., 2020).

Another challenge concerned the failure of the visualisations (e.g. social network diagrams) to demonstrate student knowledge development processes. In this regard, teachers asked for additional and more in-depth information to support the meaningful translation of the visualisations into relevant pedagogical actions (Kaliisa et al., 2020). In addition, teachers wanted LA dashboards to be integrated within the Canvas LMS to allow easy access. Since teachers are already loaded with so many tasks related to their teaching responsibilities, it is hard to implement LA visualisations if they are presented outside the LMS. This justifies the recent efforts to develop CADA, which is now integrated within Canvas LMS.

Several lessons and implications for future research and practice have been derived from the two case studies. In the following section, we highlight implications for design (e.g. taking a human-centred design approach, involving teachers as co-designers), research (e.g. moving beyond self-reports, considering ethics) and implementation (e.g. role of context, training of teachers) for the future advancement of LA dashboard research and practice.

2.3 Design Implications

The Need to Take a Human-Centred Design Approach While Designing LA Visualisations The two case studies revealed that teachers expressed concern about complicated LA visualisations that are not easy to interpret. Thus, as also noted by Echeverria et al. (2018), for LA dashboards to support teachers' practice, there is a need to present relevant visualisations that also explain their insights. In other words, while educational researchers and developers are highly motivated and suitably skilled to invest time exploring LA visualisations, the same may not be true for teachers with limited time and data literacy skills, who may find it more difficult to analyse and interpret advanced visualisations. The findings of the current work are similar to those presented by Howell et al. (2018) who reported that teaching staff expected LA services to be simple and not unnecessarily increase teachers' workloads. Following this argument, the challenge for LA researchers and developers is to discover and communicate insights rather than leaving teachers to play the role of data analysts, at the risk of gaining no insight (Echeverria et al., 2018). Previous studies have emphasised teachers' limited technological and pedagogical expertise in connecting LA visualisations with everyday teaching practices (Rienties et al., 2018; Kaliisa et al., 2021a). This implies that if LA dashboards are to be embraced by teachers, the visualisations they produce should be easily understood by all such users, irrespective of their technology proficiency.

Involving Teachers as Co-designers One of the common aspects identified from the two case studies is the active involvement of teachers during the design of LA visualisations. At the OU, the EAI LA dashboard has been designed and redesigned following feedback from teachers. The UiO is following the same approach, where a design-based approach is being used to develop a Canvas analytics discussion application, following different iterations and feedback from the teachers. This approach to co-designing LA visualisations could be a response to the challenges highlighted in the LA dashboard literature, which suggest that teachers are rarely consulted about the design of LA dashboards (Holstein et al., 2017). The challenge that remains is that despite teacher involvement, uptake in terms of using the dashboards is still low, and further research is needed to continue to address the reasons for this.

2.4 Implementation Implications

The Role of Context The analysis of the two case studies revealed that dashboards are used for different purposes at the two institutions. For example, on the one hand, the Canvas LA visualisations at UiO are primarily meant to support traditional face-to-face lectures, to enable teachers to adapt their teaching or to engage students during lectures. On the other hand, the EAI LA dashboard at the OU is primarily used to support online teachers by identifying students' predicted learning outcomes using traffic signals, based on student progress with the assigned tasks, past performance and other variables. The differences in the way LA dashboards are used by the two case studies presented in this chapter imply that the relevance of the different LA dashboards is interpreted differently across educational institutions. This implies that contextual factors (e.g. institution size, mode of instruction [online vs blended]) need to be considered before deciding what kind of LA dashboards and visualisations to apply. Traditional face-to-face institutions, like the UiO, have limitations regarding the amount of data they can collect to support teachers. This is because students use different learning environments, including physical classrooms, which cannot be captured by most LA systems. In this case, the accuracy of LA dashboards in such environments could be compromised. The OU, however, can collect more ongoing data, but it too has limitations as the ability to collect data relating to attendance at face-to-face day schools and online tutorials, or to interface data when a student is studying more than one module, is still under development.

Ongoing Training of Teachers Experiences from the OU reveal that for teachers to adopt LA dashboards into their teaching practice, there is a need for ongoing training on how to use the dashboard in terms of both new adopters and refreshers for existing teachers, especially when the dashboard is updated. This insight is relevant for institutions like the UiO, which is at the stage of piloting LA dashboards used by teachers. In other words, to achieve wide-scale application, such as that reported at the OU, continuous training, like the 4-year roll-out programme at the OU, is necessary, which has been acknowledged in earlier studies as one of the potentials for effective LA adoption in teachers' practice (Ifenthaler et al., 2018).

2.5 Research Implications

The Need to Move Beyond Self-Reports When Evaluating LA Dashboards The case studies have revealed that the evaluation of LA dashboards should go beyond self-reports (e.g. interviews and surveys) and instead focus on whether their intended objectives (e.g. improving teachers' practice) are fulfilled. For example, studies from the OU are now moving on from teachers' self-reports to include the observation of use. By observing behaviours and combining this information with self-reports, it is hoped that a clearer picture will emerge to address the actions of teachers and to highlight those that might require further improvement.

Ethics and LA Dashboards How we use student data is of utmost importance. The case studies indicate that in relation to LA dashboards, this remains a work in progress; it is necessary to ensure that students understand what is being collected and why while providing assurances that it is for their educational benefit and that it does not contain biases related to their demographic backgrounds. The OU was one of the first universities to develop an ethical policy on the use of student data (Open University, 2014), and ethical considerations have been high on its agenda. However, as discussed by Ferguson et al. (2016), the ethical and privacy aspects of LA are evolving as new data are collected; hence, this should be an ongoing process. Some teachers have expressed concerns about the ethics of using LA dashboards (e.g. are students active in giving informed consent for data collection, and do they fully understand the parameters of the data collected?).

Further ethical issues arising from this include how teachers interpret data derived from algorithms and whether they should be given guidance on how to interpret such meanings (e.g. does seeing a grade prediction (see Fig. 16.4) influence marking?). Future studies should address these issues, along with examining whether the use of algorithms has any implications for students from differing ethnic minority groups in terms of the over- or underrepresentation of the risk of non-submission. Overall, it is incumbent on LA dashboard designers to share how algorithms are produced and how these can inform teachers' ethical use of LA dashboards.

3 Conclusion

The purpose of this chapter was to provide an overview of teachers' perspectives about LA dashboards (promises, needs and challenges) and their implications for LA dashboard, research and practice. The review of relevant studies on LA dashboards and insights from the two case studies showed that, overall, teachers perceive LA dashboards as a valuable tool for understanding students' learning processes and a way to support course adaptation and individualised interventions. At the same time, teachers from both case studies raised some concerns, citing issues such as ethics, complexity and the lack of a clear connection between the visualisations and the pedagogical outcomes. In this regard, for LA dashboards to achieve their intended impact, the literature and the insights from the two case studies revealed that their development should be based on teachers' needs, presented in a simple format, and be grounded in relevant theoretical perspectives and with ongoing support and training. Furthermore, the differences in the way LA dashboards are used at the two institutions imply that LA implementation is context specific and could have different implications for teachers' practice. Thus, researchers and developers of LA dashboards should avoid a *one size fits all* approach in the development of such tools. Researchers and practitioners can benefit from the insights highlighted in this chapter, particularly the section that highlights the way LA dashboards are perceived by teachers and implemented at the two unique institutions. We have also identified key areas that LA dashboard researchers and developers should address to advance work on the low adoption and use of LA dashboards in teachers' everyday practice.

References

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270).

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(7), 244–254. https://doi.org/Article.

Bakharia, A., & Dawson, S. (2011, February). SNAPP: A bird's-eye view of temporal participant interaction. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 168–173).

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418.

Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., & Verbert, K. (2018, March). Open learner models and learning analytics dashboards: A systematic review. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 41–50).

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982.

Echeverria, V., Martinez-Maldonado, R., Buckingham Shum, S., Chiluiza, K., Granda, R., & Conati, C. (2018). Exploratory versus explanatory visual learning analytics: Driving teachers' attention through educational data storytelling. *Journal of Learning Analytics, 5*(3), 72–97.

Ferguson, R., & Clow, D. (2017). Where is the evidence? A call to action for learning analytics. *ACM International Conference Proceeding Series*, 56–65. [Online]. https://doi.org/10.1145/3027385.3027396.

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T., & Vuorikari, R. (2016). Research evidence on the use of learning analytics – Implications for education policy. In R. Vuorikari & J. C. Muñoz (Eds.), *Joint Research Centre science for policy report; EUR 28294 EN*. https://doi.org/10.2791/955210.

Gillespie, A., Herodotou, C., & Rienties, B. (2021). Teachers' use of Predictive Learning Analytics: Experiences from The Open University UK.

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M., & Naydenova, G. (2017). Implementing predictive learning analytics on a large scale. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference on - LAK '17* (pp. 267–271. [Online]). https://doi.org/10.1145/3027385.3027397.

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., & Hlosta, M. (2019a). A large-scale implementation of predictive learning analytics in higher education: The teachers' role and perspective. *Educational Technology Research and Development, 67*(5), 1273–1306.

Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019b). Empowering online teachers through predictive learning analytics. *British Journal of Educational Technology, 50*(6), 3064–3079. [Online]. https://doi.org/10.1111/bjet.12853.

Herodotou, C., Naydenova, G., Boroowa, A., Gilmour, A., & Rienties, B. (2020a). How can predictive learning analytics and motivational interventions increase student retention and enhance administrative support in distance education?*, 7*(2), 72–83. https://doi.org/10.18608/jla.2020.72.4.

Herodotou, C., Rienties, B., Hlosta, M., Boroowa, A., Mangafa, C., & Zdrahal, Z. (2020b). The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study. *The Internet and Higher Education, 45*, 100725. https://doi.org/10.1016/j.iheduc.2020.100725.

Hlosta, M., Zdrahal, Z., & Zendulka, J. (2017). Ouroboros: early identification of at-risk students without models based on legacy data. *Paper presented at the Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, Vancouver, British Columbia, Canada.

Hlosta, M., Papathoma, T., & Herodotou, C. (2020). Explaining errors in predictions of at-risk students in distance learning education. In I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial Intelligence in Education. AIED 2020* (Lecture notes in computer science) (Vol. 12164). Cham: Springer. https://doi.org/10.1007/978-3-030-52240-7_22.

Holstein, K., McLaren, B. M., & Aleven, V. (2017, March). Intelligent tutors as teachers' aides: Exploring teacher needs for real-time analytics in blended classrooms. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 257–266). https://doi.org/10.1145/3027385.3027451.

Howell, J.A., Roberts, L.D., Seaman, K. et al. (2018). Are We on Our Way to Becoming a "Helicopter University"? Academics' Views on Learning Analytics. *Tech Know Learn 23*, 1–20. https://doi.org/10.1007/s10758-017-9329-9.

Ifenthaler, D., & Gibson, D. (2020). *Adoption of data analytics in higher education learning and teaching*. Cham: Springer.

Ifenthaler, D., Gibson, D., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology, 34*(2).

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018, March). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40).

Kaliisa, R., Kluge, A., & Mørch, A. I. (2020). Combining checkpoint and process learning analytics to support learning design decisions in blended learning environments. *Journal of Learning Analytics, 7*(3), 33–47. https://doi.org/10.18608/jla.2020.73.4.

Kaliisa, R., Kluge, A., & Mørch, A. I. (2021a). Overcoming challenges to the adoption of learning analytics at the practitioner level: A critical analysis of 18 learning analytics frameworks. *Scandinavian Journal of Educational Research*, 1–15. https://doi.org/10.1080/00313831.2020.1869082.

Kaliisa, R., Mørch, A. I., & Kluge, A. (2021b). 'My point of departure for analytics is extreme skepticism': Implications derived from an investigation of university teachers' learning analytics perspectives and design practices. *Technology, Knowledge and Learning*, 1–22. https://www.researchgate.net/publication/348315041_'

Klerkx, J., Verbert, K., & Duval, E. (2017). *Learning analytics dashboards. The handbook of Learning Analytics*. https://www.researchgate.net/profile/Dragan_Gasevic/publication/324687610_Handbook_of_Learning_Analytics/links/5add21e1aca272fdaf86c95c/Handbook-of-Learning-Analytics.pdf

Kollom, K., Tammets, K., Scheffel, M., Tsai, Y. S., Jivet, I., Muñoz-Merino, P. J., Moreno-Marcos, P. M., Whitelock-Wainwright, A., Calleja, A. R., Gasevic, D., Kloos, C. D., Drachsler, H., & Ley, T. (2021). A four-country cross-case analysis of academic staff expectations about learning analytics in higher education. *Internet and Higher Education, Elsevier Inc, 49*, 100788. [Online]. https://doi.org/10.1016/j.iheduc.2020.100788.

Munzner, T. (2014). *Visualization analysis and design*. CRC press.

Open University. (2014). *Policy on ethical use of student data for learning analytics*. Available at: https://help.open.ac.uk/documents/policies/ethical-use-of-student-data/files/22/ethical-use-of-student-data-policy.pdf. Accessed 30/1/2021.

Piderit, S. K. (2000). Rethinking resistance and recognizing ambivalence: A multidimensional view of attitudes toward an organizational change. *Academy of Management Review. Academy of Management.* https://doi.org/10.5465/AMR.2000.3707722.

Raclet, J. B., & Silvestre, F. (2020, September). Git4School: A dashboard for supporting teacher interventions in software engineering courses. In *European Conference on Technology Enhanced Learning* (pp. 392–397). Cham: Springer.

Rienties, B., Nguyen, Q., Holmes, W., & Reedy, K. (2017). A review of ten years of implementation and research in aligning learning design with learning analytics at OU UK. *Interaction Design and Architecture(s) Journal, 33*(Ld), 134–154. [Online]. Available at http://www.mifav.uniroma2.it/inevent/events/idea2010/doc/33_7.pdf.

Rienties, B., Herodotou, C., Olney, T., & Boroowa, A. (2018). Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers. *International Review of Research in Open and Distributed Learning, 19*.

Rienties, B., Olney, T., Nichols, N., & Herodotou, C. (2020). Effective usage of learning analytics: What do practitioners want and where should distance-learning institutions be going? *Open Learning, 35*, 178–195. https://doi.org/10.1080/02680513.2019.1690441.

Säljö, R. (2000). *Learning in practice: A sociocultural perspective*. Stockholm: Prisma.

Sagvik, C. (2018). Implementing learning management systems in higher education: A case study of University of Oslo (Master's thesis).

Sawyer, R. K. (2014). The future of learning: Grounding educational innovation in the learning sciences. In *The Cambridge handbook of the learning sciences* (pp. 726–746).

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512.

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review, 46*(5), 30.

Sun, K., Mhaidli, A. H., Watel, S., Brooks, C. A., & Schaub, F. (2019, May). It's my data! Tensions among stakeholders of a learning analytics dashboard. In *Proceedings of the 2019, CHI Conference on Human Factors in Computing Systems* (pp. 1–14).

Venkatesh, Morris, Davis, & Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425. [Online]. https://doi.org/10.2307/30036540.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509.

Yin, R. K. (2009). *Case study research: Design and methods* (Vol. 5). Sage.

Chapter 17
Learning Analytics Dashboard Use in Online Courses: Why and How Instructors Interpret Discussion Data

Gokce Akcayir, Leticia Farias Wanderley, Carrie Demmans Epp, Jim Hewitt, and Athar Mahmoudi-Nejad

1 Introduction

Online learning has become more common, which can be seen in the proliferation of massive open online courses. Within universities, the transition from face-to-face to online courses in response to the COVID-19 pandemic emphasizes the need for better tools to support instructors as they struggle to appropriately monitor and respond to student learning needs in this medium. Instructors are also looking for better tools to observe student learning processes and experiences. Learning analytics (LA) is one of the approaches that can be used to effectively support this instructor need (Verbert et al., 2013). Learning analytics are "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Conole et al., 2011). LA can change educational practices through the use of different approaches and tools (Ifenthaler & Yau, 2020). Dashboards that report LA provide a "display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann et al., 2017, p. 37). These displays are known as learning analytics dashboards (LADs).

G. Akcayir (✉) · L. Farias Wanderley · C. Demmans Epp
EdTeKLA Group, Dept. of Computing Science, University of Alberta, Edmonton, Canada
e-mail: akcayir@ualberta.ca; fariaswa@ualberta.ca; cdemmansepp@ualberta.ca

J. Hewitt
Pepper Research Group, OISE, University of Toronto, Toronto, Canada
e-mail: jim.hewitt@utoronto.ca

A. Mahmoudi-Nejad
Department of Computing Science, University of Alberta, Edmonton, Canada
e-mail: athar1@ualberta.ca

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_17

LADs can be integrated into learning management systems (LMSs), and they can be used in both face-to-face and online learning settings (Aleven et al., 2016). While LADs have been used in a variety of contexts, these tools have the potential for higher impact in online learning because they make "the invisible visible" (Xhakaj et al., 2017) and enable instructors to monitor student learning. This monitoring is a challenge in online settings (Easton, 2003) and can be particularly useful for larger courses (Brown, 2020). Enabling monitoring through an LAD could support timely instructor adaptations to a course when the LAD provides detailed information about students (Diana et al., 2017). When this happens, an instructor can interpret and use the information to improve the learning experience of students at both the class and individual levels (Xhakaj et al., 2016) within the context of an ongoing course (Elbadrawy et al., 2016). These improvements can be made through the provisioning of feedback (Knoop-van Campen & Molenaar, 2020) or by adapting the course. For example, after observing students struggling to use for loops, a computer science instructor can check students' interaction with educational materials and see students did not interact with the content about for loops. In this case, the instructor could provide more examples of code containing for loops to the students during their synchronous sessions.

Ideally, this kind of adaptation process goes through multiple stages starting from the instructor recognizing key information in the LAD to developing an action plan to their incorporating that plan into a lesson before the use of the LAD can impact students or their experiences (Xhakaj et al., 2017). Most instructor-facing LADs aim to help instructors notice when they need to intervene (Bodily & Verbert, 2017). Instructors usually come to explore the analytics with general curiosity rather than specific questions (Wise & Jung, 2019). This presents a challenge for the effective use of LADs since data interpretation involves effort to identify patterns (Wise & Jung, 2019). In some cases, instructors interpret the analytics accurately, while in others they interpret the analytics as matching their desired pedagogy even if the analytics do not fully match that pedagogy (Brooks et al., 2014).

Consistent with the above, it appears that instructors need practical guidance for adjusting in-progress activities based on the analytics they see (Ferguson et al., 2016; Ginon et al., 2016; Knight & Littleton, 2015). This may be because interpreting and acting upon analytics involves complex self-regulation activities triggering a variety of emotions (e.g., confusion) that may differ between expert and novice instructors (Zheng et al., 2021). Moreover, studies have shown that instructors face various challenges using LADs (e.g., Govaerts et al., 2012; Scheuer & Zinn, 2007), which suggests a need to explore instructors' interpretation of the presented analytics and their views towards using those analytics, especially when the analytics are complex or new to instructors.

In a prior study, a novel LAD was developed and integrated into an LMS to show more than simple behavioral metrics of forum activities (e.g., time online and number of forum posts) (Demmans Epp et al., 2019). This novel LAD goes beyond these metrics to include linguistic and other indicators in an attempt to provide timely information about students' activities to instructors in an easy to interpret way so that instructors can adjust their course accordingly (Demmans Epp et al., 2019).

This LAD needs to be investigated from the instructor's perspective because it represents a more holistic view of student activities and engagement, as suggested by Bodily et al. (2018). However, instructors' interpretation and use of this LAD was not examined. For this reason, the present study aims to explore how instructors interpret the analytics in both this novel LAD and a pre-existing LAD. It further aims to understand how instructors use these analytics tools as part of their online teaching practices.

1.1 Learning Analytics Dashboards

Many LADs have been developed to inform instructors about students, with only a small set of studies showing that instructors can identify problems using LADs. In one case, an LAD for monitoring and orchestrating collaboration within multiple groups enabled instructors to detect the groups that fail to collaborate (Martinez Maldonado et al., 2012). In another early deployment of LADs, instructors benefited from graphical representations of the analytics, which supported their identification of patterns in course material access and helped instructors decide when students might need special attention in a distance education context (Mazza & Dimitrova, 2007). Similarly, instructor's primary choice for identifying student challenges was an LAD in another study (Xhakaj et al., 2017). In one case, the instructor was surprised by the information presented in an LAD that was part of an intelligent tutoring system (i.e., a type of adaptive learning software) (Xhakaj et al., 2016). This surprising information led the instructor to change their lesson plans to help students overcome the challenges they were facing.

To facilitate this kind of timely intervention, LADs that predict student outcomes have been developed to enable instructors to take action in a preventative manner (e.g., Diana et al., 2017). For example, the Learning Analytics Dashboard for Advisors (LADA) was developed to support the decision-making of academic advisors by allowing them to predict potential problems and then advise students accordingly; it was found to be a valuable tool especially for inexperienced advisors (Gutiérrez et al., 2020). Going beyond the identification of issues, an LAD was used to guide instructors' daily classroom activities (Molenaar & Knoop-van Campen, 2019): instructors provided feedback on which tasks students were meant to perform next and how students were doing based on the information presented in the LAD. Similarly, the WiREAD dashboard was used to enable secondary school teachers to make data-driven pedagogical decisions through real-time LAD visualizations (Tan et al., 2018). Teachers presented the LA dashboard visualizations to the class and then provided whole-class and student-specific scaffolding. Although the teachers found the tool useful, they felt their students needed further guidance to interpret the analytics (Tan et al., 2018). In another study, teachers claimed to use the LAD within an online learning system to identify student strengths and weaknesses, but no evidence of how this information would be used was reported (Ginon et al., 2016). Moreover, the study did not investigate how instructors determined student strengths or weaknesses based on the information presented in the LAD, leaving a gap in our understanding of how instructors understand and interact with analytics.

The preceding case studies suggest that while some instructors can identify patterns of interaction that conflict with their desired pedagogy, others do not know what their desired pedagogy should look like when presented with analytics. In at least one case, this lack of instructor knowledge was accompanied by the instructor's assumption that the analytics were showing him that he had achieved his goal (Brooks et al., 2014). In another case, instructors got frustrated when the presented information undermined their existing pedagogies (Brown, 2020). As these examples illustrate, simply providing the information to instructors does not mean that they will intervene appropriately (Wise & Vytasek, 2017), making it difficult to guarantee that the provisioning of analytics will enable instructors to achieve desired results.

Exacerbating this issue is the fact that instructors feel that the visuals within some LADs present conflicting (Govaerts et al., 2012) or incorrect information (Scheuer & Zinn, 2007). This could be a problem with the LAD and its underlying analytics, or it could be an issue with the interpretability of the presented analytics. Instructors may misinterpret LADs (Verbert et al., 2020) that are presented in a manner that exceeds their current data literacies. In this situation, they may perceive the analytics as unreliable or the LADs as presenting conflicting information. Some studies suggest these interpretation issues are at least part of the problem. For example, one study found that middle school mathematics teachers interpreted the same analytics differently when exploring the LAD with the research team to examine how the LAD could be used to improve practice (Ahn et al., 2019). Instructors have also made inconsistent attributions when trying to determine the causes of problems that were highlighted through the presented analytics (Wise & Jung, 2019).

In a manner consistent with scrutable models (Kay & Kummerfeld, 2012), Wasson and Hansen (2015) suggested that instructors need to understand how the tools influence the data being captured and displayed, how that data was manipulated, and how to interpret analytics in a pedagogically meaningful way. In the case of most LADs, it is not known whether instructors have this understanding, which may be why they express distrust of analytics, struggle to understand them, and do not use them to inform their teaching practice in an ongoing and timely way.

Given the conflicting information that can be gleaned from these cases and the fact that there has been limited research on how LADs are interpreted by instructors (Xhakaj et al., 2016), there is a need to better understand how instructors approach the use of LADs in LMSs, how they interpret different types of charts and data, and how they use that data within their teaching practices. Consequently, this study aims to understand how instructors interpret and respond to an LAD. The LAD used in this study provides visual representations of student interactions and the latent characteristics that can be inferred from those interactions. By examining how instructors interpret and respond to this LAD, this study reveals implications for the design of LADs.

2 Method

A design-based research approach was used to improve an instructor-facing LAD and understand the perspective of the instructors who would be using it. This method allowed us to test and explore the use of the LAD in its context of use (Anderson & Shattuck, 2012).

2.1 Participants

Study participants were recruited via email. This email originated from the Program Coordinator of the Master of Teaching program in which they taught. Six instructors (one male, five female) volunteered and received a $15 gift card following their participation. Participant ages ranged between 38 and 63 (M = 49.2, SD = 12.59).

2.2 The Studied LAD and Its Iterations

Participants interacted with both of the LAD versions described below. These LADs were integrated into a discussion-based LMS.

2.2.1 Pre-existing LAD

The LMS used provides two sets of existing analytics: the first is a table of descriptive statistics and the second is a social network visualization.

The table (see Fig. 17.1) reports a global summary of individual student interactions within the LMS. The table cells contain the number of posts (notes) written and read, the number of replies received, and the total number of words written, as well as the sum of the time spent online throughout the entire term.

The table cells are color-coded according to student performance in comparison to course averages. The information available in the table is coarser grained than that available in the new dashboard. The instructors are only given statistics at the term level and they cannot perform any type of filtering. Nevertheless, the tables provide an overview of the course and student behavior.

The social network visualization (see Fig. 17.2) shows interactions between people. It can show who has replied to whom, who has liked whose posts, and who has linked to whose post. Instructional staff are shown in red and students in blue. In Fig. 17.2, we can see that student t, who is in the upper-left corner, has not interacted with anyone.

2.2.2 First Round of Iterative Revisions

This first round of design changes was informed through a variety of methods that include consultation with an instructional designer, interviews with six instructors who used the existing system to deliver online courses, literature searches, and user feedback the system creator had received.

From the interviews, we learned that instructors liked the provided measures (e.g., number of replies, likes, links), so they were kept. Instructors also discussed how they wanted to be able to track discussion topics and see how they evolved. They reported how they repurposed features in the current system to get a sense of

Impact Report

	Time Online	Notes Written	Replies	Words Written	Notes Read
User 1031	17:12:38	40	36 (90.0%)	6,617	546 (38.7%)
User 1036	26:13:13	36	32 (88.9%)	7,958	1,011 (71.7%)
User 1043	17:31:23	18	14 (77.8%)	4,828	277 (19.6%)
User 1054	16:20:47	39	34 (87.2%)	5,308	510 (36.2%)
User 1087	25:58:21	13	10 (76.9%)	2,877	580 (41.1%)
User 1094	8:34:22	12	10 (83.3%)	3,753	162 (11.5%)
User 1127	24:07:49	46	38 (82.6%)	6,691	389 (27.6%)
User 1320	32:07:21	25	21 (84.0%)	5,423	755 (53.5%)
User 1618	31:46:32	49	46 (93.9%)	7,316	1,220 (86.5%)
User 1703	78:22:03	68	62 (91.2%)	10,190	1,127 (79.9%)
User 1993	98:06:14	115	87 (75.7%)	21,098	1,217 (86.3%)
User 2967	23:51:03	15	10 (66.7%)	3,604	882 (62.6%)
User 3049	120:27:54	88	82 (93.2%)	16,343	1,179 (83.6%)
User 3173	59:05:36	42	36 (85.7%)	10,603	1,132 (80.3%)
User 3281	10:18:31	16	13 (81.3%)	1,691	229 (16.2%)
User 3736	24:42:51	78	71 (91.0%)	10,850	763 (54.1%)
User 3752	34:26:51	39	36 (92.3%)	7,155	932 (66.1%)
User 771	14:47:12	10	9 (90.0%)	2,294	297 (21.1%)
User 787	29:28:37	57	49 (86.0%)	10,283	1,225 (86.9%)
User 836	30:53:38	49	47 (95.9%)	10,485	570 (40.4%)
User 855	38:21:57	30	25 (83.3%)	6,534	1,199 (85.0%)
User 928	15:42:53	17	15 (88.2%)	2,774	393 (27.9%)
User 968	9:49:22	11	4 (36.4%)	732	134 (9.5%)
User 995	4:44:18	9	3 (33.3%)	1,784	133 (9.4%)
rere erer	0:00:41	0	0 (0.0%)	0	0 (0.0%)
t t	0:05:46	0	0 (0.0%)	0	1 (0.1%)
Student mean	30:30:18	35.5	30.4	6,430.4	648.6
Standard deviation	28:19:23	27.8	24.4	4,890.5	417.8
Instructors					
User 1489	108:08:10	295	151 (51.2%)	12,253	1,402 (99.4%)
User 2390	36:41:08	8	3 (37.5%)	18	80 (5.7%)

Notes

1. Deleted notes are not included in the "Notes Written", "Replies", "Words Written" or "Notes Read" results.
2. An individual who has read all available notes may have a "Notes Read" percentage of less than 100.0% if some notes are private or in hidden conferences.

Key

- More than 2 standard deviations below class mean
- Between 1 and 2 standard deviations below class mean
- Within 1 standard deviation of class mean (plus or minus)
- Between 1 and 2 standard deviations above class mean
- More than 2 standard deviations above class mean

Fine Print

1. Red-coloured results are not necessarily bad. Compare results to course expectations.
2. Some measures are highly correlated (e.g., Notes Written, Replies).
3. Students who drop out early may have low results that may skew the distribution.
4. Mean and standard deviation calculations are based upon student data only.
5. Non-student results (e.g., Instructor results) are not coloured.

Fig. 17.1 Table of descriptive statistics from the LAD[1]

[1] The visualization in this figure was created using de-identified student data.

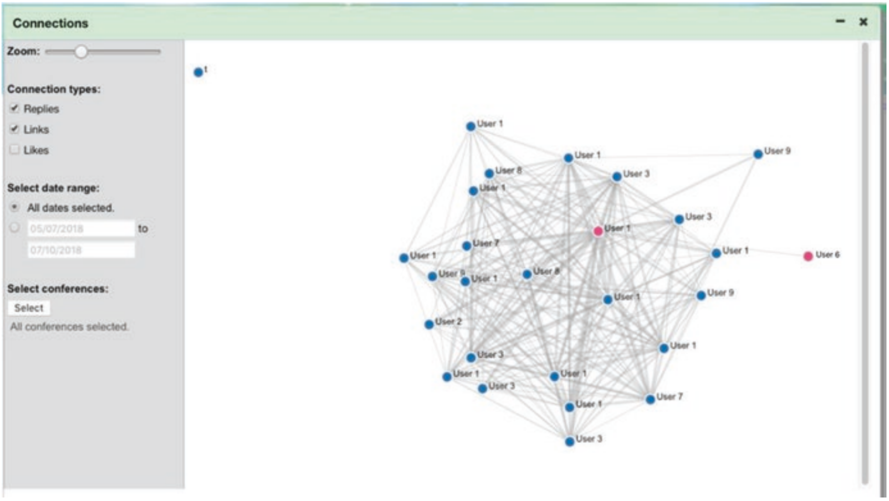


Fig. 17.2 Social network visualization, where the instructor has indicated they want to see links and replies between course participants (the visualization in this figure was created using de-identified student data)

this progression, suggesting a need for temporal analytics. This need was confirmed by the literature and led to the introduction of configurable time-sensitive analytics. While instructors liked the social network diagram and wanted it kept, they also expressed a need for the ability to exercise greater control and contextualize analytics; both were added.

The instructional designer expanded on this by specifying a need for tracking student posting and reading behavior at a weekly level. They also suggested capabilities that allowed one to focus on specific groups or subgroups of students, leading to the addition of a filter tool.

The feedback received by the system creator included the need for context sensitivity in the analytics, which is why various forms of context are enabled in the updated version that includes both temporal and topic-related contextual views. The feedback also indicated that instructors wanted to see in-depth information about specific students and that this information should be presented in a way that made temporal patterns visible.

A more detailed account of the iterative redesign process can be seen in our AERA paper (Demmans Epp et al., 2019). Rather than covering this months-long multistage process, the next section describes the resulting interface.

2.2.3 The New Dashboard

The newly designed LAD presents visual representations of student interactions and the latent characteristics that can be inferred from those interactions. Four main panels compose the LAD. Each focuses on a specific instructor perspective. The

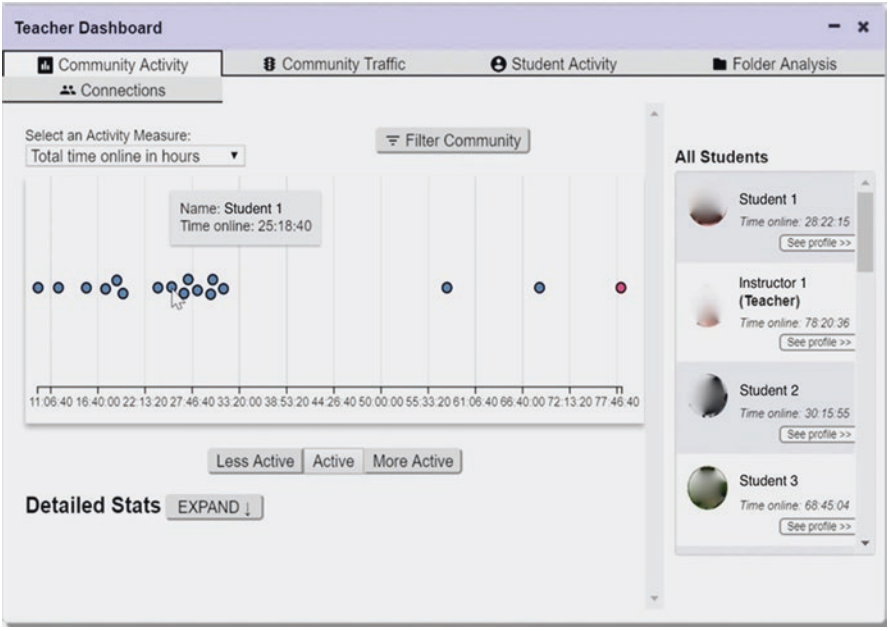


Fig. 17.3 Community Activity panel of the LAD

panels are "Community Activity," "Community Traffic," "Student Activity," and "Folder Analysis."

The Community Activity panel (see Fig. 17.3) represents student activity within a course from the beginning of the term. It allows instructors to view metrics such as time online, notes posted, and notes read for all students simultaneously. It provides a general view of all students' behavior and enables instructors to understand how individual students behave in comparison with the rest of the class. This panel allows instructors to choose a subset of students whose behaviors they want to examine. Once an instructor has selected a set of students, the visualization updates.

The Community Traffic panel displays information about the points in time when students are online, posting, reading, or replying to posts (see Fig. 17.4). It presents a temporal view instead of the cumulative, aggregate perspective presented in the Community Activity panel. It allows instructors to define the period they would like used for the time series chart; they can choose to view metrics in the context of a single day, a week, or the term as a whole. If week is selected, they can choose where within a week the visualization should start so that they can match it to their course activities. For example, an instructor with a regular Wednesday deadline may decide to start the week on a Wednesday so that activity levels can be viewed through the lens of that deadline. Instructors can also select which of the metrics they would like to inspect. This panel displays which course folder (a folder is similar to a forum) the activities were performed in and provides a link to that area of the course (see right frame of Fig. 17.4).

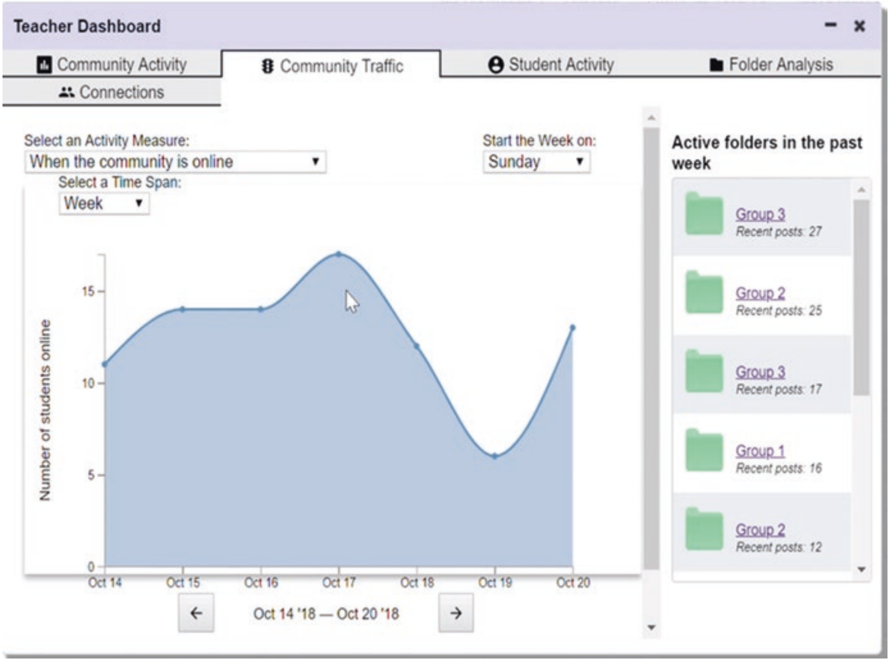


Fig. 17.4 Community Traffic panel of the LAD

The Student Activity panel focuses on each student individually. It has two visualizations that represent student behavior (see Fig. 17.5). The top visualization summarizes the balance of a student's activity across the entire course. It displays the distribution of notes read, posted, or replied to within different instructor-created discussion topics (e.g., threads). The bottom visualization is a time series chart that shows when the student is reading, posting, or replying. Akin to the Community Traffic panel, the instructor can select specific timeframes to examine. The rightmost sub-panel provides summary statistics describing the student's activities using their peers as a reference point: the light blue rectangles show the interquartile range to describe the behaviors of the entire cohort for metrics that instructors have indicated are important.

The Folder Analysis panel displays information based on the topics (folders) instructors have created within the system (see Fig. 17.6). These topics are akin to threads in other LMSs. For each folder, the instructor can see which members interacted, the type of interactions they engaged in, and the amount of interaction. This data is displayed through a bubble chart in which the size of each bubble signifies the quantity of the selected interaction (posting, replying, or reading), and each bubble represents a student.

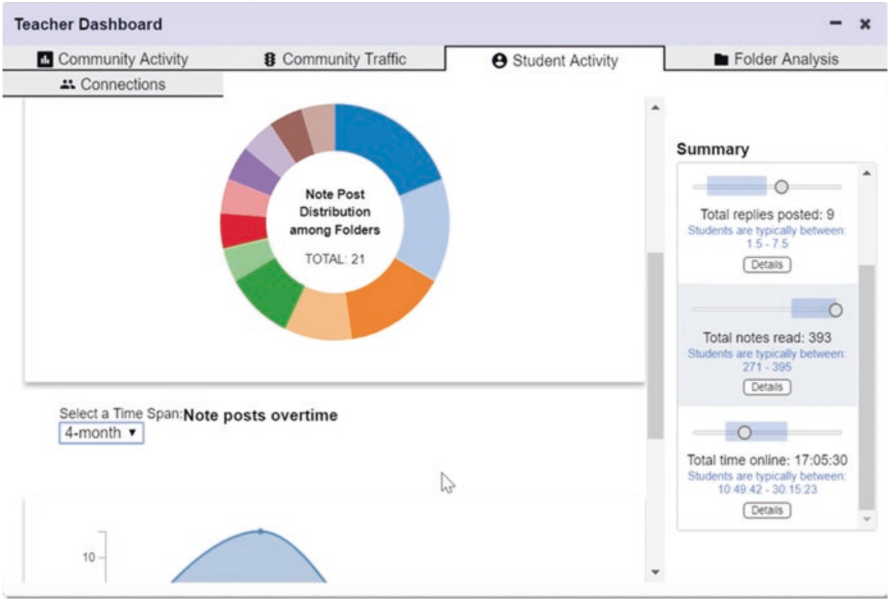


Fig. 17.5 Student Activity panel of the LAD, showing data from the full term (4 months)

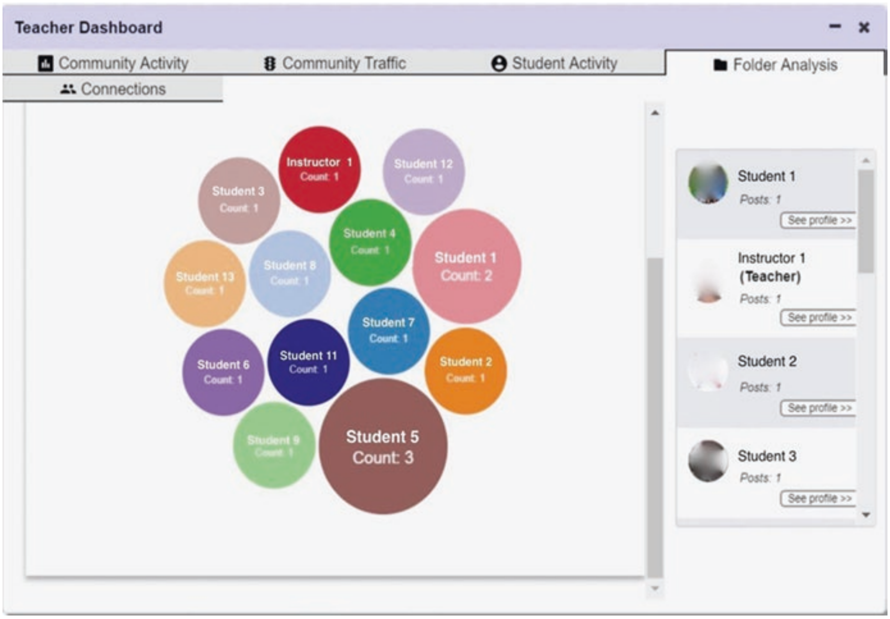


Fig. 17.6 Folder Analysis panel of the LAD

2.3 Data Collection

Instructors participated in a concurrent think-aloud session (Franz et al., 2019; Greiner, 2012), where they interpreted analytics. This method was chosen because it provides insight into usability and how people believe a system works. Prior to seeing the new dashboard, instructors analyzed their current course using the existing set of metrics and explained how they used the existing tabular report that contains a limited set of analytics. Instructors were asked to find specific types of information through the new LAD, identify and answer their own questions about how students were interacting or behaving in their current online course, and explain how they might use the new version of the dashboard. Instructors then completed a questionnaire.

Instructors also participated in a semi-structured interview (Rabionet, 2009). Interview questions focused on their experience and opinions of monitoring student activities; when to intervene; how to adapt their course; and what they expect from a dashboard in an online learning setting.

The think-aloud sessions lasted approximately 30 minutes and were conducted by the same research assistant (Author 5), with half of them observed by the principal investigator. The interviews lasted between 30 and 45 minutes; they were conducted by Author 3.

The instruments that were used to collect information about LAD usability include a perceived usefulness questionnaire and the NASA Task Load Index (TLX) (Hart & Staveland, 1988).

The NASA TLX is a widely used measure of usability that captures information about the mental demand, physical demand, temporal demand, performance, effort, and frustration a user experiences when interacting with a system. Participants rated each of these criteria on a scale from 1 to 10 (low to high).

We developed the perceived usefulness questionnaire by adapting the system usability (Brooke, 1996) and perceived competence (Deci & Ryan, 2002) scales. The questionnaire had 18 Likert-type items: 1 (strongly disagree) to 5 (strongly agree). Additional questionnaire items focused on usability issues that included how easy it was to navigate the dashboard and its components; participants' perceptions of the visuals and their usefulness; and whether they thought they could use the data to inform their teaching.

2.4 Data Analysis

Qualitative analysis followed the steps of thematic analysis: getting familiar with data, creating codes, searching for themes, reviewing, and then finalizing the themes (Braun & Clarke, 2006). During the process, codes were seen as interesting features of the data from the perspective of the study objective. Each theme emerged when semantically relevant codes gathered around a concept. Reviewing and confirming the themes was also done to ensure representativeness of the themes with regard to the original data.

The thematic analysis process was started by an experienced qualitative researcher who analyzed the interviews and think-alouds using the steps listed above to determine how LADs were being used and instructor openness to using them. Then another researcher reviewed and confirmed the analyses. This type of secondary review is a common practice for ensuring coder reliability (e.g., Cauwelier et al., 2016; Psaila et al., 2014).

Throughout the results section, pseudonyms are substituted into quotes to protect participant anonymity. Descriptive statistics of the NASA TLX and the perceived usefulness of the dashboard are provided graphically.

3 Results

3.1 Existing Analytics Use

Instructor's current monitoring strategies focused on using the table of descriptive statistics along with the system's social network tool, as can be seen from the below quotes:

> I usually go back to the percentage one with the green and red … And I want to see their network connections there [in the social network visualization] because I was curious to know which people are interested in that person's topic. (P2)
>
> I look at that [table] ... to see who's in the red and who's in the green but I'm particularly concerned about who's in the red. And then I use the, if I'm teaching online only, I use the individual messaging. (P5)

First quote above also shows some confusion about what the analytics represent. The social network visualization does not show which topics were discussed; it only presents who has interacted with whom. In the last quote, an example for when instructors intervene based on the information presented in the LAD also appears. As the instructor explained, he messages students after detecting they may need extra support. Apart from this example, the most common reason for instructor intervention was the students' misconceptions and wrong interpretations which can be seen in an instructor comment: "the way I most commonly intervene is when I see students talking about things that are wrong, you know, perpetuating misconceptions" (P1) and "I go in and just see what has been posted, and now and then I'll post something… if a concept is misunderstood or misused" (P4). Another situation requiring instructor intervention is when students get lost in the sheer quantity of posts:

> if I see that some of them are feeling overwhelmed because even though I've said 'no you don't have to look at everything', but they feel they have to then I decide ok we are gonna do some small groups here. (P5)

While not strictly an analytic, another widely used feature is the LMS search bar, with instructor use of the feature suggesting a need for more detailed analytics. This search feature retrieves all course posts in which the searched term was mentioned. Participating instructors used this search feature to contextualize and assess students' interaction in the course. By searching for a student's name, they were able to see every note and reply posted by that student and analyze the type and amount of interaction that occurred. According to instructors, this practice helped reinforce and complement the quantitative information from the summary tables as it allowed them to understand the content of the notes and replies written. Moreover, they believed that the detailed individual student behavior information was useful for restructuring student groups to help students leverage each other's strengths.

Manually checking student activity in this way suggests that the pre-existing analytics were not at the granularity needed to support instructor goals. Some of their reported processes also indicate the tabular analytics could better support their goals. Some instructors noted they used an MS Excel worksheet to keep a record of these manual checks. "We have our rubric out of the syllabus and from the syllabus then we formed an Excel file." One participant did both:

> that's just a check. Check! Check! Check! that they've contributed. But I also do look at in [LMS], now I don't remember what it's called, but in [LMS] I can look at engagement, and … It has percentages, it's like a bar graph. It also has the amount of time that they've been on. In the [LMS], so I do look at that too. (P2)

This instructor's use of both manual and automated approaches to deriving analytics shows that she does not consider either of them sufficient. Consequently, she invests extra effort to improve her ability to monitor student learning activities in her online courses. This extra effort was needed to oversee student behavior in online courses as the instructor has less or no face-to-face contact with students in these situations.

3.2 Instructor Desire for Analytics

As their current practices suggest, instructors have integrated the use of the analytics table into their practices. Moreover, they want access to meaningful analytics and will do the best they can with what they are given. Instructors would like to have additional analytics as indicators of student activities. "At the end of the term, there are things that it would be awesome to have sort of quantified… how many times did they cite?! how many times did they directly quote from the readings?!" (P3), "there are deadlines for when they need to have done things and this [LMS] doesn't actually tell me about… if they posted late or etc. so that would be really useful to have" (P3), and it "would be cool if you could use that tool [network connections] for specific forums or for one specific folder instead of whole module" (P2). These quotes show the demand for indicators of student activities that provide additional context and prevent the need for additional work (as seen in the above section).

Not being able to see students' post edit and creation times in the existing table of analytics was a problem for instructors because it makes it impossible for them to fully check whether the student did their work on time – "I always think it would be helpful if there is something that said 'posted on' and 'edited on' or something like that because sometimes I think I'm not actually getting it quite right" (P1). A concern arose from student posts showing the last edit date because students can edit their posts afterwards, which means that a later correction or change to a post makes this date unreliable for checking when students performed the required work. The requested information is currently captured by the system but is not made directly available to instructors through temporal analytics, which was a known limitation of the pre-existing analytics table and part of the reason why the new LAD provides temporal information.

3.3 Concerns over Analytic Quality

In addition to wanting analytics that capture more information or provide that information at different granularities, participating instructors expressed concern over the reliability of indicators. Specifically, the read indicator was seen as problematic because students can mark posts as read without reading them "So that feature ends up being a little bit compromised" (P3). This quote also demonstrates how teachers are bringing assumptions into their interpretation of analytics based on their understanding (correct or incorrect) of how the system works.

Another concern was the search feature because it requires at least four characters and provides a list that includes anything containing the search term. For example, if you search for John, any post written by John as well as any post where someone used the name John would be listed. Statements on these issues include "another complaint I have is that you have to put in at least 4 characters when you search for a name, and not everybody's name is 4 letters … I find it a problem" (P1) and "I'm not really happy with the lack of refinement of the search engine. It's problematic because it comes up like if I search 'Sarah' it comes up with: Hello Sarah! and it also comes up with Sarah the author!" (P5).

3.4 Planned Dashboard Usage

According to the instructors participating in the study, the new dashboard is useful for detecting potentially anomalous or concerning behaviors. They plan to use it to compare the behavior of the students in their class and take preventative actions to help students who seem to be lagging behind. These instructors believed that by using the dashboard, they would be able to detect students' lack of engagement sooner.

Indeed, the instructors identified new (to them) ways to evaluate student engagement, such as taking into account the number of notes read or the number of replies written. The instructors mentioned that they could use the dashboard to inform the attribution of participation marks, as most of their courses require students to engage with each other's posts, be it by reading or replying. According to participating instructors, information such as the word count on the folder analysis panel is a quick way to check whether students followed word limit specifications and get a sense of the post's nature. For example, short posts tend to be used to express agreement so they would know by the length of the post whether a student might have engaged in a deep interaction. Instructors also identified the potential for using the LAD to corroborate their assessment of students as it gives them a tangible activity summary for each person.

While use of the analytics for assessment was common, one participant raised a concern about this practice by saying:

> that's only really helpful at the end of the course… would be unfair for me to look at it within the middle of the course when everyone's kind of has some different circumstances around you know when they're going to contribute their work.... (P2)

This quote also implies the role of timing for instructors' use of specific analytics throughout a course as well as the potential need for temporal analytics. Expressing another concern over using the dashboard as an assessment tool, most participants indicated the usefulness of the information they can extract from the dashboard was limited because it is mostly quantitative. Therefore, they were not planning to rely solely on that information to assign marks.

In addition to using the dashboard as an assessment tool, instructors stated it can be used to define when to contact students directly: "I think it [the LAD] will help change my assessment and strategies in terms of how I would go about evaluating or checking in with students. So that would be great, but not for my instruction" (P2) and "I will contact students more directly" (P4). Moreover, a participating instructor expressed that she felt she could use the data about when students post, reply, or read to select deadlines that better fit the students: "to shift deadlines to the system like I would want to spend more time and see when they are doing most of their reading and tell me something like change deadlines" (P3).

3.5 Interpretation of Analytics

During the think-aloud portion of the study, instructors showed a few misconceptions about the displayed information. Many of those misconceptions can be overcome with some user interface improvements, such as adding metric descriptions and the accentuation of their respective units of measure.

Instructors were especially confused immediately after updating the LAD visualizations. In the Community Activity panel, the instructor can select one measure from many, such as "Total time online in hours," "Percentage of notes read," or

"Total words written." Once an option is selected, the time series plot updates to show the selected metric. However, instructors were still unsure about which metrics were displayed by the system despite their having chosen the metric that they were looking at.

A common misconception was that the "time online" metric was an average of all the time spent online in minutes when it is the sum of all time spent online in hours. With that misconception in mind, instructors would comment that the variance in the average time online was not substantial. When examining the time online visualization, one of the instructors said that "there isn't much variability between my more active students and my less active students which makes me think that it couldn't have been over a very long time period" (P1). However, instead of a 30-minute difference in the time online averages, that instructor was looking at a 30-hour difference in the total time online.

Along with this interpretation problem, instructors had trouble noticing when they changed the metric displayed. For example, one instructor was looking at a student's time online statistics, and after a while she selected the "notes read" metric but kept referring to the statistics in terms of time, not in terms of the number of notes read by students. One of the statistics indicated that students read 40 notes on average. However, the instructor interpreted the data as the students spending, on average, 40 minutes reading. This misunderstanding can be overcome by accompanying the statistic displayed with a metric indicator such as "40 min" or "40 notes." Additional visual changes, such as using an icon to also communicate the analytic being viewed, could further alleviate this problem.

The bubble chart on the folder analysis panel is a new type of visual analytic that caused some confusion. The instructors would often believe that the bubble colors signified similarity among students – the more similar the color, the more similar the students' performance for that metric. However, the colors were being used to distinguish students and map the bubbles in the chart to the profiles on the panel's sidebar; they did not indicate commonalities among students. Given instructors' interpretation, this visualization has been simplified so that it does not imply additional semantics through its use of color.

3.6 Usability

We used the raw NASA TLX score to measure various aspects of LAD usability. We report the subscale values for mental demand, physical demand, temporal demand, performance, effort, and frustration in Fig. 17.7, where 1 is very low and 10 is very high.

As can be seen in this data and as would be expected, the ratings for physical demand and temporal demand suggest that using the dashboard did not require much physical effort or user time. Instructors felt they could get information out of the new LAD reasonably quickly. Some also felt they succeeded in meeting their

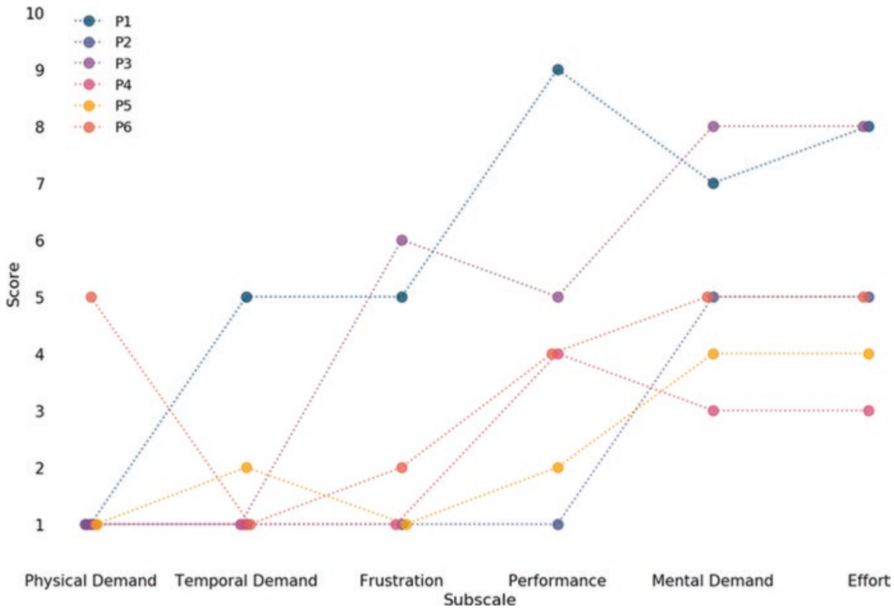


Fig. 17.7 Instructor responses to the NASA TLX

performance objectives (Performance), even though low to moderate levels of frustration were experienced by some. This frustration would be expected when encountering a new sensemaking task, and it is expected to reduce as instructors become more familiar with the interface, the analytics, and their semantics.

It is worth noting that extracting information, the main task, required moderate to high cognitive effort (mental demand) as well as moderate to high overall effort, indicating this sensemaking task is difficult for instructors, at least initially. Their task loads may decrease over time as they develop this skill.

Most of the observed usability issues that resulted in participants expressing confusion or asking questions of the person(s) leading data collection were the result of poor labelling, especially with respect to units of measurement. Additional challenges were faced because the contrast between some visual elements was inadequate or the intent of the color usage was unclear, which led instructors to mentally group certain features that were never meant to be part of the same group.

3.7 *Perceived Usability and Usefulness of the LAD*

Instructor responses to questionnaire items indicate that they could easily navigate within the LAD (see Fig. 17.8). They were able to find specific students and move between areas within the LAD. They could also easily find the dashboard.

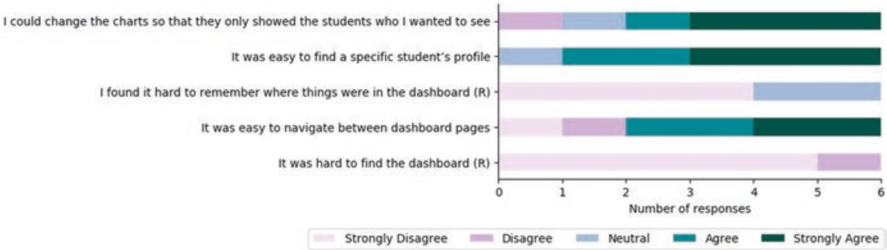


Fig. 17.8 Navigating in the LAD. (R) indicates a negatively worded item, where disagreement indicates a positive finding

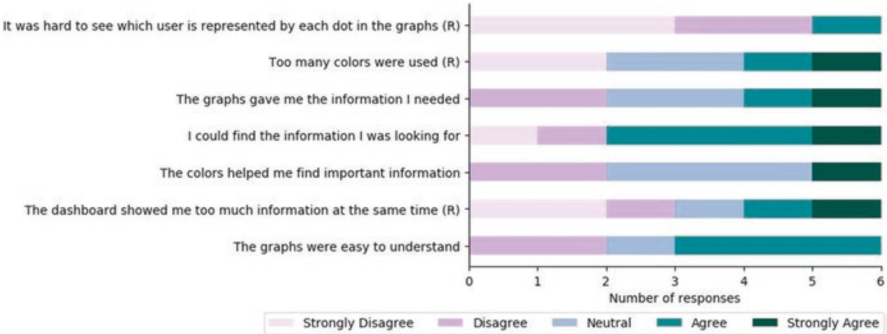


Fig. 17.9 Visualization usability. (R) indicates a negatively worded item, where disagreement indicates a positive finding

Instructors felt they understood the meaning of the visualizations (see Fig. 17.9). Instructors reported they could find the needed information and that both the color coding and graphs helped them to do that despite some of them feeling that the LAD used too many colors. Participating instructors also reported that the graphs were easy to understand even if they sometimes provided a bit too much information.

Three participants responded to and agreed with the item about easily zooming in and out of the visualizations (see Fig. 17.9). While all participating instructors were able to solve their own problems, many needed help to understand how the LAD works (see Fig. 17.10). As will be seen in the next section, their belief that they needed help is consistent with the behaviors observed during the think-aloud activity.

Instructors liked the LAD and intended to use it again (see Fig. 17.11). However, only some of them believed that they could use the LAD or the information it provided to adapt their course. The hesitation or reluctance to use the LAD may stem from concerns over the reliability of the analytics or the lack of contextualization of the analytics (as in the instructor comments about the read indicator and search feature above).

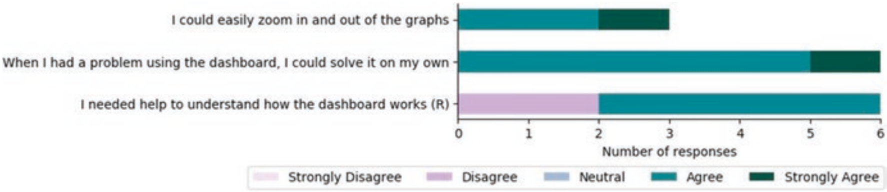


Fig. 17.10 Support needed to use the LAD. (R) indicates a negatively worded item, where disagreement indicates a positive finding

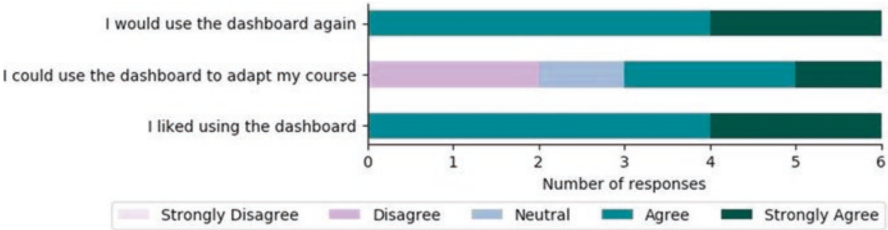


Fig. 17.11 Satisfaction of the instructors

4 Discussion and Implications

In this study, we examined instructor use of an LAD in the context of their own online course. The main findings provide insight into how instructors use analytics, their concerns over analytic quality, the perceived usefulness of specific analytics, instructors' desire for analytics, and how they planned to use those analytics. Implications based on these findings are presented along with the below discussion.

5 Instructors Are Open and Eager to Use LADs to Support Assessment and Evaluation

In many early deployments of learning analytics, instructors have only aimed to identify underperforming students (e.g., Arnold & Pistilli, 2012; Jayaprakash et al., 2014). Our study demonstrated that instructors' current practices with analytics and their expectations of them have moved beyond this objective, which supports other calls for ongoing evaluations of LAD use (Sun et al., 2019). The most powerful tendency among instructors in this study was to use the LAD as an assessment tool. Our participants expressed this tendency by explaining their use of the LAD for grading in their courses. This inclination towards using the analytics for assessment purposes was also identified in Papamitsiou and Economides' (2014) review of the literature that examined experimental case studies conducted in LA and educational data mining. To respond to this tendency and instructor needs, more research is needed to investigate how to support appropriate assessment and evaluation practices in the context of the analytics that an LAD can provide.

6 Social Network Analytics Can Support the Facilitation of Collaborative Learning Practices

Instructors in this study depended on a social network analytic to monitor student activities. This view allowed instructors to see the amount and type of interactions, such as likes, replies, or links, that took place among students and instructional staff. This visualization allows instructors to identify which students interact with each other and who may share similar interests or perspectives. Highlighting these interactions may support group formation based on whether instructors want students to interact with the same learners or others who may bring additional perspectives to the conversation to facilitate collaborative learning.

Consistent with this, features could be added to LADs that support instructors' practices by saving time on the design and implementation of pedagogical practices. Adding features to support specific teaching tasks may eliminate one of the biggest factors, time required, that prevents instructors from employing new approaches (Arnold & Pistilli, 2012) such as learning analytics. It may even motivate instructors to use LADs. For example, in a course including peer assessment practices for discussion posts, a dashboard that presents students' previous assessment assignments (who assessed whose post) and number of posts in each thread could save instructors time by helping them track and make these assignments.

7 More Qualitative and Expressive Metrics Are Needed to Enable a Holistic Understanding of Student Learning Experience

Instructors mainly wanted the addition of qualitative indicators of student activity. This is partly because quantitative indicators, such as "time online," are neither reliable nor insightful, even if they are wanted. It may be possible to satisfy this desire by adding text summarization or content from student self-reports and reflections, as suggested by Ji et al. (2013). Summarization approaches similar to those that are now being used in other educational settings could also be of benefit (Luo et al., 2016) as could measures of student language use that include the adoption or use of vocabulary (Demmans Epp, Phirangee, & Hewitt, 2017b; Rahimi et al., 2017), cohesiveness of student posts (Cade et al., 2014), topic dispersion among students, and other qualities of how or what students are discussing.

8 Instructors Value and Need Temporal Information

One of the results that stands out is the instructor's perspective on timing for reviewing analytics related to student activity, especially for assessment purposes. As previously argued and expressed by participating instructors, timing is critical for providing insight into students' learning processes. Thus, instructors should consider timing when interpreting analytics (Becker, 2013). Developers should consider how to provide information about temporal aspects of student activities and learning. For software developers to do this, a greater focus on the development, validation, and use of temporality in analytics of student learning is needed (Knight et al., 2017).

9 Interpretation Supports Should Be Improved and Enriched to Scaffold Individual Instructor Practices

Participating instructors specifically expressed that visual aids, such as color coding, helped them gain insight into student engagement. This was seen in how they used color when interacting with the tabular summary statistics (e.g., percentages), the social network visualization, and some of the newly added charts. This facilitation is expected considering how critical visual aids are for making sense of large amounts of data (Schwendimann et al., 2017; Shneiderman, 1996).

While instructors generally found the LAD usable and easy to navigate, they occasionally struggled with how to interpret the represented data. This finding supports the argument that instructors need to be encouraged to improve their educational data literacy for effective and efficient use of learning analytics (Ifenthaler & Yau, 2020). This can be facilitated with additional training or follow-up support: two approaches that were suggested based on a study that investigated LAD interpretation from a technology acceptance perspective (Rienties et al., 2018). Alternatively, the dashboard's instructions and guidelines can be improved based on direct instructor feedback or the challenges we observed (Park & Jo, 2015). Adding sensemaking process supports that encourage prediction of the ideal version of an analytic based on the course design and goals may also support sensemaking by ensuring that instructors have thought about what their students' behavior or language should look like before they begin interpreting the measured behaviors and language (Demmans Epp et al. 2017a, b). Once the instructor has extracted meaningful information from the LAD, other features could be used to scaffold the planning of subsequent learning activities or assessments (as in Demmans Epp et al. (2015) or Demmans Epp, Phirangee, Despres-Bedwward, and Wang (2017a)). These planning supports should further alleviate the sensemaking burden associated with analytics use for course adaption, whether that adaption is done at the micro or macro level. Currently, these suggestions are mostly at the ideation stage and warrant further investigation.

10 LADs Should Be Customizable to Enable Contextualization

This study showed that instructors are eager to use LADs as long as they receive accurate and meaningful analytics in a way that is easy to interpret. As it is nearly impossible to meet these requirements for different course designs and educational approaches using a static LAD structure, the results of this study strengthen the argument that LADs need to be customizable (Roberts et al., 2017), which could facilitate the design of learning analytics implementations (Wise & Vytasek, 2017).

With customizable LADs, the personal preferences of different instructors can be satisfied. LADs could then be adapted to fit within instructors' existing praxis (Brown, 2020). This configurability would help address the lack of contextualization that often hinders instructor interpretation of analytics (Wise & Vytasek, 2017). Similarly to the suggestions listed under implication 5, customization strategies and their impact on instructor use of analytics are in need of investigation.

11 Limitations

In this study, six instructors' use of an LAD was explored through interviews, think-alouds, and questionnaires. Using both qualitative and quantitative approaches within design-based research allowed us to deeply examine the experiences of this small instructor group. By doing this, we thoroughly explored how instructors interpret and respond to a specific LAD within the context of discussion-based online courses.

Even though the study was not intentionally focused on socio-collaborative learning practices within online discussions, the results showed that all the instructors involved in this study employed this pedagogical approach when using the LAD. Given these characteristics, it is likely that some of the lessons will only apply in other discussion-focused environments where instructors expect students to learn via their interactions with others.

12 Conclusion

LADs have become an essential component of LMSs. However, instructors' perspective on their practical use still needs exploration. To address this need, the present study examined instructors' interpretation of LADs in the context of an ongoing course and elicited their feedback. This kind of information about the integration of LADs into instructional practices is needed to inform the design and use of LADs for supporting online instruction.

Findings from this study revealed that what we view as relatively simple analytics are not always interpreted in the same way by instructors. This finding suggests a need for additional work on how we can present analytics in a meaningful and easy to interpret way.

Although all participants grounded their teaching approaches in socio-collaborative learning, their use and interpretation of the LAD varied, which implies that there are substantive differences across instructors regardless of the pedagogical approach employed. As the discussed implications suggest, there is a need for additional work on how to support instructors' interpretation and use of analytics. This includes developing supports to help instructors make sense of analytics, understand the temporal nature of what they are observing through the LAD, and plan course adaptations based on those analytics. The above findings also imply that analytics capturing qualities of student discourse are needed for instructors in these contexts to fully embrace the use of LADs beyond their current role of monitoring student activities.

As can be seen through this study, there is a need for change in how we design LADs. This change needs to focus on the design elements that support the appropriate interpretation of analytics, enable instructor trust of the analytics, and facilitate instructor integration of analytics into their desired pedagogical processes. Given the present study's focus on how instructors use and interpret analytics, this study can be seen as putting a spotlight on an overlooked aspect of LAD design (Shum, 2018).

Acknowledgments We acknowledge the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC) [RGPIN-2018-03834] and the Social Sciences and Humanities Research Council (SSHRC).

References

Ahn, J., Campos, F., Hays, M., & Digiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6*(2), 70–85. https://doi.org/10.18608/jla.2019.62.5.

Aleven, V., Xhakaj, F., Holstein, K., & McLaren, B. M. (2016). Developing a teacher dashboard for use with intelligent tutoring systems. In R. Vatrapu, M. Kickmeier-Rust, B. Ginon, & S. Bull (Eds.), *Proceedings of the EC-TEL 2016 international workshop on teaching analytics* (pp. 15–23). Lyon, France: Retrieved from http://ceur-ws.org/Vol-1738/IWTA_2016_paper4.pdf.

Anderson, T., & Shattuck, J. (2012). Design-based research: A decade of progress in education research? *Educational Researcher, 41*(1), 16–25. https://doi.org/10.3102/0013189X11428813.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270). BC, Canada: ACM. https://doi.org/10.1145/2330601.2330666.

Becker, B. (2013). Learning analytics: Insights into the natural learning behavior of our students. *Behavioral & Social Sciences Librarian, 32*(1), 63–67. https://doi.org/10.1080/01639269.2013.751804.

Bodily, R., & Verbert, K. (2017). Trends and issues in student-facing learning analytics reporting systems research. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 309–318). BC, Canada: ACM. https://doi.org/10.1145/3027385.3027403.

Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., & Verbert, K. (2018). Open learner models and learning analytics dashboards: A systematic review. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 41–50). New York, NY, USA: ACM. https://doi.org/10.1145/3170358.3170409.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa.

Brooke, J. (1996). SUS: A 'quick and dirty' usability scale. In P. W. Jordan, B. Thomas, B. Weerdmeester, & I. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). Bristol, PA, USA: Taylor & Francis.

Brooks, C., Greer, J., & Gutwin, C. (2014). The data-assisted approach to building intelligent technology-enhanced learning environments. In J. Larusson & B. White (Eds.), *Learning analytics: From research to practice*. New York, NY: Springer. https://doi.org/10.1007/978-1-4614-3305-7_7.

Brown, M. (2020). Seeing students at scale: How faculty in large lecture courses act upon learning analytics dashboard data. *Teaching in Higher Education, 25*(4), 384–400. https://doi.org/10.1080/13562517.2019.1698540.

Cade, W., Dowell, N., Graesser, A., Tausczik, Y., & Pennebaker, J. (2014). Modeling student Socioaffective responses to group interactions in a collaborative online chat environment. In Proceedings Educational Data Mining (EDM). London, UK. Retrieved from https://files.eric.ed.gov/fulltext/ED558339.pdf

Cauwelier, P., Ribière, V. M., & Bennet, A. (2016). Team psychological safety and team learning: A cultural perspective. *The Learning Organization, 23*(6), 458–468. https://doi.org/10.1108/TLO-05-2016-0029.

Conole, G., Gašević, D., Long, P., & Siemens, G. (2011). Message from the LAK 2011 general and program chairs. In *Proceedings of LAK '11: Proceedings of the 1st International Conference on Learning Analytics and Knowledge, i–ii*. New York: ACM. Retrieved from https://portalparts.acm.org/2100000/2090116/fm/frontmatter.pdf

Deci, E. L., & Ryan, R. M. (2002). *Handbook of self-determination research*. Rochester: University of Rochester Press.

Demmans Epp, C., Park, G., & Plumb, C. (2015). Developing an adaptive tool to select, plan, and scaffold oral assessment tasks for undergraduate courses. *Educational Technology Research and Development, 63*, 475–498. https://doi.org/10.1007/s11423-015-9375-8.

Demmans Epp, C., Phirangee, K., Despres-Bedwward, A., & Wang, L. (2017a). Resourceful instructors and students: Overcoming barriers to integrating mobile tools. In A. R. Power, M. Ally, D. Cristol, & Palalas (Eds.), *IAmLearning: Mobilizing and supporting educator practice*. Retrieved from https://iamlearning.pressbooks.com/chapter/resourceful-instructors-and-students-overcoming-barriers-to-integrating-mobile-tools/.

Demmans Epp, C., Phirangee, K., & Hewitt, J. (2017b). Talk with me: Student behaviours and pronoun use as indicators of discourse health across facilitation methods. *Journal of Learning Analytics, 4*(3), 47–75. https://doi.org/10.18608/jla.2017.43.4.

Demmans Epp, C., Perez, R., Phirangee, K., Hewitt, J., & Toope, K. (2019). *User-centered dashboard design: Iterative design to support teacher informational needs in online learning contexts*. Presented at the American Educational Research Association (AERA) annual meeting, Toronto, Canada. Retrieved from https://www.aera.net/Publications/Online-Paper-Repository/AERA-Online-Paper-Repository

Diana, N., Eagle, M., Stamper, J., Grover, S., Bienkowski, M., & Basu, S. (2017). An instructor dashboard for real-time analytics in interactive programming assignments. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 272–279). BC, Canada: ACM. https://doi.org/10.1145/3027385.3027441.

Easton, S. S. (2003). Clarifying the instructor's role in online distance learning. *Communication Education, 52*(2), 87–105. https://doi.org/10.1080/03634520302470.

Elbadrawy, A., Polyzou, A., Ren, Z., Sweeney, M., Karypis, G., & Rangwala, H. (2016). Predicting student performance using personalized analytics. *Computer, 49*(4), 61–69. https://doi.org/10.1109/MC.2016.119.

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., … Vuorikari, R. (2016). Research evidence on the use of learning analytics – implications for education policy. In R. Vuorikari & J. C. Muñoz (Eds.), *A European framework for action on learning analytics*. https://doi.org/10.2791/955210.

Franz, R. L., Neves, B. B., Demmans Epp, C., Baecker, R., & Wobbrock, J. O. (2019). Why and how think-alouds with older adults fail: Recommendations from a study and expert interviews. In S. Sayago (Ed.), *Perspectives on human-computer interaction research with older people* (pp. 217–235). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-06076-3_14.

Ginon, B., Johnson, M. D., Turker, A., & Kickmeier-Rust, M. (2016). Helping teachers to help students by using an open learner model. In K. Verbert, M. Sharples, & T. Klobučar (Eds.), *Adaptive and adaptable learning at EC-TEL 2016* (Lecture notes in computer science) (Vol. 9891, pp. 587–590). Lyon: Springer. https://doi.org/10.1007/978-3-319-45153-4_69.

Govaerts, S., Verbert, K., Duval, E., & Pardo, A. (2012). The student activity meter for awareness and self-reflection. In *CHI '12 Extended Abstracts on Human Factors in Computing Systems* (pp. 869–884). Texas, USA: ACM. https://doi.org/10.1145/2212776.2212860.

Greiner, K. (2012). A Comparison of two concurrent think-aloud protocols: Categories and relevancy of utterances. (Masters), B. Thomas Golisano college. Retrieved from https://scholarworks.rit.edu/theses/5754

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*, 1–13. https://doi.org/10.1016/j.chb.2018.12.004.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), *Human mental workload* (Vol. 52, pp. 139–183). North-Holland: Elsevier Science Publishers. https://doi.org/10.1016/S0166-4115(08)62386-9.

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*, 1961–1990. https://doi.org/10.1007/s11423-020-09788-z.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics, 1*(1), 6–47. https://doi.org/10.18608/jla.2014.11.3.

Ji, M., Michel, C., Lavoué, E., & George, S. (2013). An architecture to combine activity traces and reporting traces to support self-regulation processes. In *Proceedings of 2013 IEEE 13th international conference on advanced learning technologies* (pp. 87–91). Beijing, China: IEEE. https://doi.org/10.1109/ICALT.2013.30.

Kay, J., & Kummerfeld, B. (2012). Creating personalized systems that people can scrutinize and control: Drivers, principles and experience. *ACM Transactions on Interactive Intelligent Systems, 2*(4), 1–42. https://doi.org/10.1145/2395123.2395129.

Knight, S., & Littleton, K. (2015). Discourse centric learning analytics: Mapping the terrain. *Journal of Learning Analytics, 2*(1), 185–209. https://doi.org/10.18608/jla.2015.21.9.

Knight, S., Wise, A. F., & Chen, B. (2017). Time for change: Why learning analytics needs temporal analysis. *Journal of Learning Analytics, 4*(3), 7–17. https://doi.org/10.18608/jla.2017.43.2.

Knoop-van Campen, C., & Molenaar, I. (2020). How teachers integrate dashboards into their feedback practices. *Frontline Learning Research, 8*(4), 37–51. https://doi.org/10.14786/flr.v8i4.641.

Luo, W., Liu, F., Liu, Z., & Litman, D. (2016). Automatic summarization of student course feedback. In *Proceedings of Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL HLT 2016* (pp. 80–85).

San Diego, California: Association for Computational Linguistics. https://doi.org/10.18653/v1/n16-1010.

Martinez Maldonado, R., Kay, J., Yacef, K., & Schwendimann, B. (2012). An interactive teacher's dashboard for monitoring groups in a multi-tabletop learning environment. In S. A. Cerri, W. J. Clancey, G. Papadourakis, & K. Panourgia (Eds.), *Intelligent tutoring systems* (Lecture Notes in Computer Science) (Vol. 7315, pp. 482–492). Berlin/Heidelberg: Springer. https://doi.org/10.1007/978-3-642-30950-2_62.

Mazza, R., & Dimitrova, V. (2007). CourseVis: A graphical student monitoring tool for supporting instructors in web-based distance courses. *International Journal of Human-Computer Studies, 65*(2), 125–139. https://doi.org/10.1016/j.ijhcs.2006.08.008.

Molenaar, I., & Knoop-van Campen, C. A. N. (2019). How teachers make dashboard information actionable. *IEEE Transactions on Learning Technologies, 12*(3), 347–355. https://doi.org/10.1109/TLT.2018.2851585.

Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society, 17*(4), 49–64. Retrieved from http://www.jstor.org/stable/jeductechsoci.17.4.49.

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110–133. Retrieved from http://www.jucs.org/jucs_21_1/development_of_the_learning/jucs_21_01_0110_0133_park.pdf.

Psaila, K., Fowler, C., Kruske, S., & Schmied, V. (2014). A qualitative study of innovations implemented to improve transition of care from maternity to child and family health (CFH) services in Australia. *Women and Birth, 27*(4), e51–e60. https://doi.org/10.1016/j.wombi.2014.08.004.

Rabionet, S. E. (2009). How I learned to design and conduct semi-structured interviews: An ongoing and continuous journey. *The Qualitative Report, 14*(3), 203–206. Retrieved from https://nsuworks.nova.edu/tqr/vol14/iss3/17.

Rahimi, Z., Kumar, A., Litman, D., Paletz, S., & Yu, M. (2017). Entrainment in multi-party spoken dialogues at multiple linguistic levels. In *Proceedings of Interspeech* (pp. 1696–1700). Stockholm. https://doi.org/10.21437/Interspeech.2017-1568.

Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018). Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers. *The International Review of Research in Open and Distributed Learning, 19*(5), 187–202. https://doi.org/10.19173/irrodl.v19i5.3493.

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. *Technology, Knowledge and Learning, 22*, 317–333. https://doi.org/10.1007/s10758-017-9316-1.

Scheuer, O., & Zinn, C. (2007). How did the e-learning session go? The student inspector. In *Proceedings of the conference on artificial intelligence in education: Building technology rich learning contexts that work* (pp. 487–494). Amsterdam: IOS Press. Retrieved from https://dl.acm.org/doi/10.5555/1563601.1563678.

Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522.

Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings of 1996 IEEE symposium on visual languages* (pp. 336–343). Boulder, CO, USA: IEEE. https://doi.org/10.1109/VL.1996.545307.

Shum, S. B. (2018). *Transitioning education's knowledge infrastructure: Shaping design or shouting from the touchline?* Keynote presented at the international conference on the learning science (ICLS), London, UK. Retrieved from https://opus.lib.uts.edu.au/handle/10453/133232

Sun, K., Mhaidli, A. H., Watel, S., Brooks, C. A., & Schaub, F. (2019). It's my data! Tensions among stakeholders of a learning analytics dashboard. In *Proceedings of the conference on* *human factors in computing systems* (pp. 1–14). Glasgow Scotland UK: ACM. https://doi.org/10.1145/3290605.3300824.

Tan, J. P.-L., Koh, E., Jonathan, C. R., & Tay, S. H. (2018). *Visible teaching in action: Using the WiREAD learning analytics dashboard for pedagogical adaptivity*. Paper presented at the American Educational Research Association Annual Conference (AERA 2018), New York, NY, USA. Retrieved from the AERA online paper repository. Retrieved from https://www.aera.net/Publications/Online-Paper-Repository/AERA-Online-Paper-Repository

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509. https://doi.org/10.1177/0002764213479363.

Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A., & De Laet, T. (2020). Learning analytics dashboards: The past, the present and the future. In *Proceedings of the international conference on Learning Analytics & Knowledge* (pp. 35–40). Frankfurt, Germany: ACM. https://doi.org/10.1145/3375462.3375504.

Wasson, B., & Hansen, C. (2015). Data literacy and use for teaching. In P. Reimann, S. Bull, M. Kickmeier-Rust, R. Vatrapu, & B. Wasson (Eds.), *Measuring and visualizing learning in the information-rich classroom*. New York, NY, USA: Routledge. https://doi.org/10.4324/9781315777979.

Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics, 6*(2), 53–69. https://doi.org/10.18608/jla.2019.62.4.

Wise, A., & Vytasek, J. (2017). Learning analytics implementation design. In C. Lang, G. Siemens, A. F. Wise, & D. Gaševic (Eds.), *The handbook of learning analytics* (1st ed., pp. 151–160). Alberta, Canada: Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17.013.

Xhakaj, F., Aleven, V., & McLaren, B. M. (2016). How teachers use data to help students learn: Contextual inquiry for the design of a dashboard. In K. Verbert, M. Sharples, & T. Klobučar (Eds.), *Adaptive and Adaptable Learning at EC-TEL 2016* (Lecture notes in computer science) (Vol. 9891, pp. 340–354). Lyon, France: Springer. https://doi.org/10.1007/978-3-319-45153-4_26.

Xhakaj, F., Aleven, V., McLaren, B. M. (2017). Effects of a teacher dashboard for an intelligent tutoring system on teacher knowledge, lesson planning, lessons and student learning. In É. Lavoué, H. Drachsler, K Verbert, J. Broisin, M. Pérez-Sanagustín (Eds.) Data Driven Approaches in Digital Education at EC-TEL 2017. Lecture notes in computer science: Vol 10474 (pp. 315–329). Tallinn: Springer. doi:https://doi.org/10.1007/978-3-319-66610-5_23.

Zheng, J., Huang, L., Li, S., Lajoie, S. P., Chen, Y., & Hmelo-Silver, C. E. (2021). Self-regulation and emotion matter: A case study of instructor interactions with a learning analytics dashboard. *Computers & Education, 161*, 104061. https://doi.org/10.1016/j.compedu.2020.104061.

Chapter 18
Expanding Teacher Assessment Literacy with the Use of Data Visualizations in Game-Based Assessment

Yoon Jeon Kim, Grace Lin, and José A. Ruipérez-Valiente

1 Background

Why do teachers value games for classroom instruction? How do they want to use games in classrooms? In a 2014 national survey (Takeuchi & Vaala, 2014), the participating teachers reported that they value using games because students can be more engaged and motivated and that games can support social emotional learning in addition to academic standards. Similarly, a report from the A-GAMES Project (Teachers Use Games as a Formative Assessment Tool) highlights that teachers often use games as formative assessment by looking at students' performance in the game or asking them questions based on their gameplay (Fishman et al., 2014). In both reports, teachers emphasized the importance of selecting games that are aligned with academic standards, while they recognized games can be useful to measure and support skills beyond that.

Because games have unique affordances as a learning and assessment tool, understanding teachers' beliefs, knowledge, and desires about the use of games in the classroom should be a priority. It is particularly of importance to create assessment models and visualizations of assessment data in games because teachers' assessment practices are closely connected with their pedagogical beliefs (Lim &

Y. J. Kim (✉)
University of Wisconsin-Madison, Madison, Wisconsin, USA
e-mail: yj.kim@wisc.edu

G. Lin
MIT Education Arcade, Cambridge, Massachusetts, USA
e-mail: gcl@mit.edu

J. A. Ruipérez-Valiente
University of Murcia, Murcia, Spain
e-mail: jruiperez@um.es

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_18

Chai, 2008). Therefore, even though teachers might not draw a direct connection between their practices and the literature on game-based learning, the assessment literacy in the context of game-based learning should account for teachers' ability to fully leverage affordances of games in terms of data and assessment.

Thus, what are these affordances? First, games implement rich and complex problems that require a lot of trial and errors and creative problem-solving (Gee, 2003; Shute et al., 2009). Therefore, games can be a great environment to elicit evidence not just for content knowledge but also related cognitive and reasoning skills in a multidimensional manner. Second, because of the very nature of games as an interactive environment, they capture the full process of learning and solving problems, instead of capturing evidence at one time point, unlike how assessment is typically done at the end of unit or lesson. Therefore, teachers should understand that game environments provide evidence based on the process, not just based on something that students do at the end of the gameplay (Kim & Ifenthaler, 2019). Third, teachers should understand that specific actions and choices in the game can be linked to the following: noncognitive skills and dispositions, different strategies, different problem-solving styles, how they collaborate with other players in the game, and how they are progressing in the game. For example, given the "pleasantly frustrating" nature of the game (Gee, 2004), games can encourage learners to persist through difficult problems. And persistence has been well-documented as one of the skills that games can be good at supporting and measuring (DiCerbo, 2014; Ventura & Shute, 2013).

Fortunately, many of these affordances can be available in games environments via the rapid processing of clickstream data, thanks to the advancement of learning analytics techniques and applications of artificial intelligence. The application of data science techniques in educational games is becoming widespread in recent years. In a systematic literature review (Alonso-Fernandez et al., 2019), authors reported that learning analytics and EDM (educational data mining) techniques are used to predict performance or assess learning, to study in-game behaviors, to validate game design, and to produce student profiles. These techniques include a wide variety of models including decision trees, regression models, correlation, and clustering. For example, sequence mining—a data mining method to discover sequences of actions—can be applied in the game environment to unveil for teachers how the learner has been interacting with the game (Gomez et al., 2020; Kim & Shute, 2015). Similarly, data-driven algorithms can be created to identify when students are not productively engaged in the game (Owen et al., 2019). These techniques, through classification models, can also be used to predict which students are struggling and, therefore, more likely to quit (Karumbaiah et al. (2018). Moreover, clustering techniques can be used to extract students' profiles based on their activity with the game and provide formative feedback based on the findings (Ruipérez-Valiente et al., 2020). However, as previous authors have raised, game learning analytics is not "informagics" (Perez-Colado et al., 2018), and strong pedagogical foundations are required to avoid confounding learning behaviors with game behaviors that do not add value to the learning process (Nguyen et al., 2020).

Despite these affordances, however, there is a dearth of game-based learning systems that are widely used in classrooms for teachers' assessment of students' learning beyond content standards. Given that teachers are not familiar with some of these metrics and constructs and that they often don't have access to these data, there is a disconnect between the potential affordances and the practical affordances of game-based learning systems or assessments. To help teachers fully leverage rich affordances of games for assessment, one solution is providing these analytics coupled with visualization dashboards, which can make concepts teachers care about visible, raise their awareness, and allow them to make pedagogical decisions based on the visualized data (Martinez-Maldonado et al., 2020). These visualizations in game-based environments can present a strong opportunity to support teaching, learning, and assessment (Ifenthaler & Erlandson, 2016).

One of the proposals from the LA community has been to make the end user more central in the learning analytics design process, with approaches such as human-centered learning analytics (Buckingham Shum et al., 2019) or participatory design (Prieto-Alvarez et al., 2018). Moreover, while visualization dashboards represent an unprecedented opportunity to improve the learning process for teachers, they also require that the teachers that consume them are assessment and data literate, which was not previously required. This shortage of guidance for developing data literacy among end users has been depicted as one of the main challenges of learning analytics (Tsai & Gasevic, 2017). Additionally, to create learning analytics and visualizations for and with teachers, the field needs to reimagine what assessment literacy is aiming to support. Unlike teachers' assessment literacy with conventional forms of assessment, game-based environments also require teachers' ability to critically evaluate how the system is processing the data.

This chapter reports a work that is situated at the intersection of these two problems—the limited use of games for learning in classrooms and creating learning analytics and supporting tools to enhance practices on the ground. While multiple studies used learning analytics techniques in games, for example, to examine how students are collaborating with each other (Ruipérez-Valiente & Kim, 2020), to function as game-based assessment purposes (Kim & Ifenthaler, 2019), or to model learning behaviors within the game (Kang et al., 2017), teachers' implementation of games, coupled with learning analytics in classrooms, is still somewhat limited. A few of the barriers are the lack of actionable assessment data, the fact that teachers often do not have a clear sense of how students are interacting with the game, and if the gameplay is leading to productive learning (Martınez et al., 2020).

2 Assessment Literacy in Game-Based Learning and Assessment

The recent demand for classroom teachers' data literacy is driven by multiple factors, including the policy makers and states' push for data-driven decisions in schools, and an increasing number of government policies that require data-driven decision-making due to the increasing availability of big data in education (Mandinach & Gummer, 2013). Data literacy can be broadly defined as the ability to understand and use data effectively to inform decisions (Mandinach & Gummer, 2013). It is composed of a specific skill set and knowledge base that enables educators to transform data into information and ultimately into actionable knowledge (Mandinach et al., 2008) including (a) knowing how to identify, collect, organize, analyze, summarize, and prioritize data; (b) knowing how to develop hypotheses, identify problems, and interpret the data; and (c) knowing how to determine, plan, implement, and monitor courses of action.

Teacher assessment literacy that can be viewed as a subset of data literacy (Mandinach & Gummer, 2013), where the primary source of data is assessment, incorporates teachers' assessment knowledge base including different goals and types of assessment, pedagogical beliefs, reasoning, and communication skills (Xu & Brown, 2016). In practice, teacher's assessment literacy is often continuous compromises between what they know and believe and the influence and needs of other stakeholders (e.g., school's priorities, parents). Assessment literacy also includes teachers' ability to interpret data using statistical models (DeLuca et al., 2016b) and evaluate the quality of assessment based on psychometric qualities (e.g., reliability).

We also should note that data literacy is often confused with or interchangeably used with assessment literacy. And the distinction between data and assessment literacy in the context of technology-enabled data-rich environments is blurry, that is, while many of these environments provide rich raw and descriptive data (e.g., when did the student last log in? How long did the student play the game during the last log-in?), these systems also use algorithms and artificial intelligence to process data into meaningful categorizations or predictions (e.g., which students are at risk of falling behind?). To date, this sensemaking has been typically viewed as part of teachers' assessment literacy.

However, the meaningful use of data from technology-enhanced data-rich environments, such as digital games, in classrooms requires skills and mindsets beyond the conventional notion of assessment literacy skills. For example, one common element of the existing assessment literacy is the teachers' use and understanding of measurement theories and properties (i.e., psychometrics) (DeLuca et al., 2016a). Yet, it is very unlikely that teachers will manually process data obtained from game environments and be in a position to evaluate psychometrics qualities of the measurement models (i.e., algorithms). Also, use of AIs in such technological environments requires the teachers to understand and examine how data are being processed. Therefore, the field needs a better understanding of teacher assessment literacy that interacts with technology and uses big data to create data visualizations and algorithms that can foster evidence-informed teaching practices.

Moreover, because of the nascence of learning analytics as a field and the lack of emphasis on innovative assessment in pre-service teacher education, it is unrealistic to assume that classroom teachers would feel comfortable with the use of learning analytics coupled with rich technological environments. Even with the conventional assessment tools and data, many studies have reported that teachers do not feel prepared to use data to inform their practice (Earl & Fullan, 2003; Ikemoto & Marsh, 2007), struggle with the use of data (Huguet et al., 2014), and lack a sound understanding of measurement models (Oláh et al., 2010). Similarly, simply providing teachers with data visualizations might not be sufficient to address these challenges. For example, Means et al., (2011) worked with 52 individual teachers and 70 small groups of school staff to investigate teachers' challenges with data-informed decision-making. While most teachers were capable of finding information on a graph, they experienced difficulties comprehending complex data visualizations and showed a limited understanding of key statistical concepts of test validity, score reliability, and measurement error, leading to invalid inferences (Means et al., 2011). In addition, teachers might have challenges in using student assessment data to improve their instruction (Goertz et al., 2009).

In summary, to fully leverage the affordances of digital games and rich data affordances of games in classrooms, the field needs to envision and test new design processes that can help develop learning analytics tools that can be used by the teachers while scaffolding assessment and data literacy skills. In this chapter, we discuss the need for re-examining what teacher assessment literacy means in the era of big data and educational technology, especially in the context of game-based learning and assessment. In the following sections, we introduce a framework for research and development of learning analytics and visualizations to consider teacher assessment literacy. We situate our discussion within the Shadowspect project to illustrate how we considered different aspects of assessment literacy, in addition to teachers' pedagogical goals and purposes, to engage teachers in a collaborative design process.

3 Context: Shadowspect Dashboard Project

Shadowspect is an online geometry puzzle game where players construct a figure that matches various silhouettes with different geometric shapes (i.e., cube, sphere, pyramid, cylinder, cone, ramp). The silhouettes represent the cross-sections of the figure from different angles. In the game, players can scale and rotate the shapes, change the camera angle to view the figure they are constructing from different perspectives, and take snapshots of their figure that would produce a particular silhouette of their figure from a selected camera angle. Once players submit their solution, they are be able to see which (if any) of the silhouettes were matched. Figure 18.1 displays a sample screenshot of the game interface. There are 9 tutorial basic-level puzzles, 9 intermediate puzzles, and 12 advanced-level puzzles, and players can jump to any puzzle they would like to try.

Figure 18.1. "Bird Fez" is a puzzle from the intermediate level. Thus, more hints and constraints are in place for the players than in the advanced levels, e.g., "You can add 4 more objects." The objective is to create a figure that would match all three of the silhouettes displayed on the top of the screen. The buttons for shape manipulations are laid out on the bottom of the screen. The top right cube lets the

Fig. 18.1 A puzzle from Shadowspect

player select the camera angle. The current view is from a top/front angle. Once a shape has been inserted (picture on the left), players have the opportunity to take a snapshot with the camera button. When a player hits the "submit" button, they receive feedback on which of the silhouettes (if any) match (picture on the right).

During the development phase, the team used input from a few math teachers to determine a set of constructs to embed in the game using the evidence-centered design framework (Kim et al., 2019). While developing and refining assessment models of the game, the team began thinking about ways to make data assessment output usable for teachers, and this led to the expansion of the project with the goal of creating a generalizable framework to develop data visualization tools for game-based learning. The data visualization project using Shadowspect involved eight middle school math teachers as co-designers who participated in a year-long co-design program where (1) the teachers informed different types of analytics and models that are useful in the context of using Shadowspect in classrooms, (2) co-created and refined different functions and visualizations to match with their decision-making processes, and (3) engaged in various participatory design activities to inform iterative prototyping. These teachers, whom we call "design fellows," were selected because they had high interest and ample experience with game-based learning and assessments. One fellow, for example, was involved in the development of ASSISTments (Heffernan & Heffernan, 2014)—a math platform and tool for assigning and assessing homework.

4 Design Framework for Data Visualizations for Teachers

This chapter reports a framework that researchers and designers can consider when design learning analytics models or selecting modeling techniques accompanied with visualization tools to support pedagogical decisions in the context of game-based learning. We are constraining our scope specifically to game-based learning, rather than technology-enhanced learning environments broadly, to acknowledge unique affordances of game environments for the kinds of learning, behaviors, and patterns that can be limited either in traditional assessment or less open-ended technology-enhanced environments (e.g., tutoring systems, learning management systems).

The overarching questions that drive our research interconnect games for learning, learning analytics, data visualization, and teachers' assessment literacy: *how can different types of learning analytics and algorithms be developed in collaboration with classroom teachers to inform instructional and assessment practices? How should these data be presented, so teachers can make sense of often hard-to-comprehend algorithms? How can the development team create visualizations to be aligned with teachers' desires while unveiling new insights about learners that might not at first be apparent to teachers?*

To guide this inquiry, we propose the following framework (Fig. 18.1) to make decisions about the extent to which and the points at which we engage teachers through the development of data visualizations and data analytics models (or computational assessment models). To illustrate how this design framework can be used to guide a research team's efforts to (1) plan for research and development activities, (2) iterate learning analytics and visualizations over time in relation to each dimension of the framework, and (3) develop a series of co-design activities, we will now discuss this framework with examples from the Shadowspect project.

4.1 Assessment Literacy

To create a meaningful analytics model and data visualizations, the team of researchers and co-design teachers first needed to define what they meant by assessment literacy for game-based learning, which then helped them to define whom the target user was and clarify for or with whom the team developed these tools. In our case, we defined our assessment literacy in game-based learning as follows:

A teacher with assessment literacy in the context of educational games (1) values nonacademic, nontraditional, and process-oriented skills and attributes of learners that game environments can afford supporting; (2) understands what these constructs mean and can identify possible evidence for those constructs based on students' gameplay; (3) critically and curiously investigates how the data was processed, based on what rules, and understands the role of computing and artificial intelligence and its limitations even if he/she does not fully understand how the algorithms are being built; (4) uses data and visualization tools to identify strengths, weaknesses, growth, and productive and unproductive struggles of learners beyond proficiency; (5) strives to gain new and delightfully surprising insights about learners that they couldn't see with traditional forms of assessment, and finally (6) explores and digs the data at various levels (i.e., individual, subgroup, classroom, grade) and with diverse goals (e.g., what's the puzzle that everybody is struggling with, so I can intervene?) (Fig. 18.2).

After establishing the definition, then we decided who our target users were. We identified our target user group as teachers who are already on board with the values of video games or open-ended learning environments, such as simulations for

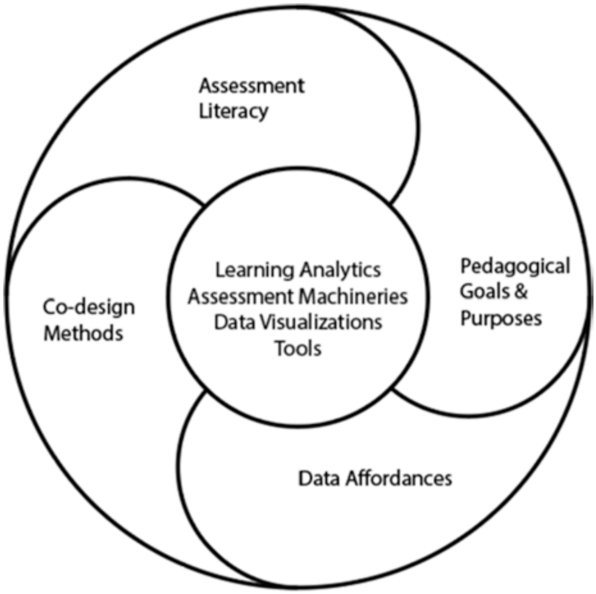


Fig. 18.2 Four dimensions of designing data visualizations and analytics model in game-based assessment

learning and assessment, and have interests in alternative/nontraditional forms of assessment. These teachers might be using games in their classrooms already and be looking for opportunities to bring in assessments that get at students' interests and creativity. This is a different target user group, for example, from teachers who don't particularly value game and are not interested in using more data for their own teaching practices. Table 18.1 illustrates professional experiences and backgrounds of the eight participated teachers:

This operating definition of assessment literacy also guided the research team to determine which aspects of assessment literacy that the analytics models and visualization tools intended to foster. That is, without a clear vision for teachers' assessment practices that one can better support by creating visualizations, it is difficult to articulate specific functions and purposes of data analytics and visualizations. In our case, establishing the assessment literacy helped us to come up with an initial set of design principles, which were as follows:

1. The visualization should be easy to navigate and inviting for teachers to "dig deeper" and play with.
2. The visualization should foster teacher curiosity to explore the data.
3. The data that teachers see on visualizations should match with their desires and intentions for using games in classrooms.
4. The visualization should allow the teachers to see multiple aspects of a learner, some of which might be surprising and unexpected.
5. The visualization should allow the teachers to see learners' growth over time.
6. The visualization should allow the teachers to identify and celebrate "productive struggle."

Table 18.1 Co-design teacher profiles

Stacy	
	• Usually teaches 7th grade math. Of 80–100 students, she has 15 ELL and 12 IEP students • Has taken on the math department coaching role, supporting and supervising other math teachers • School is predominantly white and 60% eligible for free and reduced price lunch • Has a PhD and interested as a researcher in new ways to improve teaching and learning that are research-based • Extensively implemented ASSISTments in her classroom
Chris	
	• Teaches high school seniors: probability and statistics including the topics basic probability, binomial games, sampling methods and bias, and data displays • Also teaches financial math: student loans, taxes, budgeting, and investing • Lifelong interest in game design • Favorite part of teaching: creativity that goes into lesson planning • Was involved in development of the Shadowspect game • Fascinated by potential of data interpretation and using game in classroom
John	
	• Teaches freshmen and sophomores: Algebra 1 Honors and CP • Tries to incorporate technology in classes as much as possible (e.g., Padlets and Desmos) • Finds some assessment tools too rigid • Each student has access to own computer • Sees technology as a way to engage students and push their understanding • Interested in designing learning tools that focus on learning through discovery and allow for formative/summative data to be shared with teachers • Has been working with ST Math
Tara	
	• Teaches Geometry and Algebra 2 to freshmen, sophomores, and juniors • Students are mostly minority from low-income communities; many are immigrants • Uses Desmos and Google Classroom • Sees math as a tool for social change and upper mobility for students • School is project-based, very open to innovation and collaboration • Would love to explore new types of assessment and introduce new ideas that involve more games
Noah	
	• Teaches Geometry and Algebra 2 to freshmen and sophomores at an independent school • Loosely follows Common Core curriculum • Students
o	○ Majority struggled in math in the past
o	○ Many had a variety of neurological and socioemotional challenges
o	○ Many international boarding students
	• Uses both language-based differentiation and math differentiation • Aspiration: create environment that:
o	○ Promotes math positivity
o	○ Gives students the chance to use their personal strengths to access and apply the concepts
	• Had an experience working with an EdTech company BlocksCAD to help school districts integrate coding and 3D design into traditional standards-based geometry curriculum

(continued)

Table 18.1 (continued)

Bonnie
• Teaches freshmen, sophomores, occasionally 8th and 11th graders
o ○ Integrated math, science, technology class for 9th and 10th graders
o ○ 2 hours/day, 2 teachers: 1 math, 2 science
o ○ Integrated class examples:
▪ Probability and genetics
▪ Trig and projectile motion
• School is portfolio based
• Very heavy use of laptops and tech programs in classes
o ○ EV3s and Carnegie Mellon's Virtual World online tool/environment
o ○ Attended summer program for educators at CMU for it
• Involved in developing engineering, programming, and robotics classes
• Sees technology as a way to level playing field
Melinda
• Teaches 9th~12th grades: Algebra 1, Algebra 2, and quantitative reasoning
• Students are "middle tracked" level
• Uses Google Classroom and Desmos
• Sees technology as having potential to:
o ○ Engage students
o ○ Let students interact with each other
o ○ Act as equalizer (does not favor the most outgoing students)
o ○ Give quick feedback
• Excited to dig more into incorporating technology in her classroom
Clarissa
• Teaches sophomores
o ○ Geometry CP
o ○ Inclusion Geometry CP
• School predominantly white, middle-class, native English speakers
• School has 1:1 iPads for students and MacBook Air for teachers
• Participated in Shadowspect Pilot

7. The data visualization should allow the teacher to question how the model was created.

4.2 Pedagogical Goals and Purposes

To determine a process of developing which analytics models and algorithms and accompanied visualizations, the research team also needed to consider what pedagogical goals and purposes teachers have in mind, i.e., how do they want to use the data and for what purposes? This helped to determine the scope and overall direction of the visualization tools. Also, depending on the goal, the qualities of analytics models and the scope of technical development (therefore, how to engage teachers in the process) vary.

The literature in game-based learning suggests three different pedagogical goals and purposes that are commonly observed in classrooms (Fishman et al., 2014). First, games can function as formative assessment. When the goal is formative assessment, teachers might need learning analytics models and visualizations that enable them to identify students who need support, i.e., where students are struggling, and what is the cause or source of struggle. Therefore, for formative assessment goals, providing descriptive and fine-grained analytics related to students' performance in the game might be more appropriate than providing highly processed decisions or predictions based on algorithms. Second, the teacher might choose to use the game as a motivational tool, especially for the students who typically do not like math. For this goal, instead of assessing "how well" the student is performing in the game, learning analytics models and visualizations should focus on various types of achievements beyond numbers of completed puzzles and quests. Third, the teacher might want to have students play the game as a form of summative assessment. For this use, the teacher will need high-level aggregate data that allow them to quickly gauge the overall performance of their students (e.g., Mike successfully solved 19 puzzles out of 20).

In our case, the teachers expressed their desires to use the game as a curriculum enhancement tool as well as a formative assessment tool. In addition, given the teachers' intention to implement the game as part of regular math curriculum, they expressed the need to know how student performance in the game is related to the math standards and what potential misconceptions students might hold. In our case, the team aimed to develop visualizations and analytics models that allow the teacher to monitor how productively or unproductively students are making progress in the game and how their interactions with the game can inform a teacher's understanding of how much students know about specific standards or how they might hold geometric misconceptions. Furthermore, the visualizations and analytics models need to provide actionable insights or information for the teachers to use in the classroom. For example, teachers would like to know the most common misconceptions students have, view representative video playbacks of when these misconceptions were demonstrated (see Fig. 18.3), and bring that knowledge back to the classroom

Fig. 18.3 A screenshot of the video playback on the Shadowspect dashboard. In this example, student 424 has made a total of 32 misconceptions across 2 puzzles. The video is displayed when the user clicks on "Show Full Replay" on the right panel for any of the puzzle attempts

to facilitate whole-class discussion, or "puzzle talks," as one of our co-design teachers would like to call them.

Additionally, given that every teacher's context is unique, it was critical for the research team to invite teachers in the collaborative process early on to identify their values and priorities, particularly related to what to measure. For example, early on in our collaboration in the set of metric introduction exercises to gauge teacher priorities, we included metrics as abstract as "persistence" to ones that are concrete and specific, such as "sequences of player actions within a puzzle." In midst of the widely varying metrics, the teachers identified persistence as one of their most highly valued metrics that they would like to explore and investigate in the game context.

In our case, it was clear that the co-design teachers (as well as our target audience) can look beyond the most immediate, traditional "math scores" and value nontraditional, process-oriented skills that become assessable and accessible through the game-based learning context. In fact, the co-design teachers believed persistence to be a great metric to consider because it is an "invisible" (Chris) skill that students can use "throughout their life" (Bonnie) and "beyond the math classroom" (Stacy). It is an important lifelong skill transferable beyond the game and something that the co-designer teacher believes educators must foster in students. As one teacher puts it, "persistence in the face of challenge is what leads us to success" (Clarissa). At the same time, though, the positive desire for insights into students' persistence was juxtaposed with a need for action. As mentioned and illustrated earlier, the teachers want recommendations and next steps to bring back to the classroom. Some teachers (e.g., Chris) are apprehensive about how they can help students with "low persistence" as they acknowledge that there could be other life circumstances that prevent the students from playing the game consistently and, therefore, persistently. Therefore, they would like the dashboard to provide meta information such as when the students log in—if they do so at all—to have a more comprehensive picture of students' engagement and situation beyond a simple metric.

4.3 Data Affordances

Depending on game mechanics, genres, single play vs. multiplayer collaborative, cooperative vs. competitive, how the player can progress in the game environment (i.e., linear or nonlinear), and how teachers might implement these games, the kinds of data one can acquire from gameplay can vary (Groff, 2018). Therefore, data visualizations in the context of game-based learning and assessment should consider possible skills and outcomes that the game is best suited for, as well as how the game elements affect the classroom implementation (and, thus, data collection). For example, a single-player puzzle game like Angry Birds (Rovio Entertainment) can be great at measuring physics understanding, persistence, and problem-solving. However, it would be inappropriate to assess one's collaboration skills using the in-game telemetry data. Similarly, how the game is intended to be implemented in the classroom should be considered. For example, a game like Food Fight (BrainPOP) is a turn-based game that has only single-player log-in, and it is designed for a pair to share the monitor and use one mouse and take turns. For a game like Food Fight, actionable analytics might focus less on the individual players, but the overall qualities of the food web that was created at the end, which provides insights about the pair's collective understanding of a Savannah ecosystem.

Communicating affordances of the game in terms of what is feasible to measure early on is key to create co-design activities. The co-design process should encourage the teachers to challenge and question what these constructs mean and what "evidence" will be considered to create learning analytics models and visualizations. Using our case as an example, the research team came up with a potential list of what is possible to model and measure, but a few co-design teachers cohort were aware that games can be a good context to further illustrate student effort, beyond whether they complete the work or not.

The process to communicate the affordances is often cyclical. After the potential list of what is possible to model and measure, we started out with early renditions of visualizations that we dubbed "tools to think with." The goal of these tools was to facilitate the exploration of the data, which allowed the co-design teachers to better grasp the kind of evidence available and what constructs can be created. Within those confines, the teachers were then able to illustrate the metrics they would most like to see presented on a dashboard.

For example, through the exploration of the early visualizations, it became clear that the co-design teachers had strong opinions on and understanding about the construct of persistence and were enthusiastic and capable of finding evidence for various "flavors" of persistence from data. These flavors were informed by their increased understanding of the data affordances, as they became aware of what the game data could tell them about students' activity levels within a game, their types of activities in the game (e.g., submitting a solution, taking a snapshot of their constructed figures to check the silhouettes), and the active vs. passive time students spent in the game. As the co-design teachers investigated the visualizations, they also became adept at navigating through multiple levels and perspectives of data. Figure 18.4 is an example illustrating a flavor of persistence we called *productive persistence*. It was captured by a co-design teacher, Melinda, as she explored a radar chart (one of our "tools to think with") at an individual student level, where the student's performance is compared to the class average. Typical with usage in the classroom, comparison to the class average or across multiple students may be helpful to identify students who may be struggling—or persisting—more. Along this line, Melinda and the other fellows utilized our radar chart to identify students who were outliers. For example, Melinda described Student 262 as follows: "...it looks like this student didn't check their solution very often, wanting instead to make sure that they have evaluated the correctness of this solution in every possible way before submitting it. This is evidenced by this student rotating the view many, many times, but not really ever checking the solution. It looks like this student is spending a lot of time attending to the precision of the object."

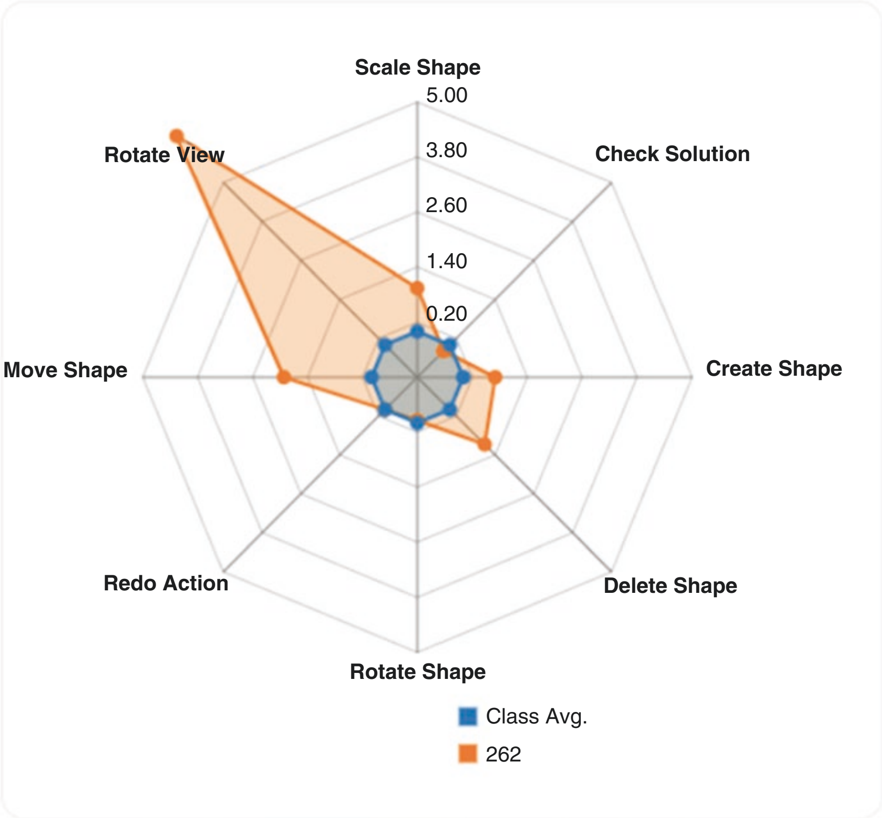


Fig. 18.4 An example of productive persistence by co-design teacher Melinda. Student 262's actions in the puzzle Bird Fez as compared with the class average. The radar chart displayed here has been normalized

On a different strain, the co-design teachers were also interested in students' individual progressions. In one example, a teacher, Bonnie, utilized the radar chart's "puzzle view" function to investigate how a student progressed across puzzles of varying difficulty (see Fig. 18.5). In this case, the fellow noted that the student "seemed to complete the puzzle Pi Henge with ease. Bird Fez was harder for him, but he stuck with it with lots more manipulations and snapshots before completing it." This progression of putting more effort into solving a more complex puzzle was indicative of the students' *persistence relative to themselves*. Too often in typical classroom settings, students were being compared to their peers or class average that if the fellows did not investigate the data on this other level (i.e., relative to students themselves but across puzzles of varying difficulty), the insight would have been missed.

The co-design teachers utilized different digital tools to think with, uncovered the affordances of the data, and identified patterns that they believed resembled the

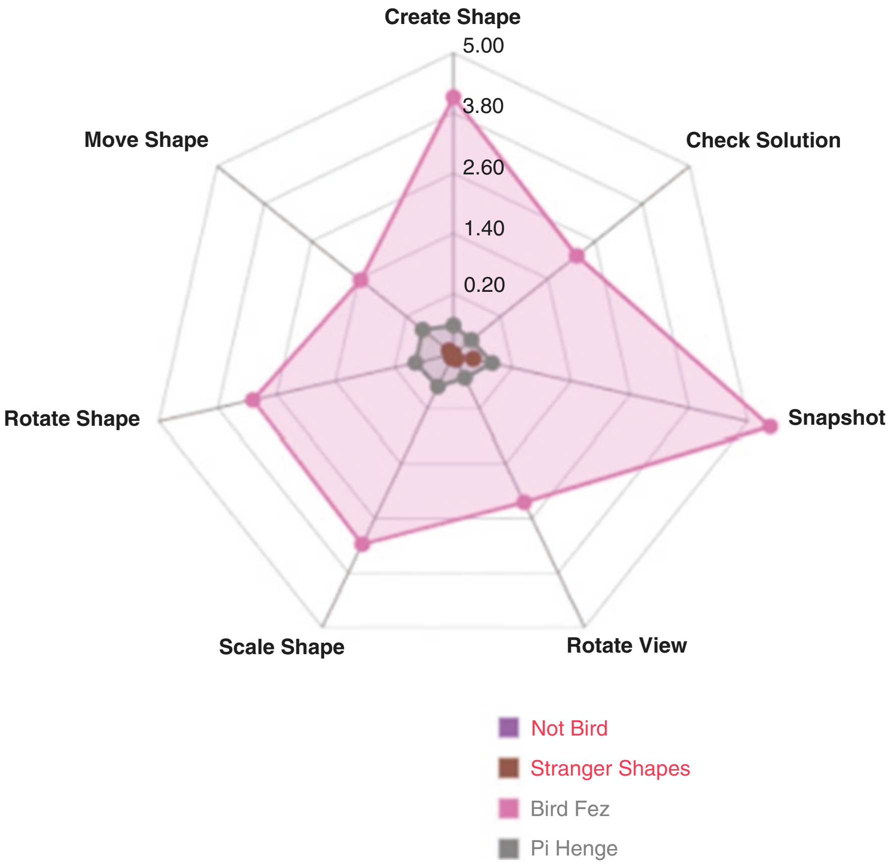


Fig. 18.5 In examining a single student's activities across multiple puzzles, design fellow Bonnie identified a flavor of persistence that hinges on putting in more effort on more difficult tasks

different "flavors of persistence" that they care about. The process resulted in five distinct patterns: (a) actions after failed submission, (b) checking solution or not, (c) precision and detail oriented (checking views), (d) more actions than others, and (e) miscellaneous (other flavors that were less common but still were identified, including unproductive persistence and lack of persistence).

4.4 Co-design Methods

While analytics models and data visualization tools can be developed without teachers actively participating in the process as collaborative partners, many argue that using participatory design methods with practitioners can increase the overall usefulness and usability of such tools in classrooms (Buckingham Shum et al., 2019).

Co-designing analytics models and visualizations with teachers, however, requires different levels of scaffolding mechanics, depending on the target audience's assessment literacy. This is because teachers often do not have technical skills that are required for model building as well as technology development. Considering specific aspects of assessment literacy and how competent the target audience is also can support the team's decision-making regarding how to structure co-design sessions.

For example, early co-design activities such as metric definition reflections and storytelling showed to us that our co-design teachers had a good understanding of how to define persistence in a general sense, yet they also had both technically feasible and non-feasible ideas about how to identify evidence for persistence based on gameplay and the existing design of the game mechanics. Some of the ideas were non-feasible because (1) the adequate data generated and/or collected by the game for those ideas are lacking or, (2) from a technical viewpoint, the process would be too complex or unclear to accomplish the proposed goals. Below is an excerpt from a storytelling activity where the research team asked the co-design teachers to come up with a story of how teachers and students might use Shadowspect in the classroom:

> Norman is in Miss Greta's class. The class is playing Shadowspect. Miss Greta is trying to monitor the class and the student's progress. Norman completed 3 of the 4 puzzles that map onto the congruence standards. He's doing well. We can tell this because Norman achieved 2 out of 3 stars for the beginning puzzles on that standard. We see that they're completing that standard, but not in a very efficient manner, suggesting that there is some guess and check and exploration still happening. The teacher then encouraged Norman to get back to play the puzzle more in order to get the 3 stars to "full" mastery. This also fits in nicely about persistence because he spent 100 moves to get to 2 stars, but he would return to it later to get to 3 stars by solving in fewer than 15 moves.

In the excerpt, co-design teachers Bonnie, John, and Stacy expressed the idea of students being able to receive full mastery of three stars and would treat students' return to a puzzle—despite fewer moves later on—as a sign of persistence. While it is feasible for the game to track if and when a student returns to a puzzle, Shadowspect does not have a star rating system built in; it is therefore unfeasible to disentangle the reason for which a student may return to a puzzle (e.g., to solve a puzzle more efficiently, to show a friend).

This potential disconnect between the focus of the teachers' design attention and the research team's goals led to a series of follow-up co-design activities that engaged the teachers with a few rounds of collaborative generations of indicators specific to Shadowspect. First, to allow for a fuller understanding of the indicators we can draw from the data, we had the teachers explore with additional "Tools to Think With." Like the radar charts showcased in the previous section, these digital data exploration tools allow teachers to try out different configurations to unveil what is working and what is not working. One of our tools was a "caterpillar chart" (Fig. 18.6) that displays the different types of student activities on a given puzzle against a time scale.

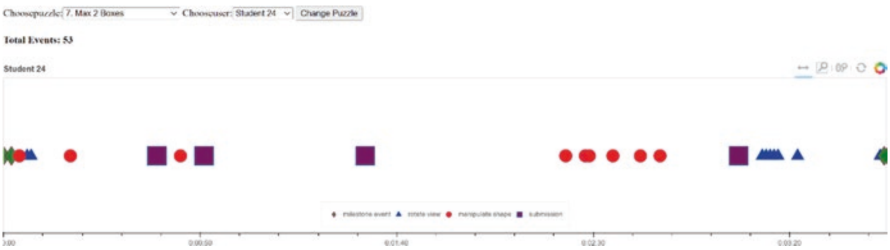


Fig. 18.6 An example of a caterpillar chart. Co-design teacher Tara selected this student as she explored the tool because "[for] this particular puzzle, you can see the student persisted and try to solve the problem multiple times (4 submissions), you can also see the big gap between minute 01:40 and 02:39, probably to consider other modifications, and the many attempts to manipulate the figure showed on number of red dots"

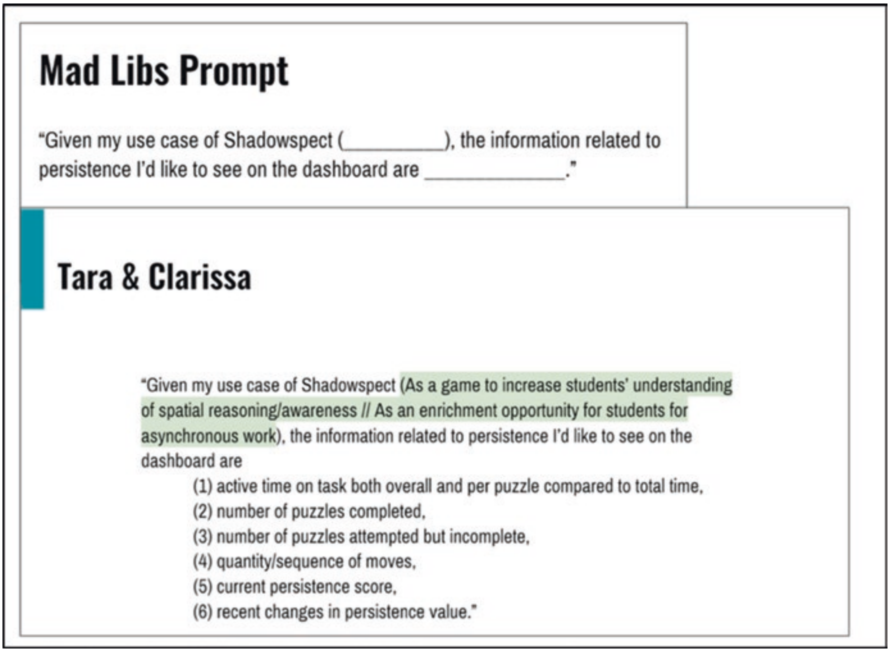


Fig. 18.7 (**a**) (the picture on the top) is the prompt that was provided at the beginning of a co-design session for persistence, and (**b**) (the picture on the bottom) is two teachers' responses

Additionally, we introduced a "Mad Libs" prompt where the teachers re-clarified what their intended use of Shadowspect is (i.e., how they envision using it in their classrooms) and the relevant persistence information given their intended use (Fig. 18.7a). Based on their responses, the teachers worked as a pair to specify what kinds of indicators they would consider as evidence for persistence and how they would use them. This process involved a blend of both generation and "remix" of indicators the research team had extracted from literature and the teachers' earlier

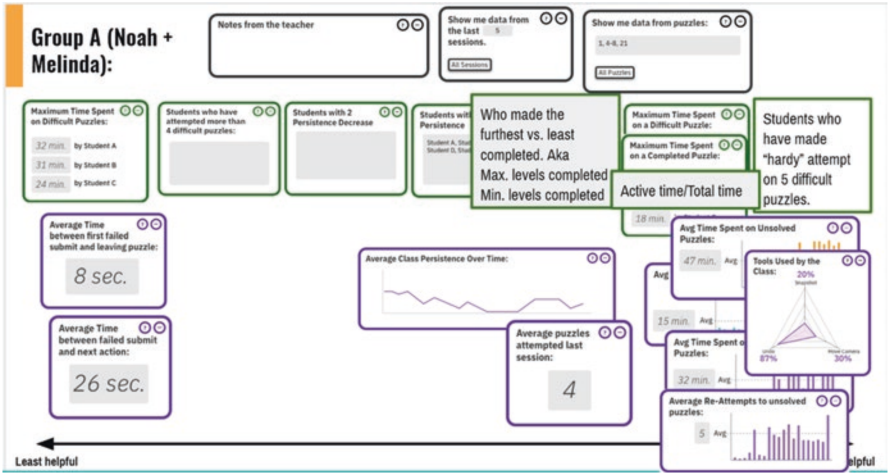


Fig. 18.8 The panel sorting activity by Noah and Melinda. The teachers added in a couple more panels for indicators that they believed would be useful in capturing persistence

inputs. (To clarify, in "generation," the teachers come up with their own ideas from scratch. In "remix," the teachers use existing ideas, modify them, and "remix" them to form different combinations of new ideas.)

Figure 18.8 displays a virtual panel sorting task where the teachers rated the usefulness of various potential indicators as well as some of the teachers' own remix of indicators. Allowing teachers to see existing indicators and remixing them to generate their own ideas appeared to be a productive co-design method. As one teacher stated in a final reflection activity, "I really liked all the opportunities to 'remix' because it allowed us to be creative, while being grounded! It also meant that we could quickly iterate because the art/design was there for us to use!"

5 Conclusion

In this chapter, we discussed a framework that the research team developed to create learning analytics and visualizations tools that enable teachers to use gameplay data to support student learning in classrooms. The goal of this framework is to guide game designers and analytics researchers to consider four interconnected dimensions—assessment literacy, pedagogical goals and purposes, specific data affordances of the game, and co-design methods—to develop learning analytics models and visualization tools. Based on what we learned from using this framework to plan both research and development activities, we further illustrated how each dimension is connected to each other using examples from the Shadowspect dashboard project.

Our goal with this chapter is to encourage researchers to apply this framework and document their process, so the field can continue to grow this body of knowledge. We also hope that by providing various use cases from different games, the field can build a greater body of knowledge about how to make design decisions with teachers as co-designers, which can be easily buried in the process or not well-documented. Particularly, we hope that this is the beginning of work where we can expand what teacher assessment literacy means in the era of big data as well as educational technology in the context of open-ended learning environments like games.

We foresee multiple directions of this work in the future. First, the current framework does not explicitly describe teacher learning. However, we believe how these co-design learning analytics models and visualization tools can help teachers to reflect and modify their existing assessment practices should be considered to evaluate the effectiveness of these tools. Xu and Brown (2016 p.156) describe that the process of "becoming assessment literate is fundamentally a transformative, consciousness-evoking one. However, teachers may be content to have conceptions and practices of assessment that are entirely consistent with external contexts without casting doubt on their own practices." To what extent these visualizations allow teachers to reflect and challenge the current practices can be an additional element of this design framework. In addition, the process of engaging teachers in the process can be also a professional development opportunity for them to build their assessment literacy skills. Future work can investigate different applications of this framework across different contexts and different types of co-designers and target users. Second, in the Shadowspect project, we aimed to build visualization tools that are targeting the teachers who are already on board with the pedagogical affordances and values of the game. Future work should investigate how different definitions of assessment literacy can lead to different co-design activities as well as visualization tools and data models. Finally, future work should investigate data visualizations and assessment models that can broaden teachers' beliefs about games as a tool for assessment and learning.

References

Alonso-Fernandez, C., Calvo-Morata, A., Freire, M., Martinez-Ortiz, I., & Fernández-Manjón, B. (2019). Applications of data science to game learning analytics data: A systematic literature review. *Computers & Education, 141*, 103612.

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centred learning analytics. Journal of Learning Analytics, 6(2), 1–9.

DeLuca, C., LaPointe-McEwan, D., & Luhanga, U. (2016a). Approaches to classroom assessment inventory: A new instrument to support teacher assessment literacy. *Educational Assessment, 21*(4), 248–266.

DeLuca, C., LaPointe-McEwan, D., & Luhanga, U. (2016b). Teacher assessment literacy: A review of international standards and measures. *Educational Assessment, Evaluation and Accountability, 28*(3), 251–272. https://doi.org/10.1007/s11092-015-9233-6

DiCerbo, K. E. (2014). Game-based assessment of persistence. *Journal of Educational Technology & Society, 17*(1), 17–28.

Earl, L., & Fullan, M. (2003). Using data in leadership for learning. *Cambridge Journal of Education, 33*(3), 383–394.

Fishman, B., Riconscente, M., Snider, R., Tsai, T., & Plass, J. (2014). *Empowering educators: Supporting student progress in the classroom with digital games*. University of Michigan. Retrieved from http://gamesandlearning.umich.edu/agames

Gee, J. P. (2003). What video games have to teach us about learning and literacy. Computers in Entertainment (CIE), 1(1), 20–20.

Gee, J. P. (2004). *Learning by design: Games as learning machines* (pp. 15–23). Interactive Educational Multimedia.

Goertz, M. E., Olah, L. N., & Riggan, M. (2009). *Can interim assessments be used for instructional change*.

Gomez, M. J., Ruipérez-Valiente, J. A., Martinez, P. A., & Kim, Y. J. (2020). Exploring the affordances of sequence mining in educational games. In *Eighth international conference on technological ecosystems for enhancing multiculturality*, (pp. 648–654).

Groff, J. S. (2018). The potentials of game-based environments for integrated, immersive learning data. *European Journal of Education, 53*(2), 188–201. https://doi.org/10.1111/ejed.12270

Heffernan, N. T., & Heffernan, C. L. (2014). The ASSISTments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. *International Journal of Artificial Intelligence in Education, 24*(4), 470–497.

Huguet, A., Marsh, J. A., & Farrell, C. C. (2014). Building teachers' data-use capacity: Insights from strong and developing coaches. *Education Policy Analysis Archives/Archivos Analíticos de Políticas Educativas, 22*, 1–28.

Ifenthaler, D., & Erlandson, B. E. (2016). Learning with data: Visualization to support teaching, learning, and assessment. *Technology, Knowledge and Learning, 21*(1), 1–3. https://doi.org/10.1007/s10758-015-9273-5

Ikemoto, G. S., & Marsh, J. A. (2007). Chapter 5 cutting through the "data-driven" mantra: Different conceptions of data-driven decision making. *Yearbook of the National Society for the Study of Education, 106*(1), 105–131.

Kang, J., Liu, M., & Qu, W. (2017). Using gameplay data to examine learning behavior patterns in a serious game. *Computers in Human Behavior, 72*, 757–770. https://doi.org/10.1016/j.chb.2016.09.062

Karumbaiah, S., Baker, R. S., & Shute, V. (2018). *Predicting quitting in students playing a learning game*. International Educational Data Mining Society.

Kim, Y. J., & Ifenthaler, D. (2019). Game-based assessment: The past ten years and moving forward. In D. Ifenthaler & Y. J. Kim (Eds.), *Game-based assessment revisited* (pp. 3–11). Springer International Publishing. https://doi.org/10.1007/978-3-030-15569-8_1

Kim, Y. J., & Shute, V. J. (2015). The interplay of game elements with psychometric qualities, learning, and enjoyment in game-based assessment. *Computers & Education, 87*, 340–356.

Kim, Y. J., Ruipérez-Valiente, J. A., Philip, T., Louisa, R., & Klopfer, E. (2019). Towards a process to integrate learning analytics and evidence-centered design for game-based assessment. In *Companion proceedings of the 9th international learning analytics and knowledge conference*, (pp. 204–205).

Lim, C. P., & Chai, C. S. (2008). Teachers' pedagogical beliefs and their planning and conduct of computer-mediated classroom lessons. *British Journal of Educational Technology, 39*(5), 807–828.

Mandinach, E. B., & Gummer, E. S. (2013). A systemic view of implementing data literacy in educator preparation. *Educational Researcher, 42*(1), 30–37.

Mandinach, E. B., Honey, M., Light, D., & Brunner, C. (2008). *A conceptual framework for data-driven decision making. Data-driven school improvement: Linking data and learning*, (pp. 13–31).

Martınez, P. A., Gómez, M. J., Ruipérez-Valiente, J. A., Pérez, G. M., & Kim, Y. J. (2020). *Visualizing educational game data: a case study of visualizations to support teachers*.
Martinez-Maldonado, R., Elliott, D., Axisa, C., Power, T., Echeverria, V., & Buckingham Shum, S. (2020). Designing translucent learning analytics with teachers: An elicitation process. *Interactive Learning Environments*, 1–15.
Means, B., Chen, E., DeBarger, A., & Padilla, C. (2011). *Teachers' ability to use data to inform instruction: challenges and supports*. In Office of planning, evaluation and policy development, US Department of Education.
Nguyen, H. A., Hou, X., Stamper, J., & McLaren, B. M. (2020). *Moving beyond test scores: Analyzing the effectiveness of a digital learning game through learning analytics*. International Educational Data Mining Society.
Oláh, L. N., Lawrence, N. R., & Riggan, M. (2010). Learning to learn from benchmark assessment data: How teachers analyze results. *Peabody Journal of Education, 85*(2), 226–245.
Owen, V. E., Roy, M.-H., Thai, K. P., Burnett, V., Jacobs, D., Keylor, E., & Baker, R. S. (2019). *Detecting wheel-spinning and productive persistence in educational games*. In International Educational Data Mining Society.
Perez-Colado, I., Alonso-Fernandez, C., Freire, M., Martinez-Ortiz, I., & Fernandez-Manjon, B. (2018, April). Game learning analytics is not informagic!. In *2018 IEEE Global Engineering Education Conference (EDUCON)* (pp. 1729–1737). IEEE.
Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Anderson, T. (2018). Co-designing learning analytics tools with learners. *Learning Analytics in the Classroom: Translating Learning Analytics Research for Teachers*, 93–110.
Ruipérez-Valiente, J. A., & Kim, Y. J. (2020). Effects of solo vs. Collaborative play in a digital learning game on geometry: Results from a K12 experiment. *Computers & Education, 159*, 104008. https://doi.org/10.1016/j.compedu.2020.104008
Ruipérez-Valiente, J. A., Gaydos, M., Rosenheck, L., Kim, Y. J., & Klopfer, E. (2020). Patterns of engagement in an educational massively multiplayer online game: A multidimensional view. *IEEE Transactions on Learning Technologies, 13*(4), 648–661.
Shute, V. J., Ventura, M., Bauer, M., & Zapata-Rivera, D. (2009). Melding the power of serious games and embedded assessment to monitor and foster learning. Serious Games: Mechanisms and Effects, 2, 295–321.
Takeuchi, L. M., & Vaala, S. (2014). *Level up learning: A national survey on teaching with digital games*. Joan Ganz Cooney Center at Sesame Workshop.
Tsai, Y.-S., & Gasevic, D. (2017). Learning analytics in higher education—Challenges and policies: A review of eight learning analytics policies. In *Proceedings of the seventh international learning analytics & knowledge conference*, (pp. 233–242).
Ventura, M., & Shute, V. (2013). The validity of a game-based assessment of persistence. *Computers in Human Behavior, 29*(6), 2568–2572.
Xu, Y., & Brown, G. T. (2016). Teacher assessment literacy in practice: A reconceptualization. *Teaching and Teacher Education, 58*, 149–162.

Part IV
Systems Design for Learning Analytics Applications

Chapter 19
Visualization of Learning for Students: A Dashboard for Study Progress – Development, Design Details, Implementation, and User Feedback

Philipp Leitner, Martin Ebner, Hanna Geisswinkler, and Sandra Schön

1 Introduction

At Graz University of Technology (TU Graz), the organizational unit Educational Technology has intensive experience in learning analytics and visualizations, including for our Austria-wide MOOC platform iMooX.at (Maier et al., 2019; Leitner et al., 2020), for the university-wide learning management system *TeachCenter* (Leitner et al., 2019), and through numerous international research cooperation (De Laet et al., 2018a, 2018b). When students expressed the wish to get a better and easier overview of their study progress, we were happy to comply.

Not only TU Graz students share this wish. Reimers and Neovesky (2015), for example, asked German students (N = 194) what they want at their dashboards. Their findings are as follows: "Nearly all questioned students stated that they would like to see all information relevant to their studies in one central place. 93% expressed agreement by selecting 1 or 2 on the scale. Almost as many (85%) agreed (selecting 1 or 2) on wanting an overview of deadlines to better organize their studies." Building up on their investigations of typical LA dashboard available for students, very often using the learning management system, but no student information system with grades, the authors complain: "Yet, none of the online platforms discussed above provides these two features" (p. 403).

In this article, we trace the development of the TU Graz students' study progress dashboard and present its design aspects in detail. We as well refer to our experiences and lessons learned so that practitioners could take our approach as blueprint and get helpful insights into our challenges.

P. Leitner · M. Ebner (✉) · H. Geisswinkler · S. Schön
Graz University of Technology, Graz, Austria
e-mail: philipp.leitner@tugraz.at; martin.ebner@tugraz.at; hanna.geisswinkler@tugraz.at; sandra.schoen@tugraz.at

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_19

2 Initial Situation and Addressed Objectives

At Graz University of Technology (TU Graz), the learning management system (Moodle) is called TeachCenter, and together with the campus management system – called TUGRAZonline – it is the main infrastructure for teaching. As central instances for both teachers and students, various services and support for teachers and students are offered. The information students could find there, concerning their study progress in 2019, were the courses successfully completed to date and ECTS achieved, including data on other examination candidates (e.g., failure rate for a particular examination). The design of this information was largely based on textual information spread across several pages (see Fig. 19.1).

The TU Graz study progress dashboard for students is intended to provide a helpful overview of students' activities, for example, their academic performance in ECTS compared to the average of their peers, their own study progress, and the official study recommendation as well as the progress in the various compulsory and optional courses. By visualizing learning data, students should keep an eye on their own learning process, which can ultimately lead to an improvement in their learning success. The advantages and objectives for students should be in detail (TU Graz, 2021):

- Students can see their learning achievements graphically.
- Students can regularly check their own learning progress.

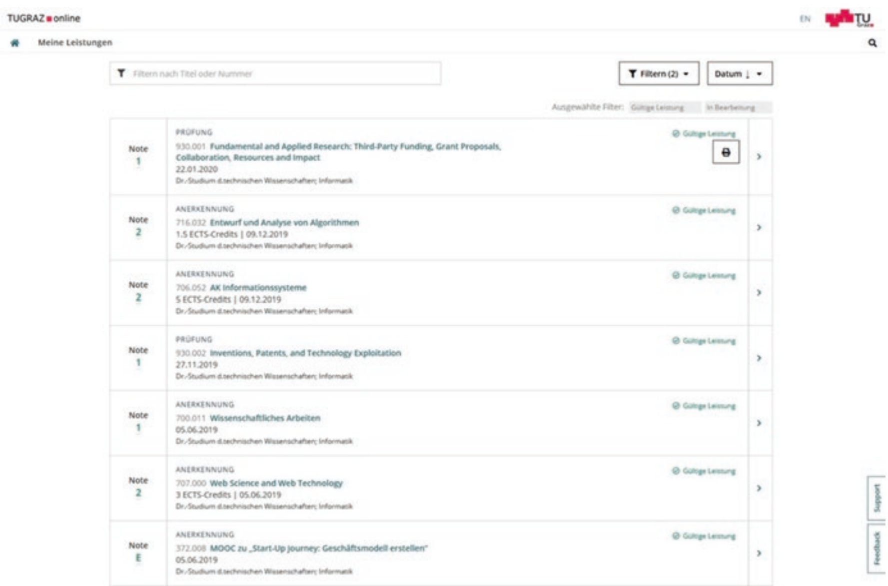


Fig. 19.1 A screenshot of students' information from the campus management system. (Source: TU Graz)

- Students determine their individual learning status on the basis of a comparison group.
- Students can optimize their learning process.
- Each student only sees his/her own results.

Teachers as well as the university administration of Graz University of Technology should also benefit from the use of learning analytics (TU Graz, 2021): The visualizations and evaluations help to better understand teaching and learning processes, reduce dropouts, lead to more transparency, result in higher examination activity, make an important contribution to the optimization of study departments and student counseling, and are the subject of research and the careful handling of data.

3 Students' Dashboards and Design Considerations

As described above, we could build upon several years of experience and research in the field of LA in higher education. Basically, we are aware of potential challenges: Greller and Drachsler (2016) have developed a well-known framework model for the development and deployment of LA applications. From our perspective for the higher education context (in particular building upon Ferguson et al. (2016)), we see seven challenges as crucial (Leitner et al., 2019): purpose and benefits of learning analytics, privacy protection, development of a clear procedure with regard to desired and undesired scenarios (ethics), the data, infrastructure, development, and operation (incl. estimation of foreseeable costs), as well as other activities, e.g., training of supervisors.

Building upon this, we decided, for example, to only *use data which is practically already available for students*, for example, the results of lectures with more than 5 years. This way we can be sure that no new examinations could arise for the use of the data.

At the same time, we had to make sure that *only students could receive the information* on their grades and study status, as nothing else has been provided for so far. We did this to as well be aware that students do not appreciate their data being used for student counseling purposes: West et al. (2020a) asked more than 2000 Australian students about their view on learning analytics, and more than a half of them had concerns that their data could be used "to trigger support services to contact you" or "trigger academic staff to contact you" or "your data being used by the university for research" (among other options, p. 80).

With regard to the *design and visualizations*, we were able to draw on corresponding previous work and developments: A literature review of the state of the art of research on learning dashboards by Schwendimann et al. (2017) included 55 papers, primarily focusing on learning dashboards in learning management systems and MOOC platforms. Concerning their analysis, 14 papers (25%) describe dashboards which builds upon data of several platforms. 28 papers (51%) are about dashboards in general and also for students. Further, the literature review gives insights into visualization types used. We have selected the results for papers that see students as dashboard users and present them in Fig. 19.1. However, we do not know how many of these papers deal with study dashboards (Fig. 19.2).

The study shows that bar charts, line crafts, tables, and pie charts are very often used in dashboards for students. Study dashboard has a focus on study results and not on learners' activities, for example, their interaction with other learners or procrastination time. Therefore, visualization at a study dashboard might use different or special visualization schemes. The type of visualization can be related with the aim of the dashboard and the addressed learning support (see Sedrakyan et al. (2018)).

In our case, it is of deeper interest what kind of visualization is used for which data in existing dashboards. For example, Charleer et al. (2018) developed "LISSA." With this tool, students and student counselors receive visualizations of students' grades and study status, also in comparison with their peers. Further, the LALA project describes several study dashboards, partly inspired by LISSA (Henriquez et al., 2020). In Fig. 19.3 we show the abstract visualisation approach of three different dashboards implemented by LALA partner universities to visualise students' progress. Colours are used to mark the status of the students (passed, failed, in progress), as well as different needs to show grades or the format of the lectures.

In all three cases, clicking on a particular lecture gives an overview of the grades for all students, including previous years. These are typically provided as bar charts of cumulative results with lines or dots for the individual student. It is important to emphasize that all of these dashboards described are not intended for the students themselves, but for counselors.

Nevertheless, for us here the *students were a central partner in the development*, and we planned from the outset to involve them strongly in the development (see de Laet et al. (2018b)). With this, we would like to create a helpful tool that meets with as little rejection as possible (Schumacher & Ifenthaler, 2018). Generally, this focus

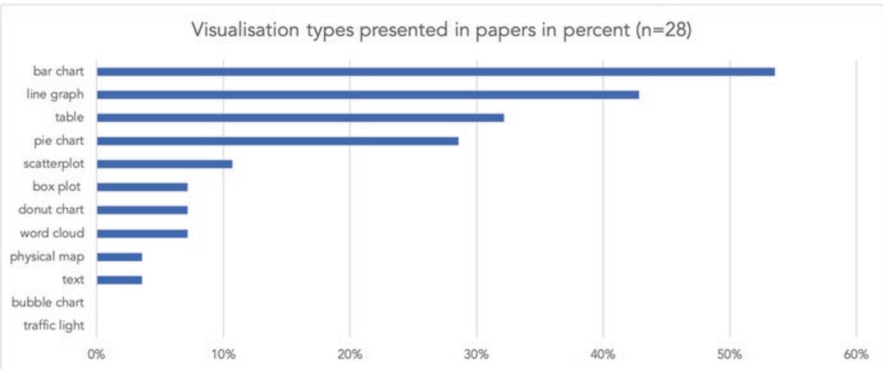


Fig. 19.2 Visualization types in dashboard addressing students in papers according to a literature review of 55 papers by Schwendimann et al. (2017). (Source: Own visualization of the results presented in Schwendimann et al. (2017) and Fig. 19.7, using the number of papers for this target group as a base (n = 28))

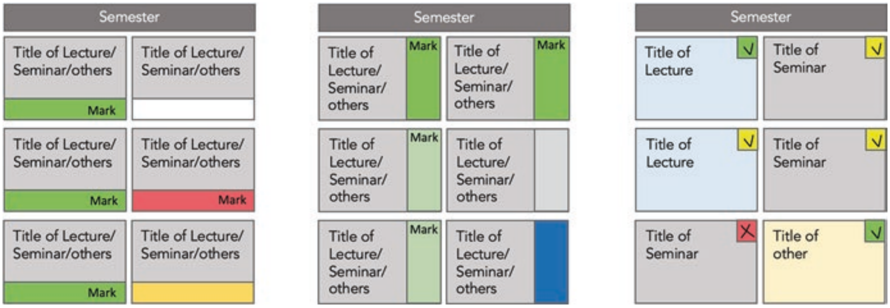


Fig. 19.3 Three abstract versions of study dashboard visualizations from partner universities of the LALA project (from left to right: AvAc, TrAC, and SiCa). (Source: Own visualization based on screenshots in Henriquez et al. (2020))

is demanded again and again, but not so often implemented: Although the learning analytics field "acknowledges the central role of students," West et al. (2020b) state that "much of the literature reflects an academic, teacher-centric or institutional view" (from abstract).

With regard to the visualization to be developed, we were aware that *visualizations are not* per se *understood by everyone* – legends and assistance must be provided (e.g., Stofer (2016) for maps). So, we were aware that we always had to question whether what we were visualizing was actually understood in the way we thought. We as well know that especially comparisons with other students are not always motivating and can as well arise feelings of superiority (Teasley, 2017). *Very exact positioning, especially at the worse end or also at the better end of the student distribution, or a clear ranking should be avoided*. But we can also imagine that visualizations with clear rankings might be less problematic in cultures where students are used to that.

4 Development and Challenges

This chapter describes the development and implementation of the students' dashboard for the TU Graz over time as well the challenges we have encountered along the way.

4.1 Development and Implementation Over Time

Our development was planned and implemented within a time frame of 2 years. In the following we describe the process from the first idea development till the current status.

As can be seen in Fig. 19.4, stakeholder involvement, especially student involvement, was a core feature of the development process. Design and technical development were developed in the "Educational Technology" team together with colleagues

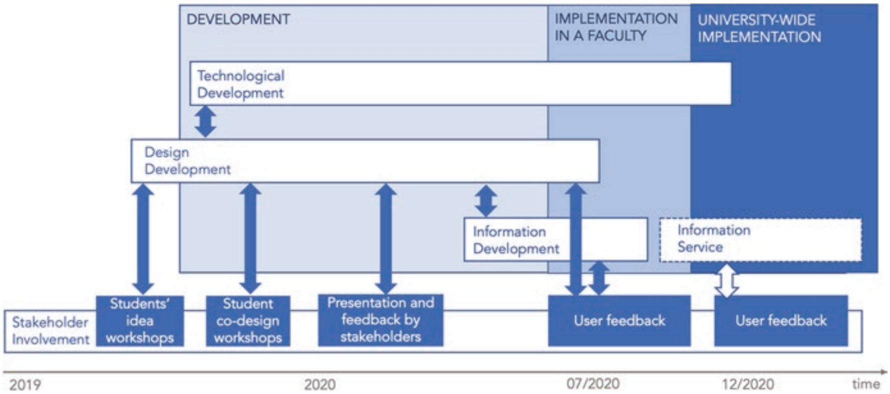


Fig. 19.4 Students' dashboard development to university-wide implementation over time

from the IT Services at TU Graz. Information and communication issues for students were developed by the "Higher Education and Program Development" team.

- March 2019: The Educational Technology teams organized workshops with in summary seven students and faculty representatives from five disciplines on general creative ideas on enhancing the study support and situation: Among many other ideas, students highlighted that a better overview about their study process would be helpful.
- March 2019–October 2019: We did a first analysis of data structures and origins and development of visualizations.
- July 2019–September 2019: We organized co-design workshops for the intermediate dashboards with student representatives.
- November 2019–December 2019: We did several tests in the internal testing phase in small groups of students.
- February 2020–March 2020: Several meetings were organized with stakeholders, including student representatives, teachers, vice-rector for academic affairs, works council, and legal department. In parallel, information materials for students were developed (TU Graz, 2021).
- June 2020: Eighteen months after the first vague idea, we implemented the new dashboard for study progress for all BA students at the Faculty of Computer Science. We collected user feedback and made small revisions.
- December 2020: After 6 months of test phase, we did the university-wide implementation for all BA students, including several information materials, setup of advisory structure, user feedback, and small revisions.

The development of the dashboard was delayed by a few weeks over time due to the closure of the university in March 2020, as all resources were needed at short notice to provide the necessary technical support for emergency teaching (Ebner et al., 2020). Overall, however, in retrospect, the implementation took place quickly and smoothly, probably also due to the existing experience with similar projects.

4.2 Development of Design and Visualization

As shown, our visualization and design team co-designed the dashboard together and within several meetings with the key (and only) user group, which are students. The design decisions are aimed at making it as easy as possible for users to get started and to understand the visualizations correctly. Design considerations were done concerning the needed information, the available data, main type of data chart, colors, as well as additional information such as labels and legends. Within the students' co-design workshop, we worked in smaller groups and asked for a brainstorming concerning the question on needed, wished information and visualization on a perfect students' dashboard (see Fig. 19.5 left). Afterward, we asked the groups to make a first sketch (see Fig. 19.5 middle). In a later phase, we asked students for feedback with the help of paper prototypes (see Fig. 19.5 on the right).

Concerning the design, we checked for familiar color schemes and chart styles that are used already at other parts of the TU Graz pages for students. The color scheme of red, orange, yellow, and green as signal color, related to the traffic light scheme, was one of the first options which made it through the development process. These colors help to identify difficult courses, conflicts, and the need for action at a glance. No signal colors are gray and blues.

Although there are several types of visualizations of the concept "parts to a whole" (Ribecca, 2021; see Fig. 19.6), only some are well-known and easy to understand according to the students' feedback within our workshops: Bar and pie

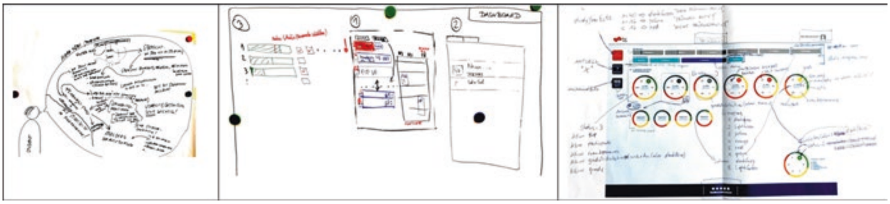


Fig. 19.5 Artifacts from the co-design with students' sessions and feedback rounds. Left, students' needs and first ideas; middle, a first sketch; right, annotated paper prototype

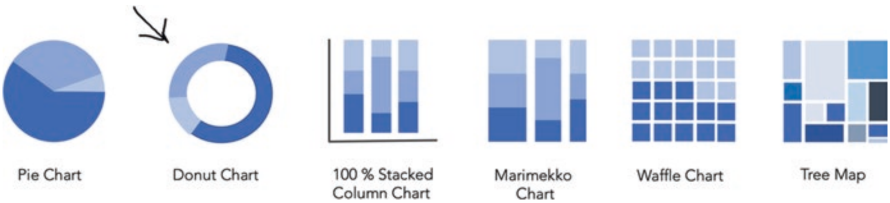


Fig. 19.6 Selection of a donut chart from several possible visualizations of parts to a whole. Own illustration of the collection by Ribecca (2021)

charts are the two best-known and easy to understand chart types. The donut chart, a variant of the pie chart, can be as well used as optical boundary.

As it will be shown later, the donut chart serves in our dashboard as a good delineation of different courses: Important key figures are arranged radially in the mid. This makes it easier to recognize and understand related data. A cluttered user interface is prevented by displaying labels and legends primarily via "mouse-over" (a graphical element that is activated when the user moves or hovers the pointer over a trigger area). This minimalism contributes to clarity and is intended to reveal the functions to the user step by step.

4.3 Challenges in Implementation

Again, and again, smaller challenges arose. With regard to the available data and its quality, or challenges in visualization, the following are among them:

- It is not clear whether students study according to the current study regulations or according to the older ones that may still be valid.
- If students are registered for several study programs (up to four are possible), it is unclear to which study program the representations should refer.
- Some degree programs are partly carried out at Graz University of Technology, partly at the University of Graz. In some cases, students are free to choose their courses. A data comparison with the University of Graz is not directly possible, also because different systems are used.
- Finally, we found several data issues such as flaws in the course lists of study programs or grading entries, which normally do not interfere with perception, as they tend to be hidden but are presented more clearly in the new overview.

Within the user involvement and discussion, the following issues were part of our discussion:

- Whether students need to compare themselves with other students and how this comparison might affect student motivation and study behavior. We decided to include this information, as it is already available due to transparency issues for all students.
- Whether students can "so easily" see information about the pass rates in the last exams of a course when they take it. We decided again that these data are available anyhow already, so we do not see why we should not show it.
- Whether teachers and counselors should or should not be allowed to view students' dashboards with or without the consent of the student.

However, despite recurring discussion with students and teachers, the agreed objectives were not changed, or, for example, insights into professors' examination data were restricted.

5 Dashboard Design and Visualization Details

The students' dashboard design and its several features will be described within the following paragraphs.

5.1 Dashboard Overview

The dashboard is displayed to all students of Graz University of Technology who are in current bachelor's program (Fig. 19.7). It is accessible as well for some and individual selected discontinuing bachelor's degree programs. The dashboard was designed to provide students with visualization to assist with the following:

- Students can see their success in their studies: The dashboard shows which courses have been completed and how the student has performed in detail. At the same time, it shows which achievements are still missing for graduation.
- Students can plan their study progress: Students can better assess their performance status and plan further learning steps with the help of the recommended semester target.
- Students focus on courses: Students can see the grade distribution of all courses in their degree program so far in the dashboard. The grade distribution can help them focus on courses that other students have found particularly challenging.

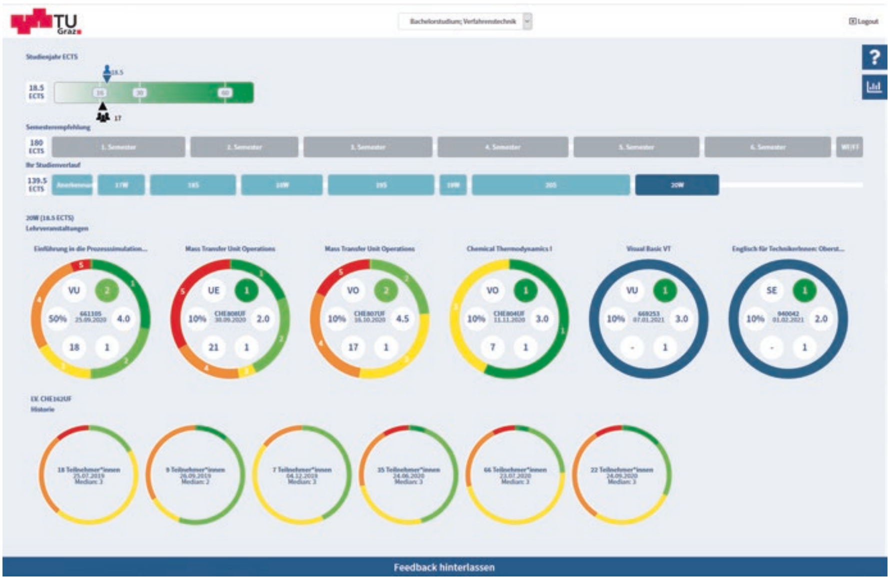


Fig. 19.7 A screenshot of a TU Graz students' dashboard. (Source: TU Graz)

- Students can compare their performance. The dashboard allows students to compare their performance with their peers. They can find out if they are ranked in the top ten for individual courses or where their performance compares to students in their year.

5.2 *Details of the Dashboard Visualization*

The dashboard is divided into the following functional areas (see Fig. 19.8): study selection (1), year of study ECTS (2), semester recommendation (3), course of study (4), courses (5), history (6), legend (7), support (8), log-out (9), and feedback (10).

By clicking on different components, further detailed evaluations can be displayed. The selection of the degree program (1) is only possible for students who are enrolled in several bachelor's degree programs.

The section "Academic Year ECTS" (2) shows the achievements in the current academic year in the form of ECTS credits (Fig. 19.9). The displayed total number of ECTS (a) ranks in the scale of study progress (b). The values 16, 30, and 60 describe ECTS points to be achieved: From 16 ECTS onward, students are considered to be exam-active. Achieving 16 ECTS is linked to the entitlement to Austrian family allowance for students. Thirty ECTS are the extent of a semester; 60 ECTS are the extent of an academic year. In addition, students see where they stand in the

Fig. 19.8 Different parts of the TU Graz students' dashboard. (Source: TU Graz)

Fig. 19.9 The "Academic Year ECTS" part of the TU Graz students' dashboard. (Source: TU Graz)

Fig. 19.10 The "semester recommendation" part of the TU Graz students' dashboard. (Source: TU Graz)

Fig. 19.11 The "course of studies" part of the TU Graz students' dashboard. (Source: TU Graz)

context of a semester or the entire academic year but also in comparison to the performance of fellow students (cohort) (c).

Under "Semester Recommendation" (3), the recommended courses per semester are displayed (see Fig. 19.10). The section is structured as follows: ECTS total number of studies (a), all semesters of studies (b), and electives and optional subjects of your studies (c).

The course of studies (4) shows the courses completed per semester (see Fig. 19.11). It is structured as follows: The tile shows how many ECTS have been completed in the course of the bachelor's degree; in the example it is 82 ECTS (a). Under "Recognitions" (b) you will find all courses that have been completed at Graz University of Technology or at other educational institutions and have been recognized for the degree program at TU Graz. The completed semesters are mapped according to the course of study (c).

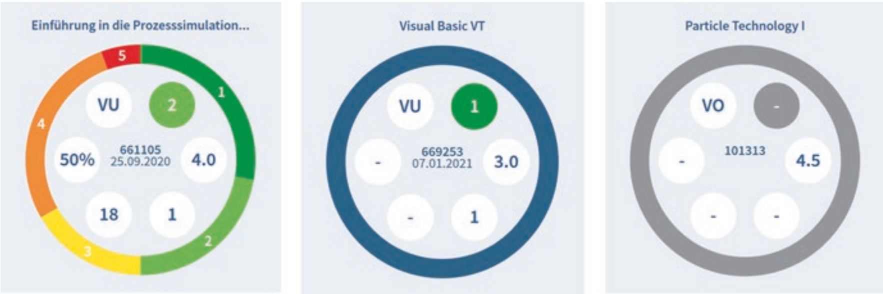


Fig. 19.12 Different ways to show lectures at TU Graz students' dashboard. Completed course with more than five participants (left), completed course with less than five participants (middle), recommended but not yet completed course (right). (Source: TU Graz)

To display the completed courses per semester, the student has to click on the corresponding semester. The last tab (d) in the course of studies is always the current semester. Since the current semester is selected by default, courses completed in this semester are automatically displayed in the Courses section.

Courses are marked with either a colored, a blue, or a gray circle. Colored circles indicate the distribution of grades from 1 ("very good") to 5 ("unsatisfactory"; see Fig. 19.12 left). Blue circles refer to completed courses with a group size of less than five persons (see Fig. 19.12 in the middle). For data protection reasons, the breakdown of grades and the number of participants is not permitted for such small groups. Courses that have not been completed are marked with a gray circle (see Fig. 19.12 right). Within the circle, students will find details of their grades (colored small circle); die number of ECTS; the number of entries; the number of participants; an indication of whether the student is in the top 10%, 20%, or 50% (not here); and an indication of the format of the course. Clicking on a course opens its history and displays the distribution of grades from all previous courses. This function is intended above all to help students better assess challenges when planning the semester.

A detailed guide helps students to use all the functions and understand the information presented (TU Graz, 2020). In addition, further support and counseling services are pointed out. The guide as well addresses that the visualization cannot take account personal circumstances, "such as caring responsibilities, employment or other studies you are pursuing. Study progress is very individual, so you should interpret this information accordingly" (TU Graz, 2020, p. 12, own translation).

6 Implementation and User Feedback

In summer term 2020, the dashboard was made accessible for all bachelor's studies of the Faculty of Computer Science and Biomedical Engineering at TU Graz. This introduction was accompanied by further information on the dashboard and communicated through emails and teachers. By 9th of June 2020, 743 students have had access to the dashboard. Twenty-seven students had taken the opportunity to provide feedback on the dashboard. The feedback was requested as free text. An analysis showed that more than half, namely, 54%, were clearly positive and reported minor errors or made suggestions for improvement and 38% others did not comment positively or negatively on the dashboard and only made suggestions for improvement. The suggestions for improvement refer to improvements in the legend up to the optimization of the mobile version. Only 8% of the responses were negative, with students saying it was unnecessary or that they did not understand the point of it because the information already existed. The comparison between students was also rejected. Among the explicitly positive feedback are those that emphasize that the dashboard helps to better assess one's own performance and to get a good overview.

After this successful start, the dashboard was made available university-wide in December 2020.

7 Recommendations and Outlook

Finally, the authors will present recommendations as guidelines for similar projects based on their experience and students' feedback and an outlook for future development and research:

1. **Limit to data and information that are already available.** When developing the dashboard, focus on the things data and information that are already available to students but, for example, are on different systems or several pages or mainly in text form. This avoids many discussions about "what students should see in the first place," because the information is already available to them. At least we were able to focus more on the visualization or technical aspects in all the discussions.
2. **Limit the access to all who had it already.** In our case at TU Graz, teachers or students' service has no full access of student study progress. Although we had some discussion about this issue, we stayed focused on a service and visualization only for the individual student. In this way, we were able to take a clear position on this issue and did not open up a discussion space that could distract from the actual plan and implementation of the student progress dashboard.
3. **Use existing pattern and colors.** Concerning visualization, all organizations as well as cultures have a more or less formally (corporate identity) or informally established specifications and pattern. Checking existing tools, pages, and online services, in our case, especially such for students, makes it easier to decide for colors and more. Practically, we use as well the traffic light colors as they are used in other existing study dashboards as well (see Fig. 19.3).
4. **Try unusual visualization type**. As the literature review of Schwendimann et al. (2017) showed, the donut data visualization is not very common in learning dashboards for students (see Fig. 19.2). Nevertheless, the donut was highly sup-

ported by our students. We see that the students not only liked our rather unusual solution but that they also understood it well.

5. **Co-design with students**. This recommendation is not only based on the insight that key users can also provide valuable feedback, but on the experience that they are highly engaged and sometimes surprisingly competent (visually and technically, we are a technical university). We have the impression that the strong involvement of the students made the process not only more effective but also significantly more efficient.
6. **Do not underestimate data management and integration of stakeholders**. In our case, we were able to carry out the described implementation relatively smoothly, but we already knew the data and its origin, as well as the systems and possible challenges, and we were also aware of which intentional units absolutely had to be involved and at which stage of the process. If a dashboard development is the first measure in the field, significantly greater efforts should be expected here at a large university.

From the perspective of the student dashboard, there are still some limitations that we have already described above, but for which no solutions are currently foreseeable, for example, for the necessary data exchange with the university with which we offer joint degree programs. We have therefore not planned any major further developments, also in view of the positive feedback on the dashboard. The extent to which other forms of support for studying and learning can be used and have an effect for students is something we will initially investigate primarily at our learning management system at the level of individual courses or individual MOOCs on the MOOC platform.

Acknowledgments Contributions and development were partly delivered within the project "Learning Analytics: Effects of data analysis on learning success" (January 2020–December 2021) with Graz University of Technology and University of Graz as partners and the Province of Styria as funding body (12. Zukunftsfonds Steiermark).

References

Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2018, July–September). Learning analytics dashboards to support adviser-student dialogue. *Transactions on Learning Technologies, 11*(3), 389–399.

De Laet, T., Broos, T., van Staalduinen, J.-P., Ebner, M., & Leitner, P. (2018a). Transferring learning dashboards to new contexts: Experiences from three case studies. In *Conference proceeding open educational global conference 2018* (p. 14). Delft.

De Laet, T., Broos, T., Verbert, K., van Staalduinen, J.-P., Ebner, M., & Leitner, P. (2018b). Involving stakeholders in learning analytics: Opportunity or threat for learning analytics at scale? Workshop. In *Companion proceedings 8th international conference on learning analytics & knowledge* (pp. 602–606).

Drachsler, H., & Greller, W. (2016). Privacy and analytics - it's a DELICATE issue: A checklist to establish trusted learning analytics. In *Proceedings of the 6th international conference on learning analytics and knowledge* (pp. S89–S96). https://doi.org/10.1145/2883851.2883893

Ebner, M., Schön, S., Braun, C., Ebner, M., Grigoriadis, Y., Haas, M., Leitner, P., & Taraghi, B. (2020). COVID-19 epidemic as E-learning boost? Chronological development and effects at an Austrian university against the background of the concept of "E-learning readiness". *Future Internet, 12*, 94. https://www.mdpi.com/1999-5903/12/6/94

Ferguson, R., Hoel, T., Scheffel, M., & Drachsler, H. (2016). Guest editorial: Ethics and privacy in learning analytics. *Journal of Learning Analytics, 3*(1), 5–15. https://doi.org/10.18608/jla.2016.31.2

Henriquez, V. et al. (2020). *LALA piloting*. Project report of the LALA project. Version 3.1, 15.2.2021, URL: https://www.lalaproject.org/wp-content/uploads/2021/03/VF4Pilots_English_-all_universities.pdf

Leitner, P., Ebner, M., & Ebner, M. (2019). Learning analytics challenges to overcome in higher education institutions. In D. Ifenthaler, D. K. Mah, & J. K. Yau (Eds.), *Utilizing learning analytics to support study success*. Springer.

Leitner, P., Maier, K., & Ebner, M. (2020). Web analytics as extension for a learning analytics dashboard of a massive open online platform. In D. Ifenthaler & D. Gibson (Eds.), *Adoption of data analytics in higher education learning and teaching. Advances in analytics for learning and teaching*. Springer. https://doi.org/10.1007/978-3-030-47392-1_19

Maier, K., Leitner, P., & Ebner, M. (2019). Learning analytics cockpit for MOOC platforms. In *Emerging trends in learning analytics*. Brill/Sense. https://doi.org/10.1163/9789004399273_014

Reimers, G., & Neovesky, A. (2015). Student focused dashboards—An analysis of current student dashboards and what students really want. In *Proceedings of the 7th international conference on computer supported education (CSEDU)* (pp. 399–404).

Ribecca, S. (2021). Chart Selection Guide. In *The data visualisation catalogue*, Posting from 1st of January 2021. https://datavizcatalogue.com/blog/chart-selection-guide/

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017, January–March, 1). Perceiving learning at a glance: A systematic literature review of learning dashboard research, *IEEE Transactions on Learning Technologies*, *10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522.

Sedrakyan, G., Mannens, E., & Verbert, K. (2018). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Visual Languages & Computing*. https://doi.org/10.1016/j.jvlc.2018.11.002

Stofer, K. A. (2016, August). When a picture Isn't worth 1000 words: Learners struggle to find meaning in data visualizations. *Journal of Geoscience Education, 64*(3), 231–241.

Teasley, S.D. (2017, October). Student facing dashboards: One size fits all? *Technology*, *Knowledge and Learning, 22*(3), 377–384. https://link.springer.com/article/10.1007/s10758-017-9314-3#ref-CR27

TU Graz. (2020). *Leitfaden: Grundlagen des Studierenden-Dashboards. Internal document*. https://tu4u.tugraz.at/fileadmin/Studierende_und_Bedienstete/Anleitungen/Studierenden-Dashboard_Funktionen_Leitfaden.pdf (2021-01-15).

TU Graz. (2021). *Learning analytics (Internal Webpage)*. https://tu4u.tugraz.at/studierende/mein-laufendes-studium/learning-analytics/. (2021-01-15).

West, D., Luzeckyj, A., Searle, B., Toohey, D., Vanderlelie, J., & Bell, K. R. (2020a). Perspectives from the stakeholder: Students' views regarding learning analytics and data collection. *Australasian Journal of Educational Technology, 36*(6), 72–88. https://doi.org/10.14742/ajet.5957

West, D., Luzeckyj, A., Toohey, D., Vanderlelie, J., & Searle, B. (2020b). Do academics and university administrators really know better? The ethics of positioning student perspectives in learning analytics. *Australasian Journal of Educational Technology, 36*(2), 60–70. https://doi.org/10.14742/ajet.4653

Chapter 20
Visualization of Student-Item Interaction Matrix

Tomáš Effenberger and Radek Pelánek

1 Introduction

In digital learning environments, students do not just passively consume learning content but also actively interact with various educational items. In this work, we focus on visualizing these interactions. We consider *item* as a general term encapsulating, among others, multiple-choice questions, fill-in-the-blank and drag-and-drop exercises, interactive simulations, or programming assignments. We consider particularly items for which the student interaction can be automatically evaluated as correct or incorrect.

Data on student-item interaction are valuable for many stakeholders. For students and teachers, the data can provide insight into the state of the learning process. For developers of learning environments, the data can give impulses for the improvement of their environments. For researchers, the data can provide inspiration for the design and evaluation of personalization algorithms.

Student-item interaction can be analyzed and visualized in many ways. To put the techniques discussed in this work into a context, it is useful to consider whether the visualization is concerned with single or multiple students and items. Figure 20.1 provides illustrations for different combinations. The figure uses simplified versions of visualizations and hypothetical data about student interaction with programming items.

- *Single student, single item.* The most detailed visualization, focusing on individual actions of a single student while solving an item. The provided example visualizes student's edits and submits while solving a programming assignment.
- *Single student, multiple items.* This visualization shows the behavior of a single student across multiple items, e.g., as a bar chart showing the activity of a given

T. Effenberger (✉) · R. Pelánek
Masaryk University, Brno, Czechia
e-mail: tomas.effenberger@mail.muni.cz; pelanek@fi.muni.cz

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_20

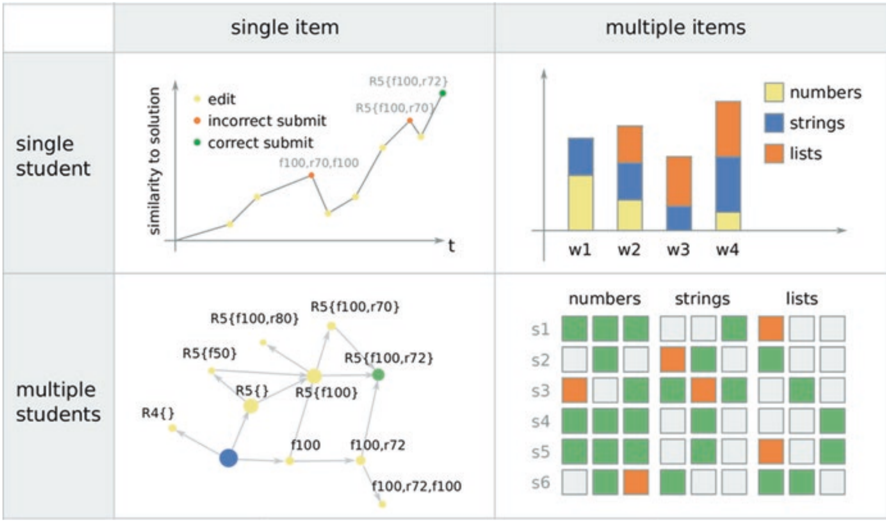


Fig. 20.1 Examples of visualizations of student-item interactions depending on the number of students and items

student through time. Other examples of this type of visualization are MasteryGrid without social features by Brusilovsky et al. (2016), the summative visualization of student activity using Chernoff faces (France et al., 2006), and line chart displaying progress and responses to test items in chronological order (Costagliola et al., 2008).

- *Multiple students, single item.* For a single item, we can visualize the activity of multiple students to show different approaches to solving the item. This can be done, for example, using an interaction network with nodes representing possible partial solutions and edges representing frequent transitions between them (Johnson et al., 2013).
- *Multiple students, multiple items.* Finally, we can consider both multiple students and multiple items, which naturally lead to a matrix-based visualization. This approach is the focus of this chapter.

We focus on student-item interaction visualization taking into account multiple students and multiple items, particularly in the form of a *student-item matrix* with rows and columns corresponding to students and items. This type of visualization can be found in the literature under various other names: student-problem matrix (Khajah et al., 2014), student-problem chart (Wang & Chen, 2013), lesson overview (Molenaar & Knoop-van Campen, 2017), and even just heat map (Confrey et al., 2017). None of these publications provides a systematic discussion of the student-item matrix. Each of them uses one particular variant of the student-item matrix (e.g., students and items ordered by their skill and difficulty, cells displaying binary correctness) for a specific purpose (e.g., providing feedback to teachers about struggling students).

Analogous matrix visualization has been used to display the interaction of students with other entities as well. For instance, the columns can correspond to knowledge components (Brusilovsky et al., 2016; Mazza & Dimitrova, 2007), courses (Bowers, 2010), errors (Fu et al., 2017), or types of learning activities (Lee et al., 2016).

Another variation on the standard student-item matrix is to use time as the horizontal axis, resulting in a sparse *dotted chart* instead of the dense heat map (van der Aalst et al., 2013; Sedrakyan et al., 2014; Trcka et al., 2010). Such visualization can be considered as a (nonstandard) student-item matrix only if the cells still correspond to individual student-item interactions. Aggregating the interactions, e.g., as the number of interactions per day, can be useful, but we do not call such visualization a student-item matrix since we cannot make inferences about the individual items.

Other research areas use closely related techniques. In recommender systems, a key data structure is a *user-item matrix* with ratings (e.g., movie ratings); Monti et al. (2019) uses 3D visualization of this matrix. In process mining, similar methods are used to visualize a *resource-activity matrix* (Janssenswillen et al., 2019).

This chapter presents a systematic treatment of the visualization of student-item matrices. The student-item matrix has many applications (Sect. 20.2), and each application leads to specific requirements that should be taken into account when designing the visualization. Although several studies already used this visualization, they do not focus on the student-item matrix per se and do not provide any guidance to its design. We provide a systematic discussion of different aspects of the visualization and also describe variations and extensions (Sect. 20.3). The chapter includes a case study with data from introductory programming, which illustrates different variants of the student-item matrix and discusses the insights they provide (Sect. 20.4).

2 Applications

The general aim of visualizing the student-item matrix is to get an understanding of data and insights into underlying behaviors and consequently to make informed decisions that will lead to the improvement in student learning. More specifically, the goal is to understand the behavior of students, algorithms, and their interactions. This is nontrivial since student's behavior is complex and noisy, personalization algorithms are adaptive, and interactions can have surprising effects.

The visualization can serve several different specific needs, depending on the target audience (students, teachers, developers, researchers). We outline several of these applications. To illustrate them, we use the matrix shown in Fig. 20.2. This example visualizes student answers to a reading comprehension exercise, where a student reads a text and then answers several multiple-choice questions. The matrix is hypothetical, i.e., it is not based on real student data but artificially constructed in order to show in a compact space many potential applications. Nevertheless, all the discussed patterns are based on our experiences with real data. Real data are, of course, noisier and we do not see so many aspects of student behavior in such a small sample.

Fig. 20.2 Hypothetical student-item matrix for reading comprehension exercise. The color is based on the correctness of student answers

2.1 *Feedback to Students and Teachers*

Teachers can use the visualization during a class to decide what to do, e.g., to give feedback to a particular student or to discuss something with the whole class (Confrey et al., 2017; Molenaar & Knoop-van Campen, 2017). In our illustrative example in Fig. 20.2, a teacher may quickly conclude that student s1 works mostly well, student s11 needs help, and student s12 is completely disengaged. Molenaar & Knoop-van Campen (2017) describe how teachers use the student-item matrix and other visualizations during class; they confirm that these visualizations influence their actions.

The visualization can be incorporated into an open learner model in order to help students to develop metacognitive skills while simultaneously serving as navigation through the system (Brusilovsky et al., 2016).

2.2 *Understanding Behavior, Decision Support*

Student-item matrix visualization can provide system developers and content authors with an understanding of student behavior. How are students interacting with the content? Is the interaction as expected? Can we detect different types of students? Do we need to modify or extend the available content (e.g., add more items or add easier items)? Consider the illustration in Fig. 20.2. Here we can see that item 4 is probably too easy, whereas item 7 is very difficult and many students stop the practice at this item. This is clearly a critical point that requires attention and suitable modification.

Previous work used related techniques and visualizations with similar aims, e.g., detection of student clusters based on sequences of their actions (Desmarais & Lemieux, 2013), visualization of data about student behavior in MOOC courses (Coffrin et al., 2014), or visualization of data about player behavior in games (Wallner & Kriglstein, 2013).

2.3 Detecting Counterproductive Behavior

Students do not always use learning environments in the productive fashion intended by designers. There are many types of counterproductive behavior, e.g., cheating, systematic guessing, or gaming the system (hint abuse) (Baker et al., 2008; Northcutt et al., 2016). There are many types of counterproductive behavior, and students are often surprisingly creative—we have, for example, encountered cases of intensive exploration of HTML source code or JavaScript console outputs. Visualizations can often provide indications of suspicious activity (Costagliola et al., 2008). Once we spot unexpected patterns in the visualization, we can build detectors to quantify them and find them systematically.

In the illustration in Fig. 20.2, students s3 and s6 are probably cheating. At the beginning of the sequence, they struggle to answer items correctly. At the end of the sequence, they have a long sequence of excellent and very fast answers. We can also see that students 12 is just guessing, which is another form of counterproductive behavior.

2.4 Understanding Biases in Data

The data from learning environments are typically skewed and may contain various biases (Nixon et al., 2013; Čechák & Pelánek, 2019), e.g., mastery attrition bias (students who know a topic are leaving earlier than weak students) or ordering bias (items presented at the beginning of a sequence are solved by many more students and under different circumstances than items presented later). These biases can significantly influence the evaluation of student models and learning environments (Pelánek, 2018). Visualizations can help us understand the biases and skews present in a particular dataset and to make informed decisions concerning the proper evaluation methodology, e.g., splitting the dataset into a training and testing set or the approach to the computation of metrics.

The illustration in Fig. 20.2 shows a typical skew in the distribution of answers due to item order. Items 9–13 are solved by only a small subset of students and these students are not a representative sample (only good or cheating students).

2.5 Inspiration and Intuition for Student Models

Learning environments often provide adaptive behavior that is guided by student modeling (Pelánek, 2017). Based on student activity, a student model provides an estimate of a student state. Student models can take many forms and use many types of input data; the choice of a suitable model depends on a specific situation. Visualizations of interaction can often provide guidance and inspiration for the design of student models. For example, in data from one system, we noticed quite frequent consecutive sequences of incorrect answers. Based on this observation, we built a simple predictor of next answer correctness, which was competitive with more sophisticated student models (Řihák & Pelánek, 2016). A specific application is the choice of performance data to use. There are many aspects of student performance that can be used in student modeling (e.g., the correctness of answers, response times, the quality of solutions, absolute timestamp, class membership). Student-item matrix can capture multiple aspects of performance, providing insight into how these performance aspects are related, which of them are noisy, and which carry a consistent signal about the student. It is useful to have intuition before one plunges into modeling. For example, for the data depicted in Fig. 20.2, it seems that response times may be indicative of affective state (disengagement) and cheating but probably would not be very useful for modeling cognitive state (at least without nontrivial filtering).

The student-item matrix visualization is also used for the illustration of methodological issues in student model evaluation (train-test data split) (Khajah et al., 2014; Pelánek, 2018; Reddy et al., 2016). After performing the modeling and evaluation, visualizations can be useful for checking the validity of results and providing interpretation.

3 Design of the Matrix Visualization

The student-item matrix is similar to heat maps and scatterplots but requires additional decisions concerning filtering, grouping, and ordering of the students and items. A large number of parameters makes the student-item matrix a rich and versatile visualization but can be intimidating the first time you use it. To help design a suitable student-item matrix, this section provides a systematic overview of the parameters and available options.

3.1 Standard Student-Item Matrix

In the standard student-item interaction matrix, rows correspond to individual students, columns to individual items, and cells to interactions between them. Each of these three graphical components—rows, columns, and cells—has a number of

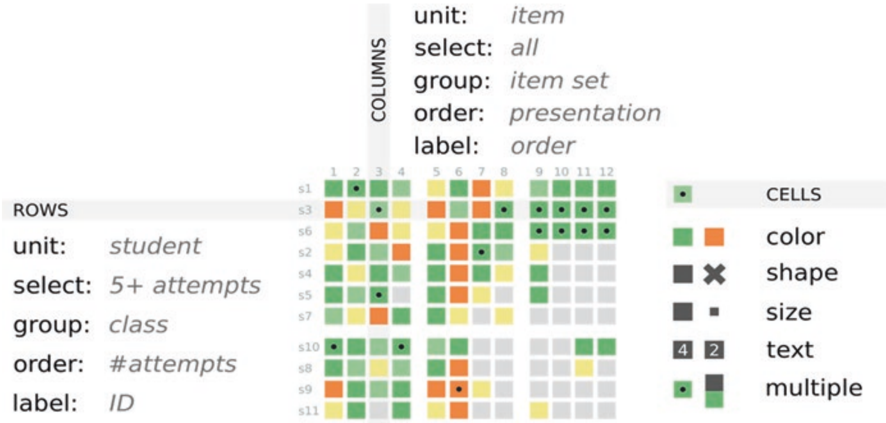


Fig. 20.3 Parameters of rows, columns, and cells in student-item interaction matrix, together with an example set of options (printed in italics)

parameters, which are shown in Fig. 20.3. In the following, we discuss typical options for these parameters.

3.1.1 Rows: Students

There might be several orders of magnitude more students than we can fit into the visualization, so we must choose just a subset of them. In addition to the selection of students, the second key parameter is the ordering, which can often greatly enhance the intelligibility of the visualization.

- **Unit**: *individual student, group of students (class, cluster)*

- Typically, we want to see individual students, but lower granularity is certainly possible. Each row would then represent a set of students, e.g., a cluster of students with similar behavior.
- **Select**: *filter by condition, random sample, top N*
- First, we can filter students satisfying a specific condition, e.g., students from a specific class or students who attempted at least ten items. Then, if there are still too many students, we take a random sample, possibly stratified (e.g., an equal number of male and female students) or blocked (e.g., students with activity within one randomly chosen week). Alternatively, we can select top *N* students with respect to a criterion such as the number of answers.
- **Group**: *grade, class, school, or another categorical attribute*
- If we want to compare multiple groups of students, we can put the rows of the students from the same group together and insert a small gap (or simply an empty column) between the groups.
- **Order**: *activity, skill, or another numerical attribute*

- A reasonable default choice is a summary of a student's activity, such as the number of interactions, success rate, or a skill estimated by a student model. Sometimes, other orderings are more appropriate. For instance, ordering by the time of students' first (or last) activity may reveal group cheating or the impact of new items. A more sophisticated way to put similar students close to each other is to define the similarity between two students and use 1D dimensionality reduction or dendrogram resulting from hierarchical clustering (Lee et al., 2016).
- **Label**: *ID, name, or another categorical attribute*
- Identifying individual students is important when the matrix is used as an overview for a teacher, but for most of the other applications, labels are not needed.

3.1.2 Columns: Items

There are typically much fewer items than students, so it might be feasible to show all of them. If not, we can either aggregate them to larger units or select just a subset of items. As for the students, the ordering of items is an important decision.

- **Unit**: *individual items, steps, item sets, knowledge components, courses*
- The default choice is individual items, but both lower and higher granularity are possible; e.g., units of higher granularity are steps within an item, and units of lower granularity are item sets.
- **Select**: *all, filter by condition, random sample*
- If there are too many items, we can select a group of closely related items such as an item set or a knowledge component. Alternatively, we can use a random sampling strategy, analogically as for students.
- **Group**: *item set, type of item, or another categorical attribute*
- There are often natural groups of items, such as item sets or item types (e.g., multiple-choice vs. free-response questions). It might be helpful to visually separate these groups.
- **Order**: *presentation order, difficulty, or another numerical attribute*
- If the items have some predetermined ordering within the system, it is natural to use the same ordering also in the student-item matrix. For some use cases, alternative orderings might make sense, e.g., by difficulty (e.g., success rate) or by the time when the item was created. Using per-student ordering of items is possible (e.g., in the order they solved the items), but then columns do not correspond to unique items; this is discussed separately in Sect. 20.3.2.
- **Label**: *ID, or another categorical attribute*
- There is not much space in the header for each item. If we want to show the names (or even complete item statement), we need to either rotate the labels, transpose the matrix (i.e., dedicate rows to items), or use interactive features such as mouse hover.

3.1.3 Cells: Interactions

Given a student-item pair, we can display various data about their interaction:

- Student's performance (e.g., correctness, solution quality, response time, the number of attempts or requested hints)
- Time of the interaction (e.g., date, the time within a day, the time from the first student's interaction, the order of the student's interaction)
- Prediction of a student model (e.g., the predicted probability that the student solves the item, that he is frustrated, or that he is cheating)

These *data attributes* can be mapped to any subset of the cells' *graphical attributes* shown in Fig. 20.3: color, shape, size, and text. The graphical and data attributes are nearly orthogonal and can be combined in many ways. One constraint is that some graphical attributes are only suitable for categorical data attributes. It is, however, possible to discretize a numerical attribute into a few categories, e.g., using "short/long solution" instead of the continuous length of the solution.

- **Color**: *performance, time, any categorical or numerical attribute*

- Changing the color is the least disruptive way to vary the appearance of the cells without making the matrix more difficult to navigate. Color can represent both categorical data (using a qualitative colormap) and numerical data (using a sequential colormap). It is even possible to show multiple performance aspects, either by mapping separately hue and lightness to two different aspects (e.g., correctness and response time) or by combining multiple aspects into a single category, e.g., "weak performance" when either the response time is high or the quality of the solution is low. Recommendations on how to perform such answer classification in various domains exist (Pelánek & Effenberger, 2020).
- **Shape**: *suspicious behavior, correctness, or another categorical attribute*
- If the matrix is dense, using multiple shapes would produce unintelligible visualization. This graphical attribute can be useful if there are a few interactions that we want to highlight, e.g., detected cheating. Another example might be using crosses for serious unfinished attempts in a problem-solving exercise where nearly all of the items are eventually solved.
- **Size**: *response time, or another numerical attribute*
- We can either change just the width or height of the shape or both dimensions simultaneously. For example, we can scale crosses representing unfinished attempts proportionally to the response time in order to make the nonserious attempts less prominent.
- **Text**: *item ID, or another categorical or numerical attribute*
- If there are not many interactions and the cells are large enough, we might be able to fit a short text (letter, two-digit number) in each cell. However, in a more typical scenario, there are many interactions and the cells are thus too small. A possible remedy is to use interactive features—showing the text on mouse hover, click, or after sufficient zoom-in.
- **Multiple**: *composing graphical attributes, nesting shapes, stacking cells*

- Often, we want to directly compare two data attributes, e.g., two aspects of performance, predicted vs. actual performance, or the performance vs. the difficulty of the item. The most obvious way to show multiple data attributes for each interaction is to vary multiple graphical attributes of the cells. For instance, a shape can denote correctness and color response time. There are two other approaches, which might better preserve the grid regularity: nesting and stacking. Figure 20.2 illustrates nesting multiple shapes in a single cell. The nested shape might not be just a binary indicator; it can possess any of the discussed graphical attributes.

3.2 Nonstandard Student-Item Matrix

In the standard version of the student-item interaction matrix, each row corresponds to a unique student, each column to a unique item, and each cell to the interaction between them. If we drop the requirement on the rows and columns but insist that each cell still corresponds to a student-item interaction, we obtain a much broader set of visualizations, which we call *nonstandard* student-item interaction matrices.

A prominent class of nonstandard student-item interaction matrices uses the x-axis to display time instead of to identify the items. Such visualization is called *dotted chart* in the process mining community (Janssenswillen et al., 2019; Song & van der Aalst, 2007). It is useful when the temporal aspect is important, e.g., for debugging a student model or investigating possible cheating before the homework deadline.

There are many notions of time to consider, and the appropriate choice depends on the specific application. There is a fundamental trade-off between the fidelity of the time axis and the compactness of the visualization, which is illustrated in Fig. 20.4. Three basic choices are absolute, relative, and logical time.

- **Absolute time**: The columns represent discretized absolute time. To avoid overlapping interactions, we may use just absolute dates, using the specific time only to order the interactions within the day. To avoid too wide visualization, we can decrease the width of each cell; this strategy is used in Fig. 20.9.
- **Relative time**: Absolute time becomes impractical if the times for the set of selected students differ widely. In such a case, we might use time relative to a given student, e.g., nth day since the student's first interaction.

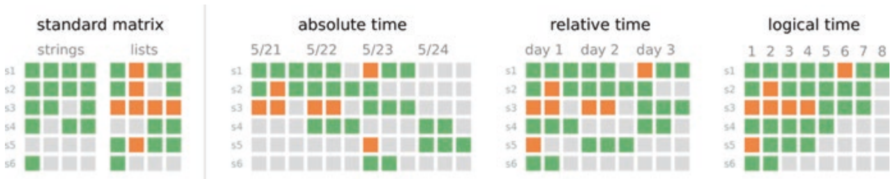


Fig. 20.4 Comparison of standard and nonstandard student-item interaction matrices. The nonstandard versions use three different notions of time for the x-axis

- **Logical time**: The most compact—and least faithful—visualization is obtained by keeping only the information about the ordering of the interactions, i.e., nth column corresponds to nth interaction for a given student. The resulting time-ordered student-item interaction matrix is dense, with no empty cells between interactions; see Figs. 20.7 and 20.8.

Other variants of nonstandard student-item interaction matrices are possible but much less frequently useful. For instance, if new content was added to our learning system and we want to explore how this change impacted performance on the existing items, we could use rows to identify items (instead of students) and the x-axis to display time before and after the content update.

3.3 *Extensions*

Figure 20.5 shows examples of additional graphical elements that can be added to the student-item interaction matrix.

3.3.1 Facets

Comparing multiple student-item matrices might bring a deeper insight than looking at just one matrix. We can compare sets of students (e.g., control vs. treatment group), sets of items (e.g., code comprehension vs. code writing), or time periods (e.g., June vs. November). In some cases, the comparison can be performed within a single matrix, using either groups or stacked cells (e.g., to compare predictions of multiple student models). If a single matrix is not sufficient, we can always arrange multiple matrices into a *facet grid*.

3.3.2 Margins

Any relevant student/item attributes can be added to the margins of the matrix. These attributes can be summaries of the displayed values in the rows and columns, facilitating the exploration of multiple levels of abstraction. Various summary

Fig. 20.5 Four examples of student-item interaction matrix extensions

curves can be seen as a projection of a specific student-item matrix. For example, a *survival curve* (Eagle & Barnes, 2014) is a projection that counts the number of interactions in columns of a time-ordered matrix, and an *item ordering bias curve* (Čechák & Pelánek, 2019) is a projection that averages columns in a time-ordered matrix with values set to the item presentation order. Figures 20.7 and 20.8 show these two summary curves represented as *heatlines*, which are a compact alternative to point plots or bar charts.

3.3.3 Annotations

When the matrix is used to deliver a message (e.g., in a research paper), we may want to highlight or delineate some parts. Examples of such annotations include a line showing a homework deadline, background highlight in columns of new items, and icons with exclamation marks put on the cells corresponding to interactions where a student model made a huge error in the predicted performance.

3.3.4 Interactivity

Interactive features can greatly simplify exploration on multiple levels of abstractions, readily providing details on demand (e.g., hovering over or clicking on a cell). Dropdowns and sliders can allow to easily select different subsets of data and change all the parameters of the student-item matrix discussed in previous sections. A valuable feature for debugging student models would be an option to interactively change the data, such as the observed performance of a student, to see how it would impact the model behavior.

4 Case Study

In this section, we show several examples of student-item matrices using real-world data from an online learning system for learning programming. For this case study, we selected a single high-school class (28 students) and 5 item sets from a Python programming exercise (51 items in total). Each item asks students to write a short function, e.g., to compute a factorial or to detect a palindrome. In contrast to multiple-choice questions, these programming items take much longer to solve and most attempts are eventually successful. Also, the binary success is not the only relevant aspect of performance: the speed of the students and the quality of the code matter as well. Effenberger and Pelánek (2021) showed that considering these other aspects of performance is necessary for valid and reliable student models in this context.

4.1 Standard Student-Item Matrix

Figure 20.6 shows a standard student-item matrix for this data. Cell colors represent the performance of a student on an item, considering both the product quality (code length) and fluency (speed of the student). The thresholds for each performance category are computed per item, using the length of the author's solution and data from all students (not just the single selected class). Unsuccessful interactions that took less than 1 min are labeled as *not serious*. Effenberger and Pelánek (2021) demonstrated that for this programming exercise, such performance measure leads to valid and reliable estimates of skills and difficulties, while binary correctness does not. Computing the mean performance—which is shown in the margins—requires specifying a mapping from the discrete performance categories to numbers.

To the teacher, this visualization confirms that the selected exercise was a rather good fit for the class: neither were the items trivial for the students nor is any student extremely struggling. There are not huge differences in skills—the mean performance of all students is similar—but a few students did not even try to solve most of the items, indicating a lack of motivation.

Some topics are worth further practicing with the whole class: logic expressions, loops, and strings. A quick glance at the bottom margin suggests specific items that the teacher can analyze with the whole class (e.g., item 11 from the logic item set). In the last two item sets, the students managed to solve the items, just with a too long code, so the teacher can prepare an activity to specifically address this shortcoming, e.g., letting the students find a shorter solution to one of these items.

The same visualization would provide different insights to the developers and content authors, although they should select a larger and random sample of students

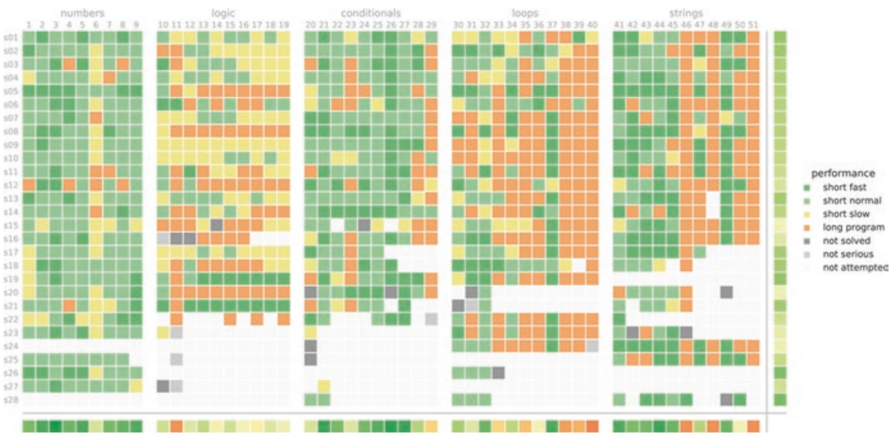


Fig. 20.6 Standard student-item matrix for one class of students and a programming exercise with 51 items. Students are ordered by the number of attempted items. Items are grouped by item sets and ordered as in the learning system. The color of each cell represents performance and margins show mean performance for each student and item

to get a more representative picture. Had this been a random sample, we would conclude that some items are too difficult (e.g., item 11). We then could either make these items easier (e.g., by adding a hint or scaffolding) or make the students who encounter them more skillful (e.g., by moving the item at the end of the item set or adding similar but easier items to pretrain students).

Observing the frequency of too long programs, we might want to help the students to write shorter solutions. First, we should dig deeper and find what causes the excessive length. For example, in the logic item sets, many students fail to use "return (logic expression)" idiom instead of a four-line if-else block. With this knowledge, we can think of many possible interventions: adding scaffolded items demonstrating the use of this idiom, adding code refactoring items, showing a targeted feedback message to students who fail to use this idiom, and possibly even enforcing usage of this idiom by item structure, e.g., limiting the length of the program or the available code structures.

Yet different insights would this visualization provide to researchers who would like to use this data for student modeling. There are only a few unsolved attempts, rendering most of the current student modeling techniques useless since they focus on predicting the correctness of answers (Pelánek, 2017). A useful student model would need to consider also the other aspects of performance. Looking at the student-item matrix, we can guess which information is necessary for any student model to perform well. In our case, there is more variability across items than across students, and the item-average model seems like a reasonable baseline.

4.2 Time-Ordered Student-Item Matrix

For student modeling, the information about the order in which the students solved the items is crucial. In the time-ordered student-item matrix (Figs. 20.7 and 20.8), we can see which information is already available to the student model—just the previous cells on the same row—which can help us to understand its performance. Figure 20.7 shows the information used by a student model that disregards items and uses just the series of previous performances. While using only binary success for adaptation would be hopeless, there are streaks of the same performance category. We could use stacked or nested cells (discussed in Sect. 20.3.1) to simultaneously show the difficulty of the attempted item or the prediction of a specific student model that we debug.

Figure 20.7 also reveals that the data are skewed, i.e., the number of interactions differs considerably between students; the bottom margin corresponds to the *survival curve*. Figure 20.8 uses the same ordering but different aspect of the interactions: the presentation order of the item in the learning system. We can clearly see strong item ordering bias (Čechák & Pelánek, 2019), i.e., a high correlation between the presentation ordering and the order in which the students solve the items.

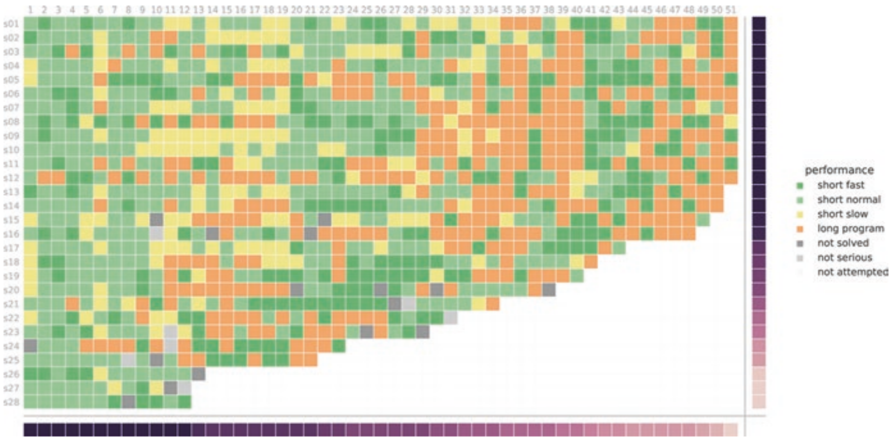


Fig. 20.7 Time-ordered student-item matrix for the same class and items. Each cell represents one student-item interaction and its color denotes the student's performance. The columns correspond to the within-student order of the interactions. Margins show the total number of interactions

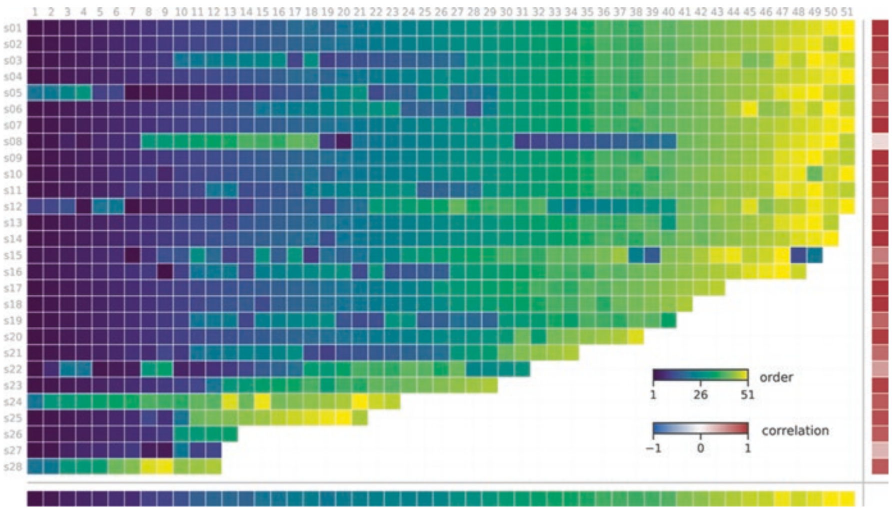


Fig. 20.8 Time-ordered student-item matrix illustrating ordering bias. Each cell represents one student-item interaction; its column corresponds to the within-student order of the interaction, while the color corresponds to the presentation order of the item. The bottom margin shows the mean presentation order, and the right margin shows the correlation between the presentation order and the within-student order

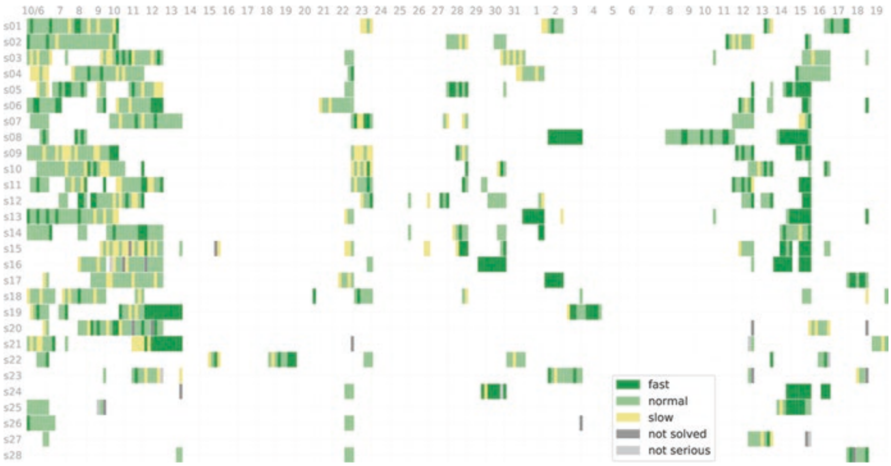


Fig. 20.9 Absolute-time student-item matrix for the same class. Each cell represents one interaction; its horizontal position corresponds to the date, color to the relative speed of the student

4.3 Absolute-Time Student-Item Matrix

Instead of using the time just to order the interactions, we can directly place the interactions according to the specific date they happened. The resulting visualization is much less compact but gives a more complete picture of the student behavior over time. We can even see possible interactions between the students. Figure 20.9 illustrates such an *absolute-time* student-item matrix. Unlike the previous examples, here we use relative response time to color each interaction so that we can see suspicious streaks of fast solutions. It seems that there was a deadline on November 15 and many of the students might have been cheating. To confirm our suspicion, we looked at the submitted solutions of the suspicious students before the deadline. Indeed, many of these solutions were identical or unlikely similar.

5 Summary

In this chapter, we provided a detailed discussion of the visualization of the student-item interaction matrix, which is one of the approaches to visualizing interaction between students and educational items, focusing on a global overview of student activity (“multiple students, multiple items” view).

In practical applications of this visualization, it is important to start with the clarification of the purpose. The student-item interaction matrix can be visualized in many ways; the purpose of the visualization should guide the design choices. To facilitate these choices, we provided a systematic discussion of visualization aspects and design options.

The visualization is also useful for researchers. Before applying statistical or machine learning techniques, we recommend inspecting data using the visualization of student-item interactions. This visualization provides insight into the biases and peculiarities of the dataset. It can also be useful for understanding and explaining results.

There is also a potential for future research on the visualization itself. In Sect. 20.3.3, we outlined several extensions of the basic visualization approach; most of these deserve further attention and elaboration. Another important direction is the evaluation of visualization. The usefulness of a particular visualization depends on a particular use case and a dataset, so we cannot expect simple, universal evaluation results. However, the description of evaluation methods and specific case studies would certainly be useful.

References

Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., & Koedinger, K. (2008). Why students engage in “gaming the system” behavior in interactive learning environments. *Journal of Interactive Learning Research, 19*(2), 185–224.

Bowers, A. J. (2010). Analyzing the longitudinal K-12 grading histories of entire cohorts of students: Grades, data driven decision making, dropping out and hierarchical cluster analysis. *Practical Assessment, Research, and Evaluation, 15*(1), 7.

Brusilovsky, P., Somyürek, S., Guerra, J., Hosseini, R., Zadorozhny, V., & Durlach, P. J. (2016). Open social student modeling for personalized learning. *IEEE Transactions on Emerging Topics in Computing, 4*(3), 450–461.

Čechák, J., & Pelánek, R. (2019). Item ordering biases in educational data. In *Proceedings of Artificial Intelligence in Education* (pp. 48–58). Springer.

Coffrin, C., Corrin, L., de Barba, P., & Kennedy, G. (2014). Visualizing patterns of student engagement and performance in MOOCs. In *Proceedings of Learning Analytics and Knowledge* (pp. 83–92).

Confrey, J., Gianopulos, G., McGowan, W., Shah, M., & Belcher, M. (2017). Scaffolding learner-centered curricular coherence using learning maps and diagnostic assessments designed around mathematics learning trajectories. *ZDM, 49*(5), 717–734.

Costagliola, G., Fuccella, V., Giordano, M., & Polese, G. (2008). Monitoring online tests through data visualization. *IEEE Transactions on Knowledge and Data Engineering, 21*(6), 773–784.

Desmarais, M., & Lemieux, F. (2013). Clustering and visualizing study state sequences. In *Proceedings of Educational Data Mining*.

Eagle, M., & Barnes, T. (2014). Survival analysis on duration data in intelligent tutors. In *Proceedings of Intelligent Tutoring Systems* (pp. 178–187). Springer.

Effenberger, T., & Pelánek, R. (2021). Validity and reliability of student models for problem-solving activities. In *Proceedings of Learning Analytics and Knowledge* (pp. 1–11).

France, L., Heraud, J.-M., Marty, J.-C., Carron, T., & Heili, J. (2006). Monitoring virtual classroom: Visualization techniques to observe student activities in an e-learning system. In *Proceedings of Advanced Learning Technologies* (pp. 716–720). IEEE.

Fu, X., Shimada, A., Ogata, H., Taniguchi, Y., & Suehiro, D. (2017). Real-time learning analytics for C programming language courses. In *Proceedings of the Learning Analytics & Knowledge* (pp. 280–288).

Janssenswillen, G., Depaire, B., Swennen, M., Jans, M., & Vanhoof, K. (2019). BupaR: Enabling reproducible business process analysis. *Knowledge-Based Systems, 163*, 927–930.

Johnson, M., Eagle, M., & Barnes, T. (2013). Invis: An interactive visualization tool for exploring interaction networks. In *Proceedings of Educational Data Mining*.

Khajah, M., Wing, R., Lindsey, R., & Mozer, M. (2014). Integrating latent-factor and knowledge-tracing models to predict individual differences in learning. In *Proceedings of Educational Data Mining*.

Lee, J. E., Recker, M., Bowers, A., & Yuan, M. (2016). Hierarchical cluster analysis heatmaps and pattern analysis: An approach for visualizing learning management system interaction data. In *Proceedings of Educational Data Mining* (pp. 603–604).

Mazza, R., & Dimitrova, V. (2007). CourseVis: A graphical student monitoring tool for supporting instructors in web-based distance courses. *International Journal of Human-Computer Studies, 65*(2), 125–139.

Molenaar, I., & Knoop-van Campen, C. (2017). Teacher dashboards in practice: Usage and impact. In *European Conference on Technology Enhanced Learning* (pp. 125–138). Springer.

Monti, D., Rizzo, G., & Morisio, M. (2019). Visualizing ratings in recommender system datasets. In *IntRS@ RecSys* (pp. 60–64).

Nixon, T., Fancsali, S., & Ritter, S. (2013). The complex dynamics of aggregate learning curves. In *Proceedings of Education Data Mining* (pp. 338–339).

Northcutt, C. G., Ho, A. D., & Chuang, I. L. (2016). Detecting and preventing "multiple-account" cheating in massive open online courses. *Computers & Education, 100*, 71–80.

Pelánek, R. (2017). Bayesian knowledge tracing, logistic models, and beyond: An overview of learner modeling techniques. *User Modeling and User-Adapted Interaction, 27*(3–5), 313–350.

Pelánek, R. (2018). The details matter: Methodological nuances in the evaluation of student models. *User Modeling and User-Adapted Interaction, 28*(3), 207–235.

Pelánek, R., & Effenberger, T. (2020). Beyond binary correctness: Classification of students' answers in learning systems. *User Modeling and User-Adapted Interaction, 27*(1), 89–118.

Reddy, S., Labutov, I., Banerjee, S., & Joachims, T. (2016). Unbounded human learning: Optimal scheduling for spaced repetition. In *Proceedings of Knowledge Discovery and Data Mining* (pp. 1815–1824).

Řihák, J., & Pelánek, R. (2016). Choosing a student model for a real world application. In *Building ITS bridges across frontiers (ITS workshop)*.

Sedrakyan, G., Snoeck, M., & De Weerdt, J. (2014). Process mining analysis of conceptual modeling behavior of novices–empirical study using JMermaid modeling and experimental logging environment. *Computers in Human Behavior, 41*, 486–503.

Song, M., & van der Aalst, W. M. (2007). Supporting process mining by showing events at a glance. In *Proceedings of Workshop on Information Technologies and Systems* (pp. 139–145).

Trcka, N., Pechenizkiy, M., & van der Aalst, W. (2010). Process mining from educational data. *Handbook of Educational Data Mining*, 123–142.

van der Aalst, W. M., Guo, S., & Gorissen, P. (2013). Comparative process mining in education: An approach based on process cubes. In *International symposium on data-driven process discovery and analysis* (pp. 110–134). Springer.

Wallner, G., & Kriglstein, S. (2013). Visualization-based analysis of gameplay data–a review of literature. *Entertainment Computing, 4*(3), 143–155.

Wang, C.-H., & Chen, C.-P. (2013). Employing online SP diagnostic table for qualitative comments on test results. *Electronic Journal of E-Learning, 11*(3), 263–271.

Chapter 21
Discovering Generative Uncertainty in Learning Analytics Dashboards

Ha Nguyen, Fabio Campos, and June Ahn

1 Introduction

K–12 schools in the United States have experienced a proliferation of data-driven decision-making (DDDM) tools and routines (Schildkamp, 2019). Learning dashboards can serve as a DDDM tool that fits into classroom routines to provide data about student interactions with one another and with learning artifacts, student performance in quizzes, or time spent on tasks (Verbert et al., 2013). An example of a routine is instructional coaching, where experienced educators (coaches) support school teachers in generating insights based on classroom data (Nelson & Slavit, 2008). Within this context, we aim to understand the sensemaking strategies that coaches and teachers enact when using a learning dashboard. In this chapter, we explore sensemaking by observing how educators frame an instructional scenario from data, explain the patterns, and reflect on their action or propose follow-up actions that may bring about instructional changes.

Our initial data exploration, gathered through a series of interviews and think-aloud sessions with teachers and coaches, revealed fine-grained, multifaceted sensemaking actions that are *emotional*, *analytical*, and *intentional* (Campos, Ahn, DiGiacomo, Nguyen, & Hays, in press). This sensemaking framework allows us to explore a combination of response patterns that different types of K–12 educators (teachers and coaches) present when viewing dashboards, which helps us better understand the rich experiences people have with dashboards. Our guiding question

H. Nguyen (✉) · J. Ahn
University of California – Irvine, Irvine, CA, USA
e-mail: thicn@uci.edu; junea@uci.edu

F. Campos
New York University, New York City, NY, USA
e-mail: fabioc@nyu.edu

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_21

is: What patterns of sensemaking does our framework reveal, and how are these patterns potentially conducive to instructional improvement?

A core idea that is vital to our analysis is the phenomenon of "not knowing." Within teaching and learning, researchers have argued that "not knowing" when trying to make sense of information may be productive if it opens up space for reflection (Schön, 1987). The *uncertainty* of not knowing may trigger question asking and conversations, key practices when making sense of data and taking action upon the data (Horn et al., 2015; Knight, 2011; Wise & Jung, 2019). Our field observations of coaches and teachers in their daily practices also revealed that their interactions were often inquiry-driven, where coaches guided teachers to formulate questions rather than prescribing a path of improvement. However, extant LA research has not examined how to foster productive forms of not knowing when approaching learning data, which is important to help educators revisit existing practices, uncover novel instructional insights, and open up opportunities to explore different pedagogical moves to enrich student learning. Exploring how LA dashboards can support uncertainty for deeper reflection became the motivation for this chapter.

Our approach reveals a particular pattern of sensemaking: the combination of asking questions and other analytical actions that is potentially productive in sustaining inquiries about what data represents and leading to conjectures about instruction. We term this pattern *generative uncertainty*, an intentional ambiguity that may lead to further judgment and inference, in LA dashboards. We illustrate what generative uncertainty looks like from the perspective of K–12 educators and discuss the design for uncertainty in LA dashboards, to bridge the gap between insights from data and action (Verbert et al., 2020).

With this chapter, we make two contributions. First, we explore the notion of generative uncertainty and its implications for human-centered learning analytics – the development of LA tools and practices that take into account a diverse range of human factors (Buckingham Shum et al., 2019). Second, we offer conjectures for future design experiments, with special attention to dialogic protocols that might facilitate generative uncertainty. To that end, we present theory and empirically driven recommendations for improving LA dashboards.

2 Theoretical Background

2.1 Data Sensemaking with LA Dashboards

The design and evaluation of learning dashboards is a major area of inquiry in LA research (Duval, 2011; Verbert et al., 2013). LA dashboards typically support and augment human decision-making by offering visualizations of learning data (Verbert et al., 2020). For example, many dashboards provide information about student progress and learning behaviors, which can be useful for students to reflect on their learning or for teachers to augment their practice (Schwendimann et al., 2016).

As dashboard tools proliferate, researchers have focused on how sensemaking occurs with such tools. In general, sensemaking describes a broad array of practices and cognitive processes, which people undertake to comprehend, interpret, and attach meaning to data visualizations (Klein et al., 2007; Lee et al., 2015). Ultimately, the hope is that more productive sensemaking with dashboards may lead users – in our case, educators – to develop insights and that well-designed interfaces or user experiences with data may promote these insights (Yi et al., 2007).

Prior research has illuminated the innovative potential for dashboards to organize educators' reflection and prevent teachers from "driving blind" (Duval, 2011). At the same time, researchers have argued that dashboards may fall short in transforming classroom insights into pedagogical action (Few, 2013; Verbert et al., 2020; Wardrip & Shapiro, 2016; Xhakaj et al., 2017). Just showing data to stakeholders is not enough. Even if teachers or students interpret the data correctly, they may fail to understand the "call to action" or make meaningful changes to their behaviors (Greller & Drachsler, 2012).

Researchers have argued that making sense of data involves analytical reasoning, where users interact with the information at hand and create a plausible narrative for the data (Echeverria et al., 2018). Thomas and Cook (2006) define analytical reasoning as a process to generate insights that, combined with the user's judgment, create an overall narrative about the phenomenon described by data. This analytical act often combines multiple data sensemaking operations such as comparing, monitoring, or exploring information (Voyiatzaki & Avouris, 2014). Even in learning dashboards that provide teachers with direct recommendations for action, such as alerting teachers to groups in need of support, researchers observe that teachers still try to acquire as much information about other groups and classroom contexts as they could before making decisions (Martinez-Maldonado et al., 2020; van Leeuwen & Rummel, 2020).

In sum, educators' sensemaking of data likely involves not only recall and reporting of events but also the ability to notice and contextualize these data. There are limited examples in LA that have attempted to distill these sensemaking patterns, especially in K–12 schools. To this end, we draw from the education research in teacher noticing and data use in schools to illuminate the different ways that educators may interact with learning dashboards.

2.2 Data Use in K–12 Schools

Using data to inform instruction is a common practice in K–12 schools, and the unique organizational features of K–12 schools influence the sensemaking process (Means et al., 2011). Educators' interpretations of snapshots of student learning data contain multiple parts: identifying the notable moments, bringing in contextual knowledge to reason about classroom interactions, and making connections between classroom observations and teaching and learning principles (Borko et al., 1990; van Es & Sherin, 2006; van Es & Sherin, 2008). Educators may apply different frames of reference, for example, drawing from past experiences of familiar situations, recounting classroom events, or thinking about broader principles of teaching and learning (Borko et al., 1990; Dervin, 2005; van Es & Sherin, 2002). Interpretive acts combine multiple responses, to examine what triggers the noticing act and how educators analyze what they notice.

Educators improve their noticing for instructional improvement when they move from simply recounting events to analytical and responsive comments on instructional practices (van Es & Sherin, 2008). Asking questions and building narratives around data is central to moving from recounting to analyses of evidence of student learning (van Es & Sherin, 2002). In fact, several frameworks on improving teacher noticing emphasize the importance of question prompts that direct teachers to consider evidence of student thinking and make connections between their practices and student understanding (Santagata, 2011). The act of questioning moves teachers away from focusing on their individual practices and, instead, opens space for connecting the dots to explain student learning and participation patterns and building conjectures for alternative instructional practices (Santagata, 2011; van Es & Sherin, 2008).

In K–12 schools, educators often form interpretive communities around classroom data to inform future instructional moves (Bocala & Boudett, 2015; Cobb et al., 2020). This collective sensemaking process is particularly significant when conducted between classroom teachers and their instructional coaches (Horn et al., 2015; McCoy & Shih, 2016; Nelson & Slavit, 2008). Coaches are experienced educators who collaborate with classroom teachers on learning content and pedagogy to improve student learning (Knight, 2011). Coaches and teachers can work together in one-on-one routines or group mentorship between a coach and several teachers. In either case, asking the right questions during the conversation between coaches and teachers is key to effective coaching (Knight, 2011). For example, coaches and teachers can pose questions around certain student learning patterns and devise a concrete action plan to address those patterns. Such practice may support and augment educators' data sensemaking (Murnane et al., 2005; Nelson & Slavit, 2008) and even improve student achievement (Marsh et al., 2010).

2.3 The Role of Uncertainty in Sensemaking Process

How can we support educators to "ask the right questions" and build narratives around data, given the importance of such practices in effective teacher noticing and coaching (Knight, 2011)? To answer this question, we bring in insights from education and data visualization research. Scholars of teaching and learning have emphasized how uncertainty may be conducive to teachers' reflection and questioning (Floden & Clark, 1987; Helsing, 2007). Teachers experience uncertainty regularly when they determine which content to include, how difficult the content can be for different student groups, or how to improve teaching. In fact, "teaching is a profession characterized by inherent uncertainty, and learning to cope with uncertainty is a major part of developing professionally" (Munthe, 2003, p. 801). Floden and

Clark (1987) argue that the appropriate responses to uncertainty should not be a discouragement. Rather, teachers should use uncertainty to reflect on pedagogical choices and take "the best bets" (p. 11). Alternatively, they can seek additional information to reduce uncertainty and arrive at better teaching practices.

Data visualization researchers have highlighted similar needs to recognize uncertainty and visualize it to inform practice (Johnson & Sanderson, 2003; Thomson et al., 2005). Visualizations can denote uncertainty using a range of techniques, such as blurring the data points that are less certain than others, showing deviation, or leveraging graphical distance (i.e., the closer two data points are, the more related they are; Epp & Bull, 2015; Potter et al., 2011). Questioning data certainty, like how credible and consistent different data sources are, can help to produce less biased analyses and more informed decisions (Thomson et al., 2005). However, in a review of 106 visualizations of educational data, Epp and Bull (2015) find that uncertainty has a minimal presence in those visualizations. Wiring cues and opportunities for questioning data displayed by learning systems can provide additional information to improve users' decision-making (Epp & Bull, 2015).

In sum, research on teacher learning and data visualizations both suggest the need to denote uncertainty as a means to improving insights and future actions. In our research, we did not focus on specific techniques to visualize uncertainty. However, we examined specific patterns of responses from educators that suggested recognition of and responses to uncertainty, to illuminate their roles in teacher-facing LA dashboards. These responses included recognition of opportune moments that contradict a priori knowledge or assumptions, finding the appropriate time to ask questions and seek information, or envisioning potential actions (Floden & Clark, 1987). These patterns become our starting point to frame how educators respond to uncertainty when interacting with dashboards.

3 Methods

In this chapter, we draw from a larger, mixed-method study where we attempt to create a typology of sensemaking patterns when looking at data from a LA dashboard (Campos et al., in press). We first outline the study context and the overall analytical approaches from the larger study. Then, we illustrate the affordance of delving into code co-occurrences to reveal finer-grained sensemaking patterns, as opposed to looking for the presence of single codes.

3.1 Study Context

This study takes place in part of a larger network of four research-practice partnerships (RPP) between four universities, designers, and four school districts in different regions of the United States (South 1, South 2, Northwest, and West). This context gives us a unique way to deeply explore how sensemaking happens from different vantage points of teachers and coaches in coaching cycles. The goal of the RPP is to develop practical measures (PMs) of classroom instruction for teachers and instructional coaches in sixth- to eighth-grade Mathematics classrooms. PMs are frequent, formative measures that aim to support teachers' daily practice by providing actionable data to inform instructional practice (Yeager et al., 2013).

In this study, PMs come in the form of a survey on student opinions of the quality of whole class and small group discussions, as a proxy of their mathematical thinking (Jackson et al., 2016). An example of survey questions is "In your small group, did listening to other students help you make your thinking better?" (Fig. 21.1). Student responses are collected electronically (via Google Forms) or with pen and paper, anonymized, and communicated to educators via Edsight, a dashboard that our research team developed with educators from the RPP during the course of 3 years (2018–2020).

Figure 21.1 presents example visualizations from the dashboard. A range of visualizations invite educators to conduct queries of student learning in single or multiday reports, make comparisons of student responses to different instructional strategies, and take notes for future pedagogical decisions. The dashboard is focused

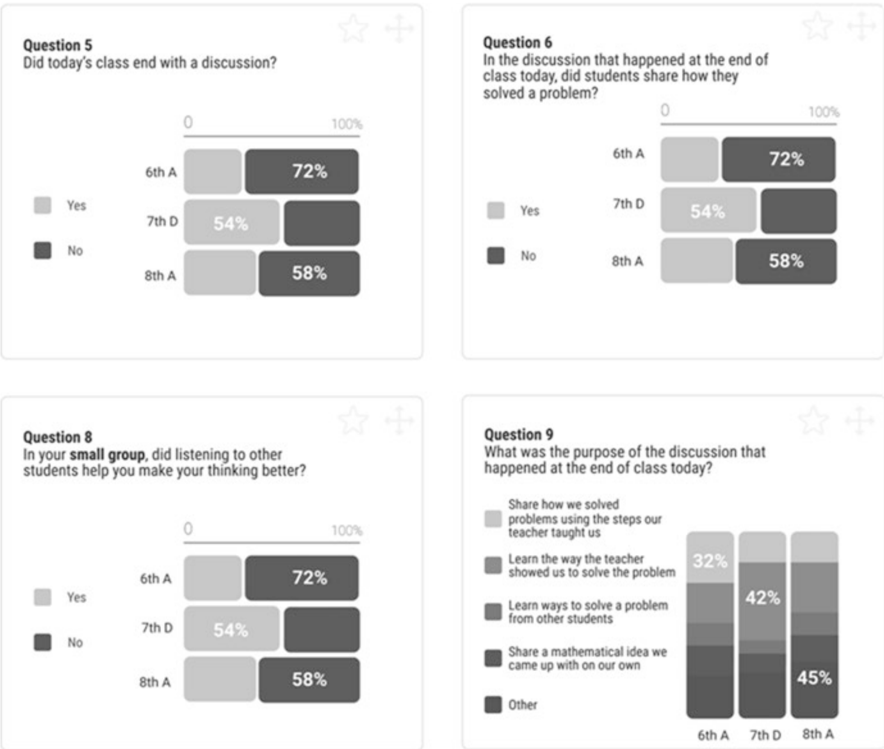


Fig. 21.1 Example visualizations in our LA dashboard

on PMs and does not include information such as student grades and attendance. Still, the rich interface provides a space for teachers and coaches to reflect on instruction.

3.2 Participants

Participants included nine middle-school Mathematics teachers and nine instructional coaches, who were sampled by convenience from the partner school districts (South 1, South 2, Northwest, and West). We purposefully recruited coaches and teachers, because both roles collaborate in different settings (e.g., one-on-one coaching or department meetings) and may thus offer complementary sensemaking perspectives of data visualizations. Most of the sample was female (15 female, 3 male). The majority of participants, except one coach, reported no experience with visual LA tools. Participants were distributed as follows: six teachers from South 1 district, five coaches from South 2 district, three teachers and two coaches from Northwest district, and two coaches from West district. On average, participants reported 4 years of experience in their current roles.

3.3 Data Collection

Data sources included think-aloud sessions and semi-structured interviews, conducted through video call ($n = 12$) or in person ($n = 6$). All sessions were conducted by our research team and took approximately 1 h. Sessions were video and audio recorded and automatically transcribed, with research team members checking each transcript's quality.

We invited participants to engage in the think-aloud tasks and the interviews individually, rather than having teachers and coaches look at data together. In collaborative interactions, individuals can influence one another's interpretation to co-construct understanding (Knight et al., 2013). Because our goal was to capture potential differences in how each professional role made sense of the visualizations, we opted for the individual procedures.

In each session, we asked participants to think aloud as they interacted with a series of visualizations of student survey data (Fig. 21.1). The visualizations came from teachers' own data (when the participating teachers and coaches had administered the surveys to their students) or exemplar data (modeled to parallel actual, anonymized classroom data, when teachers' own data were unavailable). Prior to the think-aloud tasks, we confirmed with our RPP educators that the exemplar visualizations reflected their work contexts. In addition to the think-alouds, we asked open-ended, semi-structured questions to understand whether the visualizations of student surveys reflected participants' work contexts.

We chose think-aloud (TA) protocols as our primary method for data collection because these protocols can reveal heuristics involved in participants' data sensemaking (Fonteyn et al., 1993; Liu & Stasko, 2010). TAs permit participants to use their own language and contextual references when reacting to stimuli (Charters, 2003). Moreover, TAs are often utilized when participants need to engage in problem-finding and/or problem-solving tasks, such as when using visualizations to make inferences (Fonteyn et al., 1993). In our study, we asked participants to verbalize their thoughts as they navigated through the dashboard and interacted with graphs. To avoid biasing the data, we refrained from directly guiding or stimulating participants' responses (Van Es & Sherin, 2002). Instead, we provided minimal guidance with prompts such as "What did you notice in this report?" and "What does this data tell you?". If participants remained silent for longer than a few seconds, we reminded them to "please, keep thinking aloud."

Meanwhile, the open-ended interview questions aimed to capture contextual factors that may influence participants' sensemaking. Example questions included "Walk us through a normal day at work for you. What does it look like?", "In what ways is the information presented in the dashboard helpful to you?", and "In what ways does this information reflect your work context?".

3.4 Analyses

Our data analyses consisted of five phases, which we describe in more detail in Campos et al. (in press). In *phase one*, we identified interpretive acts from the transcripts. Each interpretive act consisted of a complete reaction to a visualization or the data report as a whole. Our decision to divide the data into smaller excerpts is grounded in the research on teacher noticing (Sherin & Russ, 2014; van Es & Sherin, 2006; van Es & Sherin, 2008). The following excerpt illustrates an interpretive act from Coach P. (District Northwest) when viewing a single graph:

> If the teacher is doing a lot of showing the process and everything, this is something that we've really worked hard trying to switch. The students are doing more of the talking than the teacher. So this would also be one that I would try and watch overtime with this teacher to see if we can increase student talking.

In *phase two*, we grouped response types into three overarching categories: emotional, analytical, and intentional. The *emotional* dimension captured participants' affective responses, such as feelings of confusion (e.g., "I am not sure what this means") or positive surprise (e.g., "I was pleasantly surprised that students for the most part thought they were contributing to discussion"). We built on prior work in LA and organizational studies and included the emotional dimension, which has noted the importance of attending to participants' emotions when reacting to visualizations (e.g., Wise & Jung, 2019). The *analytical* dimension reflected responses focused on reasoning and creating narratives with data. This dimension included question asking behaviors, comparisons, and connections to contextual information beyond what was displayed by the dashboard. Finally, the *intentional* dimension indicated whether participants communicated intentions or plans for instructional adjustments (Borko et al., 1990). We did not include a "Pedagogical Action" category, because we did not capture actual instructional practices following participants' interactions with the visualizations.

After defining the analytical dimensions and units of analyses, in *phase three*, we engaged in an open coding process to generate descriptive codes for each dimension (Miles & Huberman, 1994). Several codes emerged from this stage, for example, "empathy for students," under the emotional dimension, "recalling events," in the analytical dimension, or "improvement plan" under the intentional dimension.

In *phase four*, the research team refined the list to generate a final codebook. We discarded or merged codes with low frequencies into more significant codes. Table 21.1 presents the final codes and their definitions.

Finally, *phase five* involved a new round of coding, where the team applied the final codebook to all excerpts. Each excerpt received codes for all three dimensions: one for emotional, up to two for analytical (due to participants' focus on reasoning, compared to the other two dimensions), and one for intentional responses. In all three categories, a "No response" code was included, indicating either no evident emotion, analysis, or intention. We established substantial inter-rater reliability (Cohen's $k = 0.82$) and resolved code disagreements through discussion.

3.5 Examining Code Co-occurrences

We argue that a more granular understanding of educators' data sensemaking can provide key insights into how K–12 teachers' and coaches' different vantage points may render distinct heuristics when facing learning data. While it is expected that professionals with distinct roles might approach data differently, we were curious about how coaches – who are typically recruited from pools of more seasoned teachers – would engage in data inquiry (e.g., conjecturing about underlying causes of a given result) in comparison with classroom teachers.

To observe how such professionals responded to learning data, we added a final layer of analysis by building a matrix of code co-occurrence per excerpt, considering all three dimensions (emotional, analytical, and intentional). For example, we counted the frequency of "asking questions" (analytical dimension) and "planning" (intentional dimension) for each professional role (i.e., teachers and coaches). While this matrix provided a myriad of different cases, in this study we focused our analysis on how educators manifested *uncertainty* towards data (Fig. 21.2). We focused on question asking because it is a key practice to building conjectures around data and contributing to more effective DDDM (Knight, 2011; Santagata, 2011; van Leeuwen & Rummel, 2020). We paid close attention to diverse patterns (co-occurrence of codes and not single codes) involving question asking (which we associated with uncertainty). In the following section, we illustrate and analyze the most salient cases.

Table 21.1 Framework of educators' responses to visual data

Dimension	Response type	Definition
Emotional	Positive surprise	Educators see results superior to expectations
	Negative surprise	Educators see results inferior to expectations
	Satisfaction	Educators are satisfied with what the data shows
	Empathy	Educators consider what motivated students to provide a certain answer
	Distrust	Educators distrust the data, the instrument of collection, or the visualizations
	Responsibility	Educators feel directly responsible for the results
	No response	Educators do not express any emotion related to the data
Analytical	Restating	Educators restate what is represented by the data in their own terms
	Asking questions	Educators ask further questions from data
	Recall	Educators remember or backtrack to past events from data
	Attribution of causes	Educators attribute the cause of the result to something external to the data
	Confusion	Educators are confused by what the data displays
	Gap filling	Educators fill in the gap of what the data displays with opinions, beliefs, stances on teaching, etc.
	Connecting the dots	Educators connect multiple instances or aspects of the data
	Comparing	Educators compare more than one instance or feature of the data
	Part vs. whole	Educators interpret a part of data as representative of the whole, or vice versa
	Prediction	Educators predict how results would happen under different conditions
	Multiple lenses	Educators consider that data can be analyzed from multiple lenses
	Judgment	Educators formulate an opinion (about teachers, other students) based on data
	Confirmation	Educators confirm a belief or prediction based on what they interpret
	No response	Educators do not convey any form of analysis of the data
Intentional	Action intention	Educators communicate the intention of improving their (or someone's) instruction
	Planning	Educators list actions they would like to take in order to improve instruction
	Seek information	Educators communicate the need to know more (e.g., causes) to act upon the data
	No response	Educators don't mention potential actions of instructional change

Adapted from Campos et al. (in press)

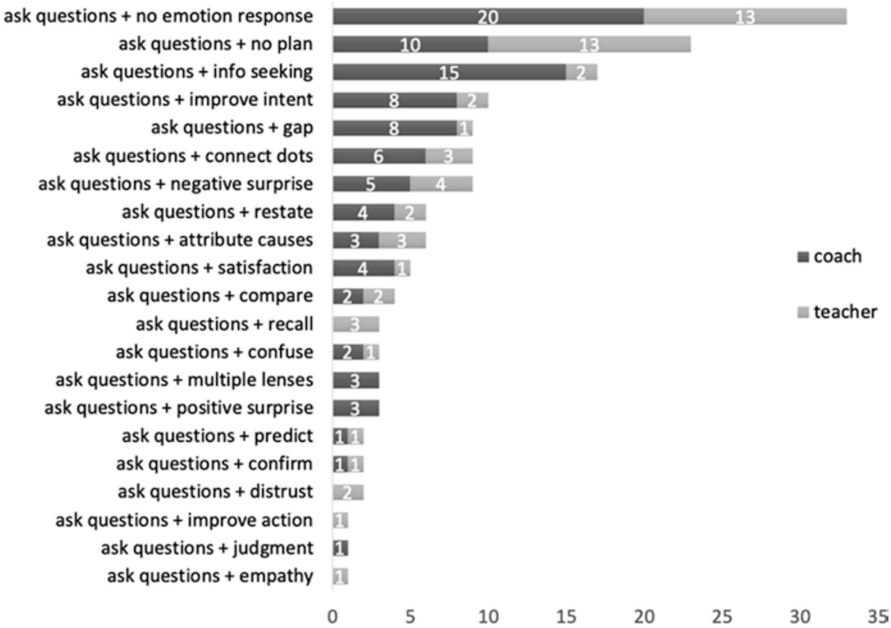


Fig. 21.2 Co-occurrences of asking questions and other sensemaking actions, by professional roles

4 Illustrative Cases of Uncertainty

4.1 Asking Questions and No Plan

Asking questions, with no intention plan, was one of the most common patterns among both coaches and teachers (coach, 10 occurrences; teacher, 13 occurrences). We used this pattern to differentiate between uncertainty that could be generative; that is, leading to further meaning-making and potential action, versus responses that may not lead to clear plans. In one case, teacher L (District South 2) was asking questions about several items in the same survey, looking for the same pattern of student participation (e.g., “are students sharing? are they comfortable”):

> Did students share how they solved it or not? Just to know that at least they are sharing in the same way of looking at the one asking if they're comfortable or not. Are they sharing? Are they comfortable? Then you can try to figure out if they are sharing, let's see what else I can get them to share. That's good. That's good. I think this on that same line, what do they feel like they're getting out of it? Then this one I was getting to. Let me glance over this one more time. Yeah, I would say as far as what's guiding my instruction the most, I would say this one, truthfully.

We highlighted this instance, because even though educators may ask questions as they interacted with data dashboards to make sense of the data, they may not push the questions further to reflect deeply on their practices or gain new insights. Teacher L’s questions, for example, were meant to confirm his beliefs about how students responded to his instructional practices. We contrasted the case with the following excerpts, which illustrated the deeper engagement of educators when facing uncertainty.

4.2 Asking Questions and Connecting the Dots

Our data analysis revealed a notable pattern, where educators asked questions to make sense of the data trends and link multiple data instances to form narratives. This behavior was observed among both coaches (six co-occurrences) and teachers (three co-occurrences). In one instance, Coach A (District West) articulated a "disconnect" when comparing the data patterns in two questions. She pointed out that in this context, the teachers were likely giving direct instruction and doing a majority of the talking. She immediately noticed that this hypothesis would not fit with how students answered another question, with half of the students stating that listening to other students helped their thinking. This dissonance led the coach to ask follow-up questions: "Like why, I want to know why. Why are students responding in this way". Teachers also expressed the potential of *connecting the dots* across multiple survey instances.

> One of the things I would want to see over time would be, how comfortable my students are with sharing their thinking in class. I think that as the school year goes on that we're building that sense of community and that they're more comfortable sharing. And so if it's a consistent question on all the surveys that would be actually just easy to see with the whole class discussion. And then I would like to compare their comfort, or their level of comfort with sharing [in] whole class versus small group [survey]. (Teacher M, District Northwest)

In this example, teacher M identified students' level of comfort in sharing their thinking as the focal point of inquiry. She raised questions about how this comfort level may change over time, as well as how it may differ between different learning situations (i.e., whole group versus small class). We note that such wondering may open up further opportunities for information seeking and reflection in ways that facilitate teachers to improve their instructional practices.

4.3 Asking Questions and Gap Filling

This pattern was particularly prevalent among coaches (eight co-occurrences, compared to one occurrence from teachers). When looking at survey results from a question that asked whether students were comfortable sharing their thinking, Coach D raised several points of inquiries:

> And today's whole class discussion so 20% said yes. And I wonder who is doing the talking. And how many students were really doing the talking. And what their statuses in the classroom and how again, we could shift that. (Coach D, District Northwest)

As she raised those questions, she attempted to draw from her experiences, values, and beliefs about classroom experiences and shifting the learning responsibilities from teachers to students, an important noticing shift for improvement (van Es & Sherin, 2008).

> So students are making meaning together. And then really start thinking about how to help the teacher values student discourse and looking at ways to shift that responsibility for learning to students. (Coach D, District Northwest)

Triangulating observation from data with external explanations (i.e., one's own experiences) can serve as the first step towards insight generation (Wise & Jung, 2019), which in this case promotes an improvement intention to investigate ways to encourage teachers to value student-driven discourse.

4.4 Asking Questions and Seeking Information

Asking questions and seeking information was among the most frequent co-occurrences along the analytical-intentional dimension (17 co-occurrences). When educators wondered about the data contexts or the underlying reasons for students' survey patterns, they naturally expressed an intention to seek additional information. This pattern was more frequent among coaches (15 occurrences) than teachers (2 occurrences). For example, Coach A (District West) expressed an intent to consult the teacher's ideas to understand the classroom contexts and see if their ideas about student learning aligned.

> I think I would, I would ask her what she did. Had she seen this data. That's my first question. What are her questions that came up for her and looking at his data because I already know the question that came up for me, but it may not be the same question that she asked. I want to ask her what she thinks about. … And, what did she think about this % of students who said that it was helpful to hear other people in the classroom. And what did that look like and sound like to her in her classroom.

Collective inquiry between teachers and coaches requires a common language that accounts for the range of potential reactions to data that teachers and coaches might have. The initial questions that Coach A has in this question can serve as the starting point to facilitate dialogue and reflection with teachers while highlighting the need for further information and respect of the diverse stances across multiple professional roles.

4.5 Asking Questions and Action Intention

We observe that inquiry-oriented questions in response to the data co-occur with improvement action intention, most notably among coaches (eight co-occurrences, compared to teachers, two co-occurrences). Take an example of Coach P (District

Northwest), who transitioned from asking a series of questions around the data, for example, “What kind of lessons are they doing on those days?”, to pinpointing the areas of focus for improvement:

> ... these two days here that they’re gaining a better understanding when other kids are sharing. So that’s good, so this might be something to kind of celebrate. But then, maybe even be asking, Okay, so what happened on these two days you’re doing these, all the rest look fabulous. But you know what’s going on these days that we could move this further along.

In sum, our vignettes highlight the different ways educators engage with data representations. The desire to make data inquiries or triangulate different data aspects tends to co-occur with an intent to seek future information or act upon the data. Interestingly, we observe more patterns of asking questions – action intent and asking questions – information seeking among coaches than teachers. This difference points to potential variance in frames of reference between the professional roles and highlights the design opportunities to facilitate more interpretative acts in LA dashboards.

5 Discussion

5.1 Generative Uncertainty

When writing about how individuals think, Dewey (1910) observed that uncertainty is the antecedent of judgment and, by extension, inference. In his words, “Unless there is something doubtful, the situation is read off at a glance; it is taken in on sight, i.e. there is merely apprehension, perception, recognition, not judgment” (p. 102). Revisiting what Dewey suggested a century ago, we propose that to encourage insight generation and data sensemaking habits among educators, we may do well to promote *generative uncertainty* in our systems and tools of visual analytics. We define generative uncertainty as an intentional analytical stance, a within-boundary ambiguity about the data that may benefit further meaning-making and exploration.

Our illustrative cases illuminate the different patterns of question asking and hypothesizing that K–12 teachers and instructional coaches manifested when reacting to LA visualizations. Uncertainty as revealed by question asking, in combination with other analytical and intentional acts, was more prevalent within coaches who were typically more experienced teachers. These responses denote a degree of uncertainty towards the data and often lead to instructional intent, whether to seek more information or to pinpoint action areas for improvement. Such reactions may stand in opposition to others such as showing no additional actions, recounting classroom events, or attributing causes, which suggest certainty about what data represents and leave less room for further inquiry. These actions suggest a certain “knowing” stance, which were more common among teachers in our study. Because uncertainty is inherent in the teaching profession (Munthe, 2003), recognizing and supporting the uncertainty of "not knowing" is crucial because it can push educators towards deeper reflection of their instructional practices.

5.2 Design Requirements for Generative Uncertainty

How do we promote generative forms of uncertainty in LA tools? We offer a few conjectures as inspirations for future design.

First, system designers should consider how to *build routines for generative question asking*. Our analyses reveal that a combination of question asking and analytical responses such as connecting the dots, gap filling, or action intention is potentially a relevant habit to be encouraged by a digital learning dashboard, to facilitate productive emotional, analytical, and intentional reactions from users. This finding parallels what Wise and Jung (2019) found when studying sensemaking in the higher education sector: learning dashboards need to support sustained question generation across multiple sessions of use. Question asking routines might be especially applicable towards classroom teachers, who appeared in our data set to be more assertive in finding explanations, thus leaving less space for filling gaps or imagining new questions to pursue, compared to instructional coaches.

Tools that promote question asking may stand in contrast to recommendation systems that prescribe specific instructional actions based on the data (Bocala & Boudett, 2015). Thus, the most effective dashboard design may need to strike a balance between automating recommendations and stimulating the development of new mental models of the data (Liu & Stasko, 2010). Consonant with the extant HCI literature, our analyses point to the potential of interactive tools and functionalities, such as screen annotation and information juxtaposition, in ways that promote user question generation, reflection, and insights (Grammel et al., 2010; Romat et al., 2019; Srinivasan et al., 2018).

Second, generative uncertainty may also be promoted by *scaffolding inquiry-driven, dialogic interactions between users and platforms*. In a school setting, data sensemaking might benefit from sustained and structured dialogue among peers. This view is supported by Verbert et al. (2020) who suggest that LA researchers need to pursue conversational systems that facilitate analytical reasoning and move away from "one-way" awareness dashboards. In one sense, our think-aloud protocol served as a tool to promote reflection and dialogue for the teachers and coaches in our partnership. Our protocol balanced neutrality with open-ended probes to encourage reflection and spur insight. We often started the interviews with low inference questions such as "what do you notice? ", "what's the story here?", and "what else do you see?". This open-ended structure allowed us to capture potential pedagogical implications following data interpretation. We also intentionally stimulated the users with follow-up probes such as "what might this mean for your practice?" and "why is this important for you?". We found that both neutral questions and follow-up probes were beneficial for keeping the flow of sensemaking and that these two communicative moves might serve as models for also designing meaningful prompts in data dashboards.

Considering that human mediation will not always be available, designers and researchers may need to intentionally develop communicative interventions to promote sensemaking. Scaffolding communicative prompts into learning dashboards requires attention to the nature of interactions between educator and machine. It requires a deliberate, designed reframing of communication processes (Dervin, 2005). Van Es and Sherin (2002), through their work with video-recorded classroom data, found that scaffolding interactions among educators was key to facilitating sensemaking. In a dashboard, this could take the form of simple question prompts, annotations, or shared notes between users. For example, Echeverria et al. (2018) found that teachers who were exposed to exploratory data – charts infused with narrative text and highlights – were more likely to articulate thoughts and insights, as well as make connections to potential improvement strategies, and then those exposed to simple data visualizations. Through shared annotations placed over data points, or intentionally designed narrative elements, simple graphs might convert into storytelling tools to encourage data sensemaking.

Such critical examination of how to scaffold inquiries in data dashboards is especially important given that educators' sensemaking can be overshadowed by biased views about students' abilities. We contrast these biases with productive forms of generative uncertainty – sensemaking acts that can invite subsequent meaning-making and exploration. Each of the illustrative cases that we draw on in this chapter can take a counterproductive direction, such as when teachers ask questions and fill in the gap to construct a deficit-oriented narrative (Bertrand & Marsh, 2015; Garner et al., 2017). Bertrand and Marsh (2015), for example, observed teachers' making sense of student learning data and noted that teachers' questions and interpretation about next steps for instruction frequently focused on student characteristics. These practices may reinforce low expectations for certain student groups, such as exceptional students or English language learners. Wise et al. (2021) proposed alternative stances in learning analytics, such as prompting users to develop counter narratives that reflect on and recognize the different strengths of minoritized groups. We call for future research to consider how to detect and design for combinations of asking questions that are generative, as opposed to exacerbating biases.

6 Conclusion

Our data suggests that the vantage points from teachers and coaches are reflected by distinct patterns of response to dashboard data visualizations. We find that some of these patterns may represent what we termed *generative uncertainty*, or an intentional and potentially productive ambiguity that may lead to further judgment and inference. Considering that learning dashboards still often fall short in transforming insights into action (Verbert et al., 2020), we see generative uncertainty as a key stance to information delivered through learning dashboards, and one that can be intentionally designed for. We offer insights for future design needs, such as to build explicit routines for question asking and to scaffold inquiry-driven, dialogic reactions. We hope that these first steps towards exploring and designing for generative uncertainty offer a critical space for future research to foster data sensemaking and, ultimately, meaningful instructional improvement upon data.

Acknowledgments This material is based upon work supported by the National Science Foundation under Grants No. 1719744, 1620851, 1621238, and 1620863. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the view of the National Science Foundation. We thank all teachers, instructional coaches, and district leaders who participated in this study.

References

Bertrand, M., & Marsh, J. A. (2015). Teachers' sensemaking of data and implications for equity. *American Educational Research Journal, 52*(5), 861–893.

Bocala, C., & Boudett, K. P. (2015). Teaching educators habits of mind for using data wisely. *Teachers College Record, 117*(4), n4.

Borko, H., Livingston, C., & Shavelson, R. J. (1990). Teachers' thinking about instruction. *Remedial and Special Education, 11*(6), 40–49.

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonaldo, R. (2019). Human-Centred learning analytics. *Journal of Learning Analytics, 6*(2), 1–9. https://doi.org/10.18608/jla.2019.62.1.

Campos, F., Ahn, J., Digiacomo, D., Nguyen, H., & Hays, M. (in press). One chart, many meanings: Making sense of sensemaking in learning analytics dashboard design. *Journal of Learning Analytics*.

Charters, E. (2003). The use of think-aloud methods in qualitative research: An Introduction to think-aloud methods. *Brock Education: A Journal of Educational Research and Practice, 12*(2), 68–82.

Cobb, P., Jackson, K., Henrick, E., & Smith, T. M. (2020). *Systems for instructional improvement: Creating coherence from the classroom to the district office*. Harvard Education Press.

Dervin, B. (2005). Sense-making theory and practice: An overview of user interests in knowledge seeking and use. *Journal of Knowledge Management*.

Dewey, J. (1910). What is thought. How We Think, 1–13.

Duval, E. (2011, February). Attention please! Learning analytics for visualization and recommendation. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 9–17).

Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018). Exploratory versus explanatory visual learning analytics: Driving teachers' attention through educational data storytelling. *Journal of Learning Analytics, 5*(3), 72–97.

Epp, C. D., & Bull, S. (2015). Uncertainty representation in visualizations of learning analytics for learners: Current approaches and opportunities. *IEEE Transactions on Learning Technologies, 8*(3), 242–260.

Few, S. (2013). *Information dashboard design: Displaying data for at-a-glance monitoring* (Vol. 5). Burlingame: Analytics Press.

Floden, R. E., & Clark, C. M. (1987). *Preparing teachers for uncertainty*.

Fonteyn, M. E., Kuipers, B., & Grobe, S. J. (1993). A description of Think aloud method and protocol analysis. *Qualitative Health Research, 3*(4), 430–441.

Garner, B., Thorne, J. K., & Horn, I. S. (2017). Teachers interpreting data for instructional decisions: Where does equity come in? *Journal of Educational Administration*.

Grammel, L., Tory, M., & Storey, M. A. (2010). How information visualization novices construct visualizations. *IEEE Transactions on Visualization and Computer Graphics, 16*(6), 943–952.
Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Journal of Educational Technology & Society, 15*(3), 42–57.
Helsing, D. (2007). Regarding uncertainty in teachers and teaching. *Teaching and Teacher Education, 23*(8), 1317–1333.
Horn, I. S., Kane, B. D., & Wilson, J. (2015). Making sense of student performance data: Data use logics and mathematics teachers' learning opportunities. *American Educational Research Journal, 52*(2), 208–242.
Jackson, K., Henrick, E., Cobb, P., Kochmanski, N., & Nieman, H. (2016). *Practical measures to improve the quality of small-group and whole-class discussion* [white paper]. Retrieved January, 1, 2019.
Johnson, C. R., & Sanderson, A. R. (2003). A next step: Visualizing errors and uncertainty. *IEEE Computer Graphics and Applications, 23*(5), 6–10.
Klein, G., Phillips, J. K., Rall, E. L., & Peluso, D. A. (2007, January). A data-frame theory of sensemaking. In *Expertise out of context: Proceedings of the sixth international conference on naturalistic decision making* (pp. 113–155). New York, NY: Lawrence Erlbaum Assoc.
Knight, J. (2011). What good coaches do. *Educational Leadership, 69*(2), 18–22.
Knight, S., Buckingham Shum, S., & Littleton, K. (2013). *Collaborative sensemaking in learning analytics*.
Lee, S., Kim, S. H., Hung, Y. H., Lam, H., Kang, Y. A., & Yi, J. S. (2015). How do people make sense of unfamiliar visualizations?: A grounded model of novice's information visualization sensemaking. *IEEE Transactions on Visualization and Computer Graphics, 22*(1), 499–508.
Liu, Z., & Stasko, J. (2010). Mental models, visual reasoning and interaction in information visualization: A top-down perspective. *IEEE Transactions on Visualization and Computer Graphics, 16*(6), 999–1008.
Marsh, J. A., Sloan McCombs, J., & Martorell, F. (2010). How instructional coaches support data-driven decision making: Policy implementation and effects in Florida middle schools. *Educational Policy, 24*(6), 872–907.
Martinez-Maldonado, R., Echeverria, V., Fernandez Nieto, G., & Buckingham Shum, S. (2020, April). From data to insights: A layered storytelling approach for multimodal learning analytics. In *Proceedings of the 2020 chi conference on human factors in computing systems* (pp. 1–15).
McCoy, C., & Shih, P. (2016). Teachers as producers of data analytics: A case study of a teacher-focused educational data science program. *Journal of Learning Analytics, 3*(3), 193–214.
Means, B., Chen, E., DeBarger, A., & Padilla, C. (2011). *Teachers' ability to use data to inform instruction: Challenges and supports*. Office of Planning, Evaluation and Policy Development, US Department of Education.
Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. Sage.
Munthe, E. (2003). Teachers' workplace and professional certainty. *Teaching and Teacher Education, 19*(8), 801–813.
Murnane, R. J., Sharkey, N. S., & Boudett, K. P. (2005). Using student-assessment results to improve instruction: Lessons from a workshop. *Journal of Education for Students Placed at Risk, 10*(3), 269–280.
Nelson, T., & Slavit, D. (2008). Supported teacher collaborative inquiry. *Teacher Education Quarterly, 35*(1), 99–116.
Potter, K., Rosen, P., & Johnson, C. R. (2011, August). From quantification to visualization: A taxonomy of uncertainty visualization approaches. In *IFIP Working Conference on Uncertainty Quantification* (pp. 226–249). Berlin/Heidelberg: Springer.
Romat, H., Henry Riche, N., Hinckley, K., Lee, B., Appert, C., Pietriga, E., & Collins, C. (2019, May). ActiveInk: (Th)Inking with data. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–13).

Santagata, R. (2011). From teacher noticing to a framework for analyzing and improving classroom lessons. *Mathematics teacher noticing: Seeing through teachers' eyes, 152*, 168.
Schildkamp, K. (2019). Data-based decision-making for school improvement: Research insights and gaps. *Educational Research, 61*(3), 257–273.
Schön, D. A. (1987). *Educating the reflective practitioner: Toward a new design for teaching and learning in the professions*. Jossey-Bass.
Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.
Sherin, M. G., & Russ, R. S. (2014). The role of interpretive frames. In Digital video for teacher education (pp. 11–28). Routledge.
Srinivasan, A., Brehmer, M., Lee, B., & Drucker, S. M. (2018, April). What's the difference? Evaluating variations of multi-series Bar charts for visual comparison tasks. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (pp. 1-12).
Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. *IEEE Computer Graphics and Applications, 26*(1), 10–13.
Thomson, J., Hetzler, E., MacEachren, A., Gahegan, M., & Pavel, M. (2005, March). A typology for visualizing uncertainty. In *Visualization and Data Analysis 2005* (Vol. 5669, pp. 146-157). International society for optics and photonics.
van Es, E. A., & Sherin, M. G. (2002). Learning to notice: Scaffolding new teachers' interpretations of classroom interactions. *Journal of Technology and Teacher Education, 10*(4), 571–596.
van Es, E. A., & Sherin, M. G. (2006). How different video club designs support teachers in "learning to notice". *Journal of Computing in Teacher Education, 22*(4), 125–135.
van Es, E. A., & Sherin, M. G. (2008). Mathematics teachers' "learning to notice" in the context of a video club. *Teaching and Teacher Education, 24*(2), 244–276.
van Leeuwen, A., & Rummel, N. (2020, March). Comparing teachers' use of mirroring and advising dashboards. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 26-34).
Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500–1509.
Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A., & De Laet, T. (2020, March). Learning analytics dashboards: The past, the present and the future. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 35-40).
Voyiatzaki, E., & Avouris, N. (2014). Support for the teacher in technology-enhanced collaborative classroom. *Education and Information Technologies, 19*(1), 129–154.
Wardrip, P. S., & Shapiro, R. B. (2016). Digital media and data: Using and designing technologies to support learning in practice. *Learning, Media and Technology, 41*(2), 187–192.
Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics, 6*(2), 53–69.
Wise, A. F., Sarmiento, J. P., & Boothe, M., Jr. (2021, April). Subversive learning analytics. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 639–645).
Xhakaj, F., Aleven, V., & McLaren, B. M. (2017, September). Effects of a teacher dashboard for an intelligent tutoring system on teacher knowledge, lesson planning, lessons and student learning. In *European conference on technology enhanced learning* (pp. 315–329). Cham: Springer.
Yeager, D., Bryk, A., Muhich, J., Hausman, H., & Morales, L. (2013). *Practical measurement* (p. 78712). Palo Alto, CA: Carnegie Foundation for the Advancement of Teaching.
Yi, J. S., ah Kang, Y., Stasko, J., & Jacko, J. A. (2007). Toward a deeper understanding of the role of interaction in information visualization. *IEEE Transactions on Visualization and Computer Graphics, 13*(6), 1224–1231.

Chapter 22
Designing and Developing a Learning Analytics Dashboard to Support Self-Regulated Learning

Mehmet Uysal and Mehmet Barış Horzum

1 Introduction

In recent years we have witnessed increased technology use in education. The importance of online and blended learning has increased (Allen & Seaman, 2016). They are not just alternative forms of education; they are the only available form of education in emergencies such as COVID-19. In these digital learning environments, it is easier to capture learners' interactions with the system. Therefore, we have more data, which accumulates quickly and is in diverse formats. However, its authenticity is questionable (Behrens & DiCerbo, 2014; Behrens & DiCerbo, 2014). This situation led to the emergence of learning analytics, which will tackle these issues with the data.

One of the most widely used definitions of learning analytics has been done during the First International Conference on Learning Analytics and Knowledge which is:

> *the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.*

Brown (2011) defines learning analytics as the collection and analysis of usage data associated with student learning with the purpose of observing and understanding learning behaviours in order to make appropriate interventions. Ifenthaler

This study is based on the primary author's doctoral dissertation with the supervision of the second author.

M. Uysal (✉) · M. B. Horzum
Sakarya University, Serdivan, Sakarya, Turkey
e-mail: mehmetuysal@sakarya.edu.tr; mhorzum@sakarya.edu.tr

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_22

(2015) points out the nature of the information that can be static or dynamic and states that learning analytics aim to optimise learning processes, learning environments, and educational decision-making. Administrators, policymakers, managers, and content creators become important stakeholders of learning analytics by including educational decision-making. A common theme in these definitions is the desire to understand and improve learning. Opening up the black box of learning will enable us to adapt learning and its environments for individuals' needs.

Learning analytics is an emerging field, but it can grow on well-established learning theories. However, learning analytics applications do not take advantage of this situation (Matcha et al., 2019). One of the prominent learning theories is SRL which is also widely adopted in learning analytics dashboard research (Jivet et al., 2018).

This chapter will introduce how SRL theory can guide designing and implementing a learning analytics dashboard. First, we will present SRL theory and its synergy with learning analytics. Then we will introduce the design process along with the developed learning environment and the dashboard.

2 Self-Regulated Learning

Today, learning happens everywhere. Institutions', schools', or classrooms' physical limitations do not constrain learning. Also, unlike a few decades ago, even a university degree will not set a person for life. Students learning how to take control and the responsibility of their learning will be more ready for tomorrow. In other words, students need to have "will and skill" to learn without the strict guidance of parent/teacher/computer (Pintrich & De Groot, 1990).

Technology empowers students to be more active in their learning, but it can have a negative impact on learning as well. It is very easy to be distracted by mobile phones, social media, computer games, and other digital tools. Learners who lack regulatory skills will have a hard time continuing their education with these constant distractions. Research in SRL reveals that learners often do not make use of self-regulatory skills during learning, which results in inferior learning outcomes (Azevedo, 2009; Winne & Hadwin, 2008; Zimmerman, 1990, 2002, 2008). If students employ more SRL strategies, their academic achievements will improve (Zimmerman & Schunk, 2001).

Winne (2017) suggests that when learners self-regulate their learning, they are active in their learning process. They try to find ways to learn and monitor if their learning goals are met and how they can vary their approaches to learning. Zimmerman and Schunk (2001) also point out that learners are active when they self-regulate. Accordingly, self-regulated learners define their goals, make plans to achieve these goals, continuously monitor their progress towards these goals, and, if needed, revise their plans. Hattie and Donoghue (2016) showed that SRL is one of the most effective methods for reaching learning goals in his meta-analysis.

Zimmerman et al. (1996) suggest that students can avoid being a victim of learning by taking control of their learning process. Teachers can help their students in their personal journey to succeed, but the ultimate responsibility lies with the student. Students should realise that learning is a personal experience, and they should be active, informed, and dedicated in their participation. In short, *learning is not something that can be done for students; rather it is something that is done by them*.

One category of technology-enhanced learning solutions is adaptive systems and intelligent tutoring systems that can customise their content and behaviour according to the needs and preferences of the learners (Brusilovsky & Millán, 2007). However, self-regulated learners need to be more responsible and never give complete control to the system. In addition, the original vision for intelligent tutoring systems is changing, and they are being designed in a way to *leverage human intelligence* (Baker, 2016). Supporting SRL is a balance between freedom and guidance. Learners need enough freedom while not feeling overwhelmed by lack of any guidance (Nussbaumer et al., 2015).

SRL has cognitive, metacognitive, behavioural, motivational, and emotional aspects, and there are several models which focus on different aspects. Panadero (2017) reviewed and compared six of the most relevant SRL models that form an integrable and consistent framework that can be used in research and education.

One of the research areas in SRL is the measurement of it. As Lord Kelvin suggests, "You cannot improve something you cannot measure". Measuring SRL started with self-reports. Questionnaires, scales, and interviews are used to determine students' perspectives and beliefs (Panadero et al., 2016). There are fundamental problems with using self-reports for dynamic processes, so better, more observational and performance measures were needed to measure SRL (Zeidner et al., 2000).

There was a shift of understanding of SRL at the beginning of the new millennium. SRL viewed as events that are unfolding during learning rather than aptitude enabled new forms of measurements such as think-aloud protocols, error detection tasks, trace methodologies, and observations of performance (Winne & Perry, 2000). In digital learning environments, especially in online learning environments, collecting and working on clickstream data became valuable. In the third wave of measurement of SRL, methods and instruments used together to foster SRL while measuring students' progress (Panadero et al., 2016).

SRL theory got special attention from learning analytics researchers. SRL and learning analytics research have a great synergy since monitoring the learning process and accordingly adjusting actions is important in both of them. The *Journal of Learning Analytics* (Gasevic et al., 2015) and *Journal of Educational Data Mining* (Winne & Baker, 2013) published special issues for SRL. Both issues point out the possibilities of advancing research on motivation, metacognition, and SRL using the vast amount of readily available educational data (Roll & Winne, 2015; Winne & Baker, 2013).

Learning analytics research that is grounded on SRL goes through similar steps. First the SRL construct is defined; then events logged in the system are mapped to that construct. However, alignment of the SRL theory with the data digital sensors produce is required for better learning analytics results (van der Graaf et al., 2021). Kim et al. (2018) have chosen three critical self-regulated skills in asynchronous online learning. First is the time investment in content learning, which consists of online lecture study time and online lecture access frequency. Second is the study regularity of the students. Indicators for this skill are LMS login interval regularity and online lecture access interval regularity. Lastly, help seeking, which has contradictory findings in the literature (Aleven et al., 2016; Papamitsiou & Economides, 2019), was tied to questions and answers board with frequency, time spent, and the number of postings. Montgomery et al. (2017) studied SRL in flipped blended learning setting for music teacher education by assessing the association between categorical variables and academic achievement. In their SRL construct, they have chosen activating-type SRL behaviours (location on-off campus, day of the week, time of the day), sustaining-type SRL behaviours (LMS access, module view), and structuring-type self-regulated behaviours (regularity logins per week). Access frequency and day of the week were the strongest indicators for student success. More examples can be found in Siadaty et al. (2016), Kizilcec et al. (2016), and Kizilcec et al. (2017).

In short, students will be more willing to take responsibility when they recognise they are capable of achieving on their own (Zimmerman et al., 1996). If students become successful self-regulators, they will be more successful in the twenty-first century. Although research on learning analytics is in its infancy, with the help of more established learning theories such as SRL, it is possible to design and develop learning environments more suitable for students' and teachers' need.

3 Learning Analytics Dashboards

The word dashboard was initially used to define a panel that was placed in horse-drawn carriages to stop dirt/dust from getting inside. Later dashboards are used in most vehicles (land, sea, air), giving information about the status of the vehicle and the surrounding environment ("Dashboard", 2020). Dashboards are an integral part of the vehicles that ensure a safe and comfortable journey. The situation is also similar when considering learning analytics dashboards that support learners in their learning journey.

The computing power of digital devices has increased enormously over the years. They can beat humans in games like chess and go which were considered impossible previously. But still, the human visual system is considered superior to any hardware and software combination for understanding visuals. The eye and the brain form a massively parallel processor that is connected to human cognition. For humans, perception and cognition are closely interrelated, even so, that in some languages such as English and Turkish, the words "understanding" and "seeing" are synonymous. Visualisations can be an effective strategy for supporting users in knowledge and information-heavy situations (Ware, 2019).

Few (2006) defines dashboards as "a visual display of the most important information needed to achieve one or more objectives that has been consolidated on a single computer screen so it can be monitored at a glance". There are three key points in this definition; they can be transformed into questions for learning analytics dashboards:

1. What is the most important information for learning/teaching?
2. What are the objectives of learners/teachers?
3. How can we present the data so it can be understood at a glance?

Trying to answer these questions is a good starting point for designing and implementing learning analytics dashboards. First two questions are fundamental to learning sciences. For the last question, an understanding of the human visual system is needed.

There are mainly two approaches for using the vast amount of data for enhancing learning. First one focuses on automated decision-making on behalf of learners, teachers, and/or other stakeholders. In the second one, with *modest computing* (Verbert et al., 2013), data is used to support learners', teachers', and/or other stakeholders' decision-making. In the context of learning analytics dashboards, automobile analogy is being used to exemplify these approaches. Data mining applications in education, like self-driving cars, use the strength of computer hardware and algorithms to come up with best moves, while dashboards use visualisation techniques in order to activate outstanding perceptual abilities of human sight. One advantage of activating students' cognitive processes with visuals is that students can only develop the much needed twenty-first century skills such as critical thinking, communication, collaboration, and creativity only if they have the freedom to do so (Klerkx et al., 2017).

Information visualisation techniques can be put into practice so that teachers can have a better teaching experience and students can have a better learning experience. The design of visualisations needs to be goal oriented and can include resource, activity, and people recommendations (Duval, 2011).

Dashboards visualise the key information in a way that can be understood quickly and easily. Research on learning analytics dashboards focus on finding this key information and aggregating and then displaying it to enhance learning and teaching. Learning dashboards can increase awareness, support control and observation, promote reflection, and evoke understanding in a visual manner by summarising the data stored in the learning environments. The data come from *virtual sensors* which report user actions within the system (Verbert et al., 2014). Learning analytics dashboards visualise the progress of learning by investigating the traces left behind by the learners and/or teachers interacting with the system (Duval et al., 2012). Yoo and others (2015) prefer the term "educational dashboard" and then define it as a display that visualises educational data mining results in a useful way. Using education instead of learning implies that these dashboards can be utilised by other stakeholders in education, such as managers, admins, and policymakers.

Learning analytics dashboards can have an important role for teachers and students, especially in the context of online learning. Teachers can monitor all the students' learning almost in real time since data can be summarised and visualised accordingly. Students can get great value out of dashboards as well since they can monitor and reflect upon their learning before it is too late. In general, learning analytics dashboards can provide feedback and support decisions and reflection while increasing engagement and motivation (Klerkx et al., 2017).

Matcha et al. (2019) reviewed the 29 empirical studies on learning analytics dashboards looking through SRL perspective using Winne and Hadwin's SRL model. The main finding of the review is existing learning analytics dashboards were rarely grounded in learning theories. This is somewhat expected since early research is exploratory and there is complexity in mapping SRL indicators with digital traces. In addition, learning analytics dashboard research was limited in supporting metacognition, informing about learning strategies, and in their evaluations of the research conducted.

4 Moodle

This part of the chapter will introduce the features of the learning management system Moodle which can be valuable in creating more suitable learning analytics dashboards. Moodle is an open-source learning management system written mostly in PHP language. Although its initial development was done by Martin Dougiamas, as a graduate thesis, as of 2021, it has over 560 contributors listed on its GitHub page. Moodle is an acronym for modular object-oriented dynamic learning environment. Moodle's modularity enabled the platform to grow gradually. Plugins can be integrated into Moodle to answer the specific needs of teachers, students, and other stakeholders.

Romero et al. (2008) exemplified what can be done with Moodle's log data. They have used classification, clustering, and association rule mining techniques. Romero et al. (2013) developed a Moodle block plugin to visualise data mining results. Luna et al. (2017) have integrated a data mining framework written in PHP to Moodle by using a block plugin. Casey and Gibson (2010) used interaction data in Moodle and found out that daily course view is a good indicator for student performance and state that Moodle usage patterns by teachers and students affect the relation of data. Froissard et al. (2019) used assessment, forum, grade book, and login activities as indicators for finding out at-risk students. Akçapınar and Bayazit (2019) developed a tool that can be used for data mining analyses on Moodle logs using the R language.

As it can be seen, researchers have been exploring the possibilities of Moodle extensively because it is free to use and relatively easy to adapt and extend. However, the capabilities of Moodle's core and plugin APIs are not fully utilised to unlock the features that will help with answering the users' needs and the alignment of SRL theory and Moodle logs. In other words, *virtual sensors* that are available in stock Moodle configuration lack the complexity needed to map SRL actions to log data.

4.1 Moodle Logs and Reporting

Moodle reporting of its events is not static. It depends on which plugins are installed and used in the courses. Moodle was designed to be modular from the ground up, so there are over 50 plugin types[1] and 1800 individual plugins[2] available as of 2021. Themes, blocks, activities, assignments, question types, and reports are among the most used plugin types.

Block-type plugins are common for visualising Moodle log data since it is easier to implement with Moodle API and JavaScript libraries. Romero et al. (2008) used GISMO for visualisation, Şahin and Yurdugül (2019) utilised blocks in Intelligent Intervention System (In2S), and Kokoç and Altun (2021) showed that learner interaction with dashboards affects academic performance. One downside of block-type plugins is that they are not supported in Moodle mobile application as of 2021.

Activity plugins, such as interactive content (H5P), Zoom meeting, BigBlueButtonBN, Virtual Programming Lab, and wikis, are fundamental teaching/learning components of Moodle. Each course can be designed with a selection of these plugins according to the needs of the instructors and students. Assignment plugins can be used to adjust the submission – feedback processes. New types of questions and question behaviours can be included with question-type plugins. Report-type plugins can be a stepping stone for using data in decision-making in education (Dalton, 2015).

A list of events that are recorded in Moodle logs can be found under Moodle site administration/reports/events list. As it can be seen in Fig. 22.1, it is possible to filter events available in Moodle according to components/plugins. In addition, Moodle categorises events by using education level such as teaching, participating, and other. Participating usually means events fired during student interaction, while teaching corresponds to instructional activities by teachers/admins.

StudentQuiz[3] (Albrecht, 2018), an activity type plugin, is given as an example here. It enables students to create their own questions and quizzes. Students can also see their peers' questions, create a quiz from a selection of those questions, comment, and rate the questions. After installing this plugin, Moodle logs will include the records of the events fired during the usage of the plugin.

It should be noted that although StudentQuiz plugin enables students to assess their own learning and assess their peers' learning by commenting on their questions or by rating with stars, none of these actions are reported back in the Moodle logs. This is a contradiction to the belief that every single mouse click and movement is recorded in digital media (DiCerbo et al., 2014). There should not be any doubt that these actions are invaluable for SRL, but they are missing in the logs.

The number and variety of recorded events depend on the components installed in Moodle. Core components, which are readily available in Moodle installations,

[1] https://docs.moodle.org/dev/Plugin_types

[2] https://moodle.org/plugins/

[3] https://moodle.org/plugins/mod_studentquiz

are usually better in this regard. For example, wiki component reports 14 different types of participating event. Unfortunately, third-party components, even the H5P, which is the most installed plugin, neglect recording actions of the users to the Moodle logs. This situation impacts the quality of log data and hinders mapping log data with users' actions/intentions. One of the reasons for H5P's poor reporting might be the fact that it employs xAPI. As of the 3.9 version of Moodle, H5P has been included in the core. This is a promising step; new developments can be seen in this area, such as xAPI becoming a standard in Moodle or a better log output from H5P component. Equally, not all recorded data in the logs are meaningful for educational purposes (Iglesias-Pradas et al., 2015).

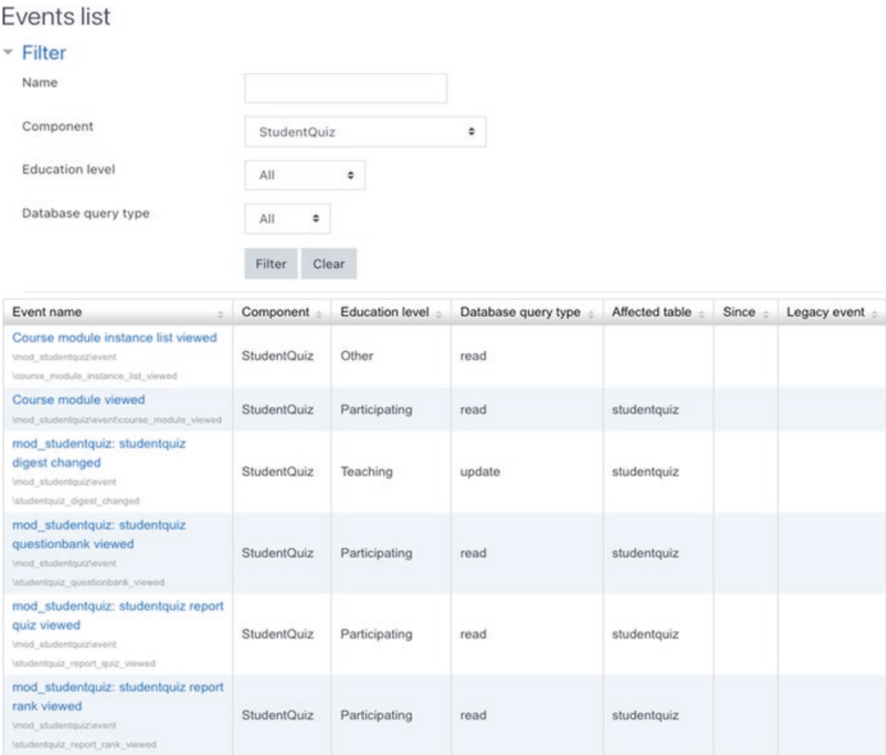
At this point, Moodle events and logging API might help resolve this issue. Moodle events API enables plugin developers to implement new events that can be recorded in Moodle logs. Since Moodle itself and most of the plugins available are open-source, their code repository can be found easily. First, a new event class must be implemented by extending \core\event\base class from the Moodle events API. The new file will be under the classes/events folder. In this class, we have to implement a few methods like initialising the event data, giving a name to our newly created event, describing it according to context, enabling easy access to the URL the event fired, etc. (Fig. 22.2). Moodle tried to standardise this process by adding naming conventions, verbs to be used, etc., similar to Tin Can API, xAPI. More details are available in the online documentation of Moodle events API.

After the implementation, these new types of events can be recorded in Moodle logs by creating new instances of this class. For example, in the checklist, an activity type plugin, which can be initialised by teachers and modified/completed by students, no event is recorded when students add or edit their own items. So first, we create the event class (similar to Fig. 22.2) and then find the appropriate place in the code to trigger this event. For this example, the appropriate place in locallib.php file can be found around line 600 (Fig. 22.3). This approach heavily depends on the readability of the source code available in the code repository.

These code snippets are given to showcase what is possible with Moodle API. After selecting the components which are best for students' and teachers' needs, and making appropriate adjustment in their reporting, it can be expected to have better reporting of students' actions/behaviours.

5 Yet Another Learning Analytics Dashboard?

In this study, in order to design and develop a learning analytics dashboard that can support SRL of the students, design-based research have been employed. Design-based research enables a stronger connection between educational research and real-world problems (Amiel & Reeves, 2008). This part of the chapter reports the steps of analysis, design, development, and implementation details.


Events list

Filter

Name

Component StudentQuiz

Education level All

Database query type All

Filter Clear

Event name	Component	Education level	Database query type	Affected table	Since	Legacy event
Course module instance list viewed \mod_studentquiz\event \course_module_instance_list_viewed	StudentQuiz	Other	read			
Course module viewed \mod_studentquiz\event\course_module_viewed	StudentQuiz	Participating	read	studentquiz		
mod_studentquiz: studentquiz digest changed \mod_studentquiz\event \studentquiz_digest_changed	StudentQuiz	Teaching	update	studentquiz		
mod_studentquiz: studentquiz questionbank viewed \mod_studentquiz\event \studentquiz_questionbank_viewed	StudentQuiz	Participating	read	studentquiz		
mod_studentquiz: studentquiz report quiz viewed \mod_studentquiz\event \studentquiz_report_quiz_viewed	StudentQuiz	Participating	read	studentquiz		
mod_studentquiz: studentquiz report rank viewed \mod_studentquiz\event \studentquiz_report_rank_viewed	StudentQuiz	Participating	read	studentquiz		

Fig. 22.1 Moodle events list for StudentQuiz component

5.1 Needs Analysis

In this step, systematic literature review and focus group discussions helped us identify students' needs for improving SRL. For literature review, Kitchenham and Charters (2007) steps were followed. Google Scholar, ISI Web of Knowledge, and Scopus databases were queried for studies that included "self-regulated learning" and "learning analytics" in their title. Editorials, reviews, and critics were eliminated and only empirical studies were included in the selection. After the selection process, 20 empirical studies were investigated according to publication date, country/region, subject matter, analytics used, SRL model employed, learning environment, participants, and data sources. The most striking finding of the literature review was the fact that even though the studies were based on SRL, there was not enough information to identify the model or the theory of SRL (12 of the 20 studies). Four studies employed Pintrich's (2000) SRL model, three Zimmerman's (2000) model, and one Winne and Hadwin's (1998) model. The other significant finding was 15 out of 20 studies developed their own specific learning environment system. Since these environments are mostly developed for that research, they are exploratory and short lived. Only three studies made use of the open-source learning code > mod > checklist > classes > event > checklist_completed.php

```php
<?php

namespace mod_checklist\event;

defined('MOODLE_INTERNAL') || die();

class checklist_completed extends \core\event\base {

    protected function init() {}
    public static function get_name() {}
    public function get_description() {}
    public function get_url() {}
    protected function get_legacy_logdata() {}
    public static function get_objectid_mapping() {}

}

```

Fig. 22.2 An example event class extending base event class

checklist / locallib.php

```php
if ($_GET['action'] && $_GET['action'] == "startadditem") {
    $event = \mod_checklist\event\student_items_updated::create($params);
    $event->trigger();
}
```

Fig. 22.3 Code snippet for triggering the newly created event

management system Moodle. There were promising findings as well. True to SRL theory's nature, numerous subjects including science, education, computer science, language, medicine, music, psychology, design, and workplace education were studied. This finding shows that, by improving SRL of the students, better results are expected almost in any subject area. The other promising finding was the variety of learning analytics methods employed in the studies. Process mining, clustering, regression, social network analysis, Bayesian networks, and coherence analysis were used to analyse the collected data.

Focus group discussions were conducted to analyse students' needs for SRL in online learning environments. Three sessions of focus group discussions hosted a total of 21 students. Semi-structured open-ended questions based on Zimmerman's (2000) cyclical three-phased SRL model (Fig. 22.4) allowed students to express their needs for SRL. Recordings of the sessions were transcribed for content analysis. Results of the content analyses revealed that students need specific tools for

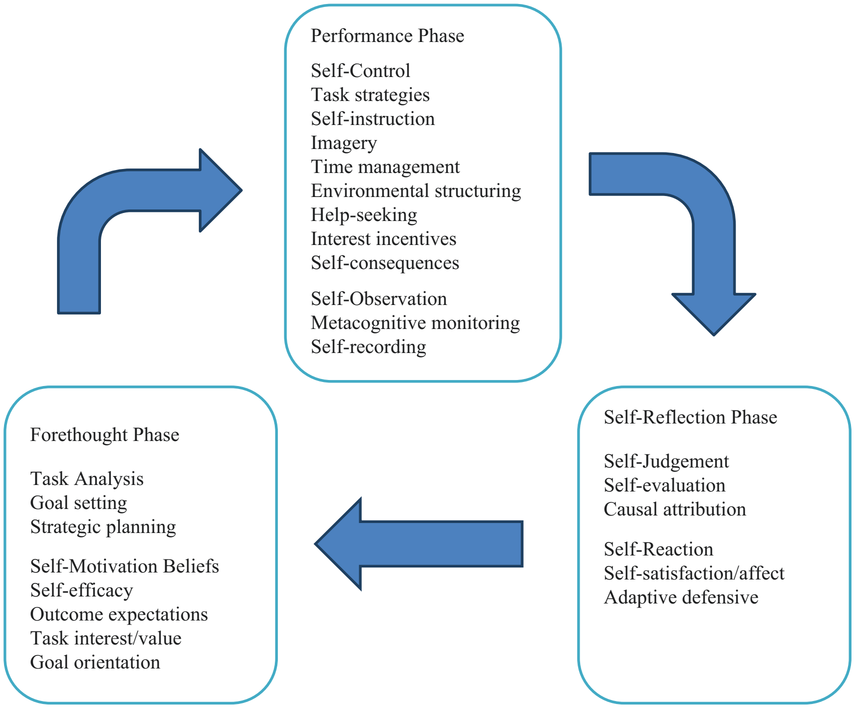


Fig. 22.4 Zimmerman's cyclical self-regulated learning model

each separate phase, and these tools change according to the subject matter of the course.

5.2 *Design and Development*

The needs analysis results showed that the learning analytics system that supports SRL should be flexible enough to accommodate the specific needs of each SRL phase. The first column of Table 22.1 summarises the needs of students for each SRL phase, the second column shows how the system should satisfy that need, and the third column is the specific Moodle component that can achieve the proposed solution.

The initial form of this table was shared with 11 academics from the field of Computer Education and Instructional Technologies. They have commented on the appropriateness of the proposed solution and the Moodle components. For inter-rater reliability, Cohen's kappa was calculated. It was between 0.82 (9/11) and 1.00 for each component. In addition, experts' suggestions, such as including ice-breaking activities in forums, were followed.

Table 22.1 Results of needs analysis, corresponding solution proposals, and system components

Needs analysis result	Solution proposal	System component
Forethought	Forethought	Forethought
Expectations from students should be clear	Identifying goals	Checklist:
Open learning process	Help students identify goals	Teachers can identify learning goals; students can add more goals or edit existing items
Reminding important dates	Listing of learning outcomes	Forums:
Relating subjects to real-world applications	Scheduling of learning process	Motivating students
	Planning	Appropriate communication and discussion platform
	Support students in planning	Calendar
	Reminding deadlines and important dates	Important dates
	Motivating students by giving real-world examples	Deadlines
		Reminders
		Lesson:
		Learning strategies
Performance	Performance	Performance
Appropriate discussion environment	Environmental structuring	H5P
Sharing different types of files	Appropriate communication, discussion, and working environment	Interactive videos learning dashboard
Privacy, anonymity	Task strategies	Information and tips about SRL phases
Interactive contents	Informing students about learning strategies	Promoting use of all components
Unlimited navigation/access	Supporting students to effectively use system components	Promoting regular usage chat/big blue button
Shared places to enable collaboration	Time management	Synchronous communication
	Encourage students to use the system regularly	Question/answer
	Help seeking	
	Provide opportunities for finding help	
Self-reflection	Self-reflection	Self-reflection
Evaluating student effort	Self-evaluation	StudentQuiz
Different metrics	Support reflection	Self-evaluation

(continued)

Table 22.1 (continued)

Needs analysis result	Solution proposal	System component
Indicators	Provide assessment and evaluation opportunities	Peer evaluation quiz
Clearer learning process	Peer evaluations	Evaluation opportunities

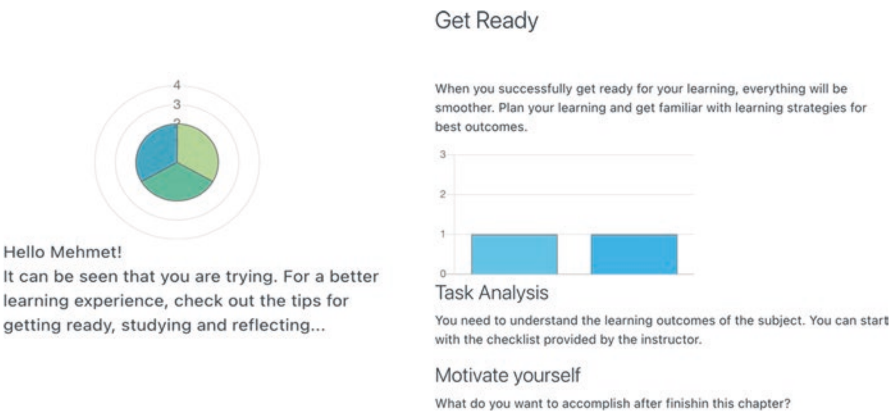


Fig. 22.5 Polar area chart that corresponds to each SRL phase and an example for more detailed info upon clicking on the get ready part

System components for Moodle environment were carefully selected, and after experts' opinion, they were modified to trigger events for better representations of students' behaviours.

Finally, a block plugin is developed using Moodle API and Chart.js JavaScript library that shows polar area representation of the SRL phases. Labels *get ready, study, and reflect* were used instead of forethought, performance, and self-reflection. Clicking on the chart's sections will take the student to a page with more information about her/his SRL processes (Fig. 22.5; the messages were translated to English for this publication).

Learning analytics dashboard block was configured using a JSON data structure. The configuration enables teachers/admins to adjust blocks appearance and the data it visualises. Top level of the JSON includes details about the chart, different suggestions for different levels of SRL. Under the phases, details about the factors and then events associated with those factors are represented. This structure of the block's configuration enables teachers/admins to adjust the dashboard according to the needs and the setup of their Moodle installation. Figure 22.6 shows the structure of the block's configuration JSON.

Building the learning system with components that are specific to each phase of SRL and then using JSON configuration to map each phase/factor with specific log event enabled fine-tuned observations. Figure 22.7 details the hierarchical structure of the SRL configuration.

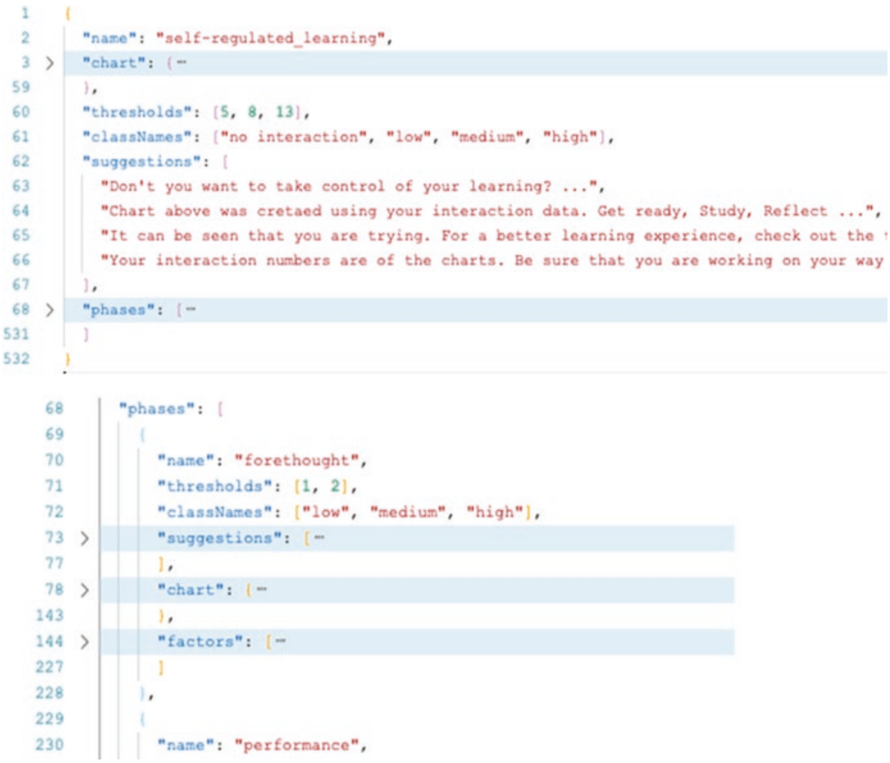


Fig. 22.6 Structure of the JSON configuration for LAD

5.3 Findings and Results

After the design and development, the system was tested with Sakarya University Education Faculty students in two iterations. In both cases, the Online Self-Regulated Learning Questionnaire (OSLQ) (Barnard et al., 2009) was used to assess change in students' use of SRL strategies. OSLQ is a 5-point Likert scale that contains 24 items in 6 subscales: goal setting, environment structuring, task strategies, time management, help seeking, and self-evaluation.

5.3.1 Pilot Study

Three hundred and five students who are taking the Assessment and Evaluation in Education course used the developed system for 5 weeks. Data for students' use of SRL strategies were collected with OSLQ at the start of the course and after 5-week period. A total of 64 students completed both pre and post questionnaires. Although there was a slight increase in mean values in post-test, t-test result was not

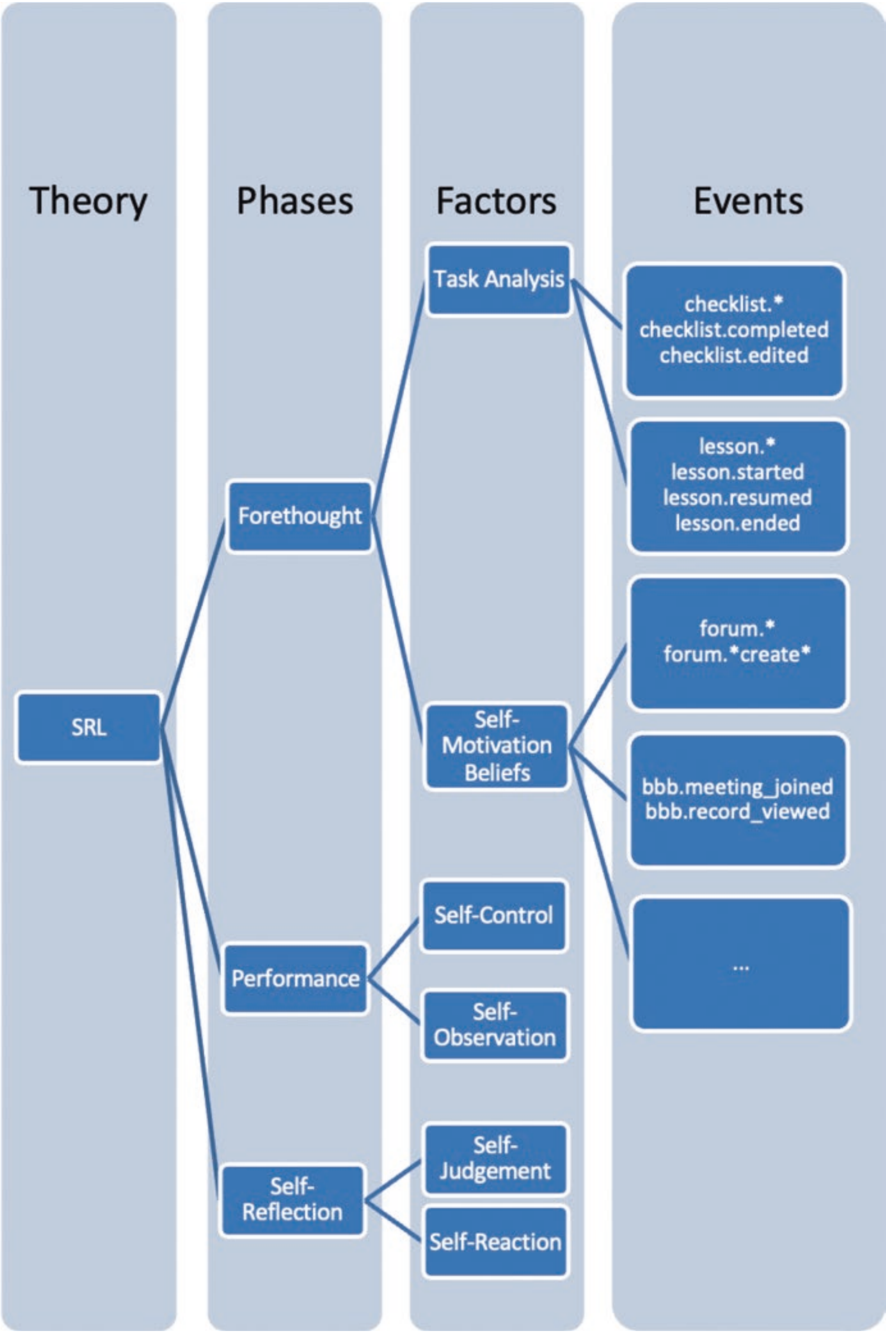


Fig. 22.7 Structure of the SRL JSON configuration

Table 22.2 t-test result for pilot study OSLQ

	Pretest		Post-test		t(63)	p
	M	SD	M	SD		
OSLQ	75.75	13.44	79.11	15.78	−2.00	0.05

Table 22.3 t-test results for second iteration OSLQ

	Pretest		Post-test		t(52)	p
	M	SD	M	SD		
OSLQ	81.62	14.07	90.25	13.75	−4.70	0.00

significant – pretest (M = 75.75, SD = 13.44), post-test (M = 79.11, SD = 15.78), $t(63) = -4.7$, and $p = 0.00$.

The findings of the pilot study were not conclusive. The duration of the system use might be a limiting factor, so for the second iteration, the system was used for the whole 14 weeks.

5.3.2 Second Iteration

For the second iteration, a Moodle book activity that contains more information on SRL strategies and how the system components can be utilised was added to the system.

After refinements, the system was tested in the Internet-Based Education course with 62 students. Data for students' use of SRL strategies were collected with OSLQ at the start and after 14 weeks at the end of the course. In the second iteration, there was a significant difference in the mean values of OSLQ in the start of the course (M = 81.62, SD = 14.07) compared to the end of the course – (M = 90.25, SD = 13.75), $t(51) = -4.7$, and $p = 0.00$.

Initial results showed that students found the dashboard insightful and helpful but wished they could modify it for their own purposes.

5.4 Discussion

This chapter has introduced a learning analytics dashboard that supports students' SRL in a learning environment that was specifically designed to include components to promote SRL. In addition, each component was customised to report appropriate messages to logs. Design-based research enabled to install missing digital sensors for better learning analytics results.

Schumacher and Ifenthaler (2018) have investigated students' expectations from learning analytics and showed that these features could be categorised under the SRL theory. Similarly, literature reviews showed that SRL is an important driver for learning analytics dashboard research (Jivet et al., 2018; Matcha et al., 2019). However, the alignment of log data with SRL construct is challenging. The main reason behind setting up a custom learning environment and fitting it with appropriate virtual sensors was to feed a better data to be used in learning analytics dashboard. As customary in learning analytics dashboard studies, an analogy with car dashboards can be made here. *A dashboard from a Tesla Model S will not be much used for 1980s' classic car with diesel engine.*

5.5 Limitations

The developed system was tested with a small number of participants. Although configuring learning dashboard via blocks global configuration parameters enabled easy adaptation and modifications, for larger groups, the number of database queries might be too much to handle for the server.

References

Akçapınar, G., & Bayazit, A. (2019). MoodleMiner: Data mining analysis tool for Moodle learning management system. *İlköğretim Online, 18*(1), 406–415. https://doi.org/10.17051/ilkonline.2019.527645.

Albrecht, P. (2018). *Moodle Plugin StudentQuiz* (Doctoral dissertation, HSR Hochschule für Technik Rapperswil).

Aleven, V., Roll, I., Mclaren, B. M., & Koedinger, K. R. (2016). *Help Helps* (pp. 205–223). But Only So Much: Research on Help Seeking with Intelligent Tutoring Systems. https://doi.org/10.1007/s40593-015-0089-1.

Allen, I. E., & Seaman, J. (2016). Online report card: Tracking online education in the United States. *Babson Survey Research Group*. Babson College, 231 Forest Street, Babson Park, MA 02457.

Amiel, T., & Reeves, T. C. (2008). Design-based research and educational technology: Rethinking technology and the research agenda. *Journal of Educational Technology & Society, 11*(4), 1176–3647. https://doi.org/10.2307/jeductechsoci.11.4.29.

Azevedo, R. (2009). Theoretical, conceptual, methodological, and instructional issues in research on metacognition and self-regulated learning: A discussion. *Metacognition Learning, 4*, 87–95. https://doi.org/10.1007/s11409-009-9035-7.

Baker, R. S. (2016). Stupid tutoring systems, intelligent humans. *International Journal of Artificial Intelligence in Education, 26*(2), 600–614.

Barnard L. Lan W. Y. To Y. M. Paton V. O. & Lai S.-L. (2009). Measuring self-regulation in online and blended learning environments. The Internet and Higher Education 12(1) 1–6. https://doi.org/10.1016/j.iheduc.2008.10.005.

Behrens, J. T., & DiCerbo, K. E. (2014). Harnessing the currents of the digital ocean. In *Learning analytics* (pp. 39–60). New York: Springer.

Brown, M. (2011). Learning analytics: The coming third wave. *EDUCAUSE Learning Initiative Brief, 1*(4).

Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The Adaptive Web.*

Lecture Notes in Computer Science, 4321. Berlin/Heidelberg: Springer. https://doi.org/10.1007/978-3-540-72079-9_1.

Casey, K., & Gibson, J. P. (2010). (m)Oodles of data: Mining moodle to understand student behaviour. In *Proceedings of the 10th International Conference on Engaging Pedagogy (ICEP10)* (pp. 61–71).

Dalton, E. (2015). Configurable reports as a learning analytics tool [video]. YouTube. https://youtu.be/lF6CuY2Qiw0

Dashboard. (2020, November 15). In Wikipedia. https://en.wikipedia.org/wiki/Dashboard

DiCerbo, K. E., Behrens, J. T., & Barber, M. (2014). *Impacts of the digital ocean on education*. London: Pearson.

Duval, E. (2011, February). Attention please! Learning analytics for visualisation and recommendation. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 9–17).

Duval, E., Klerkx, J., Verbert, K., Nagel, T., Govaerts, S., Parra Chico, G. A., … Vandeputte, B. (2012). Learning dashboards & learnscapes. *Educational Interfaces, Software, and Technology*, 1–5.

Few, S. (2006). *Information dashboard design: The effective visual communication of data* (Vol. 2). Sebastopol: O'reilly.

Froissard, J. C., Liu, D., Richards, D., & Atif, A. (2019). A learning analytics pilot in Moodle and its impact on developing organisational capacity in a university. In *ASCILITE 2017-Conference Proceedings-34th International Conference of Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education*.

Gasevic, D., Dawson, S., Mirriahi, N., & Long, P. D. (2015). Learning analytics – A growing field and community engagement. *Journal of Learning Analytics, 2*(1), 1–6. https://doi.org/10.18608/jla.2015.21.1.

Hattie, J. A. C., & Donoghue, G. M. (2016). Learning strategies: A synthesis and conceptual model. *Npj Science of Learning, 1*(1). https://doi.org/10.1038/npjscilearn.2016.13.

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE Encyclopedia of educational technology* (Vol. 2, pp. 447–451). Sage Publ. https://doi.org/10.4135/9781483346397.n187.

Iglesias-Pradas, S., Ruiz-De-Azcárate, C., & Agudo-Peregrina, Á. F. (2015). Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies. *Computers in Human Behaviour, 47*, 81–89. https://doi.org/10.1016/j.chb.2014.09.065.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40).

Kim, D., Yoon, M., Jo, I. H., & Branch, R. M. (2018). Learning analytics to support self-regulated learning in asynchronous online courses: A case study at a women's university in South Korea. *Computers and Education, 127*(2016), 233–251. https://doi.org/10.1016/j.compedu.2018.08.023.

Kitchenham, B. A., & Charters, S. (2007). *Procedures for performing systematic literature reviews in software engineering*. Keele University & Durham University.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2016, April). Recommending self-regulated learning strategies does not improve performance in a MOOC. In *Proceedings of the third (2016) ACM conference on learning@ scale* (pp. 101–104).

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behaviour and goal attainment in Massive Open Online Courses. *Computers & Education, 104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001.

Klerkx, J., Verbert, K., & Duval, E. (2017). Learning analytics dashboards. In C. Lang, G. Siemens, A. Wise, & D. Gasevic (Eds.), *Handbook of learning analytics* (pp. 143–150). Alberta, Canada: Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17.012.

Kokoç, M., & Altun, A. (2021). Effects of learner interaction with learning dashboards on academic performance in an e-learning environment. *Behaviour & Information Technology, 40*(2), 161–175.

Luna, J. M., Castro, C., & Romero, C. (2017). MDM tool: A data mining framework integrated into Moodle. *Computer Applications in Engineering Education, 25*(1), 90–102. https://doi.org/10.1002/cae.21782.

Matcha, W., Ahmad Uzir, N., Gasevic, D., & Pardo, A. (2019). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 1382*(c), 1–1. https://doi.org/10.1109/TLT.2019.2916802.

Montgomery, A. P., Mousavi, A., Carbonaro, M., Hayward, D. V., & Dunn, W. (2017). Using learning analytics to explore self-regulated learning in flipped blended learning music teacher education. *British Journal of Educational Technology, 00*(00). https://doi.org/10.1111/bjet.12590.

Nussbaumer, A., Dahn, I., Kroop, S., Mikroyannidis, A., & Albert, D. (2015). Supporting self-regulated learning. In *Responsive open learning environments* (pp. 17–48). Cham: Springer.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*(April), 1–28. https://doi.org/10.3389/fpsyg.2017.00422.

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60*(6), 723–735.

Papamitsiou, Z., & Economides, A. A. (2019). Exploring autonomous learning capacity from a self-regulated learning perspective using learning analytics. *British Journal of Educational Technology, 50*(6), 3138–3155. https://doi.org/10.1111/bjet.12747.

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 452–502). San Diego, CA: Academic.

Pintrich, P. R., & de Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*(1), 33–40. https://doi.org/10.1037/0022-0663.82.1.33.

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics, 2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2.

Romero, C., Ventura, S., & García, E. (2008). Data mining in course management systems: Moodle case study and tutorial. *Computers and Education, 51*(1), 368–384. https://doi.org/10.1016/j.compedu.2007.05.016.

Romero, C., Castro, C., & Ventura, S. (2013). *A Moodle block for selecting, visualizing and mining students' usage data*. Educational Data Mining.

Şahin, M., & Yurdugül, H. (2019). An intervention engine design and development based on learning analytics: The intelligent intervention system (In2S). *Smart Learning Environments, 6*(1). https://doi.org/10.1186/s40561-019-0100-7.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behaviour, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030.

Siadaty, M., Gašević, D., & Hatala, M. (2016). Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. *Computers in Human Behaviour, 59*, 469–482. https://doi.org/10.1016/j.chb.2016.02.025.

van der Graaf, J., Lim, L., Fan, Y., Kilgour, J., Moore, J., Bannert, M., Gasevic, D., & Molenaar, I. (2021). Do instrumentation tools capture self-regulated learning? In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 438–448). https://doi.org/10.1145/3448139.3448181.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *The American Behavioral Scientist, 57*(10), 1500–1509. https://doi.org/10.1177/0002764213479363.

Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal and Ubiquitous Computing, 18*(6), 1499–1514. https://doi.org/10.1007/s00779-013-0751-2.

Ware, C. (2019). *Information visualization: Perception for design*. Morgan Kaufmann.

Winne, P. H. (2017). Learning analytics for self-regulated learning. *Handbook of learning analytics*, 241–249.

Winne, P. H., & Baker, R. S. (2013). The potentials of educational data Mining for Researching Metacognition, motivation and self-regulated learning. *Journal of Educational Data Mining, 5*(1), 1–8.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Hillsdale, NJ: Erlbaum.

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 297–314). Lawrence Erlbaum Associates Publishers.

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531–566). Orlando, FL: Academic.

Yoo, Y., Lee, H., Jo, I.-H., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In *Emerging Issues in smart learning* (pp. 145–155). https://doi.org/10.1007/978-3-662-44188-6_21.

Zeidner, M., Boekaerts, M., & Pintrich, P. R. (2000). Self-regulation: Directions and challenges for future research. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 749–768). San Diego, CA: Academic Press.

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist, 2*, 3e17.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–40). San Diego, CA: Academic.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183.

Zimmerman, B. J., & Schunk, D. H. (Eds.). (2001). *Self-regulated learning and academic achievement: Theoretical perspectives*. Routledge.

Zimmerman, B. J., Bonner, S., & Kovach, R. (1996). *Developing self-regulated learners: Beyond achievement to self-efficacy*. American Psychological Association.

Chapter 23
User-Centred Guidelines for the Design of Curriculum Analytics Dashboards

Ed de Quincey and Martyn Parker

1 Introduction

Higher education institutions (HEIs) often have processes for continual review and development of their curricula (Jessop, 2012). These reviews typically aim to evaluate effectiveness and identify areas for improvement (Advanced HE, 2018). HEIs usually capture a yearly "snapshot" of their curricula's performance quantitatively through data proxies such as student module feedback, accreditation requirements and outcome statistics and qualitatively through academic's reflections. In the majority of UK HEIs, data is in disparate places, available at different points of the year or simply not available in a usable format. Furthermore, these review processes generally do not include consideration of other student learning data such as attendance, virtual learning environment or library/reading list usage. These challenges encourage focus on individual modules rather than the overall curriculum's effectiveness and means academics often review their modules based on their own view of the limited data available (which is often anecdotal and highly subjective) impacting the accuracy and effectiveness of reflection. Consequently, effective curriculum evaluation is limited. To illustrate these difficulties, "cohort effect" claims are often used year-on-year to explain module outcomes. It is unclear how these claims arise, but data analysis within the School of Computing and Mathematics at Keele University shows that in most cases these claims are often unsubstantiated and incorrect (Parker, 2017, Personal communication). A review of data and exam board

E. de Quincey (✉)
Keele University, Staffordshire, UK
e-mail: e.de.quincey@keele.ac.uk

M. Parker
University of Warwick, Coventry, UK
e-mail: martyn.parker@warwick.ac.uk

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_23

minutes demonstrated simultaneously the same cohort being described as "weak" and "strong" (Parker, 2017, Personal communication). The lack of data-informed decision-making, inference and reflection means curriculum review is inherently qualitative and prone to psychological bias. This leads to a lack of evaluation based on evidence, and subsequent curriculum enhancements are restricted to modules and thus lack in-depth strategic curriculum analysis.

Research demonstrates that designing informed and optimal curricula requires integrated and aggregated learning-related data across multiple sources (Mangaroska & Giannakos, 2017).

Nevertheless, as noted, current approaches usually forces focus on 1 year in isolation without adequate mechanisms to support stakeholders objective review, meaning forming a true picture of the "health" of the curriculum and comparing it over several years to see longitudinal change and impact is therefore difficult.

This chapter addresses deficiency in current approaches by describing how curriculum analytics tools and dashboards can be designed with academic stakeholders at the centre of the design of their own curriculum review and enhancement processes. The outcomes are guidelines for curriculum analytics dashboards that reflect the needs of those driving enhancements.

2 Literature Review

This section reviews common terminology and introduces relevant work in the field.

Higher education employs different terminology for closely related ideas. For instance, the terms "programme" and "curriculum" have multiple interpretations (HESA, 2011). To prevent ambiguity, in this chapter, a programme consists of modules (compulsory or optional) containing learning material that combines to form the programme's curriculum. Completing the programme leads to the award of a qualification, usually a degree. Programme teams are the academics responsible for leading and administering the programme and taking responsibility for its quality. HEIs quality assurance and enhancement processes typically utilise a continual enhancement model that aims to annually review a programme's curriculum. Different methodologies are utilised across the sector (Berrett, 2011) with work such as the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ENQA, 2015) that set out potential approaches and the UK Quality Code for Higher Education, Chapter B8 providing "indicators of sound practice" (QAA, 2018b). Nevertheless, little evidence exists showing how stakeholders data needs are supported during these reviews.

Dashboards analyse and visualise data. It has been found that dashboard can help students and academics understand engagement with learning activities (Charleer et al., 2016). This collection, analysis and reporting to enhance learning is collectively defined as learning analytics (Siemens & Gašević, 2012). These learning analytics dashboards focus almost exclusively on student-facing dashboards or those for individual modules, although exceptions do exist (de Quincey et al., 2019; Matcha et al., 2020). Dashboards supporting curriculum reviews are normally a secondary consideration and can merely take the form of spreadsheet data, or simply do not exist. Whilst some programme teams may be able to navigate and bring together information and data to perform curriculum reviews, many are unsupported, and reviews are constrained in nature. Consequently, new approaches are required.

Learning design is a methodology that provides a framework in which pedagogy informs decisions that make a design process explicit and shareable. A key feature is gathering evidence during the development of new resources (Maina et al., 2015). Research has started to show how learning design (Koper, 2005) and curriculum enhancement can be supported by learning analytics to improve teacher inquiry and reflection (Persico & Pozzi, 2015). However, integrating learning design tools and strategies with learning analytics tools and dashboards for monitoring and analysis is a challenge (Rodríguez-Triana et al., 2015) with Burgos (2010) suggesting that the failure of some of the major learning design projects is due to a low degree of user-friendliness of the representations proposed. Persico and Pozzi (2015) found that despite efforts to support the work of "learning designers", i.e. lecturers, the communities formed so far around some learning design tools or approaches find it difficult to grow and sustain themselves, meaning that the embedding of learning design and learning analytics approaches within traditional university curriculum review procedures is uncommon. A contributing factor is the shortage of studies on how educators are planning, designing, implementing and evaluating learning analytics decisions (Rienties & Toetenel, 2016) and the need for explicit guidance on how to use, interpret and reflect on learning analytics findings to refine and redesign learning activities (Mangaroska & Giannakos, 2017).

Persico and Pozzi (2015) suggest that a direction towards closing this gap is to consider establishing a participatory culture of design, and a habit among educators to see learning design as an inquiry process and learning analytics as a part of the teaching culture. Bakharia et al. (2016) identified the dimensions temporal, comparative, tool specificity, cohort dynamics and contingency for the types of analytics that are useful in evaluating a learning activity.

Building on Bakharia et al. (2016) work, this chapter describes research that investigated how curriculum analytics tools and dashboards can be designed by combining aspects of learning design and learning analytics, with the stakeholders at the centre of the design of the curriculum review and enhancement processes.

3 Aims and Objectives

The aims of this research were to investigate the types of questions users want to ask of learning data, how best to support reflection with analytics and visualisation and how this can be used to inform learning design and curriculum review. This work's objectives are to:

1. Identify questions module staff and programme leads need to answer when reviewing and reflecting module/programme delivery.
2. Identify forms of analytics and visualisation/representation to support review and reflection, focussing on ease of use and interpretation.
3. Create user-centred and data-informed module and programme-level "health reports" that aggregate information from a variety of sources such as attendance, mark distribution, student feedback, virtual learning environment (VLE) usage, historical performance and module comparison.
4. Create a set of programme-level student journey visualisations (considering different types of student).
5. Evaluate the effectiveness of the "health reports" in supporting reflection, review and learning design/curriculum enhancement.
6. Create a set of guidelines for embedding learning analytics into annual curriculum/module review and learning design.

4 Methodology

We used a variation of the user-centred design approach which is underlined by a set of specific principles and based upon an explicit understanding of users, tasks and environments (Assistant Secretary for Public Affairs, 2018a). The process is iterative and involves users throughout the design and development phases via user research methods such as think aloud, co-design and prototyping, making it ideal for both research and technology development.

For the initial analysis stage, we conducted think alouds (a verbalised description of an individual's thinking during a process) and contextual interviews with lecturers to determine the process they currently go through when creating their module evaluation reports and how learning analytics metrics and representations could then be integrated into this process.

We then iteratively designed and implemented a tool that creates a module "health report" that aggregates learning data from a variety of sources identified previously (de Quincey et al., 2019). These utilise appropriate representations identified from the literature and based on feedback from lecturers in the initial analysis stage.

An evaluation of the tool was then conducted using contextual interviews and think alouds to gather qualitative feedback.

4.1 Interview Protocol

The combination of contextual interviews (Assistant Secretary for Public Affairs, 2018b) and think alouds (Nielsen, 2014) has been used for both the initial user research sessions and the follow-on evaluation sessions to avoid common issues with techniques such as interviews with questionnaires relating to the elicitation of tacit and semi-tacit knowledge (Rugg et al., 2008). These types of knowledge are expected to be used when academics are performing tasks that are either infrequently performed (in the case of annual module review) or rely on skills passed on via a community of practice (e.g. teaching practice and learning design) and as such are not codified and may not necessarily be easily expressed (Chugh, 2015). Sessions took place in participants' university offices, helping to ensure a typical environment for the task. Specific questions were prepared in advance to guide sessions around topics such as sources of information they use/would like to use; examples of good practice they have seen; types of representation they would prefer analyses/visualisation that should be included in the report; and whether they felt that this form of report would enhance their ability to reflect more objectively. Table 23.1 sets out the initial user research and evaluation session procedure.

This study was approved by the University Ethical Review Panel (Ref: NS-190012) with all participants receiving a participant information sheet and signing a consent form.

Table 23.1 Initial user research and evaluation session procedure

Step	Protocol
Initial user research session	
1	Participants were shown a guided demonstration of the think aloud technique
2	Audio recording of the session was started
3	Participants were asked to access a blank module evaluation report template that is used within their subject area (or equivalent module evaluation practice). If one was not routinely used, an example template was supplied
4	Participants were then asked to think aloud whilst looking at the template, imagining that they were filling it in for a module they had taught this year
5	Participants were then shown a mocked-up version of a prototype module evaluation report that had been created by the authors and again asked to think aloud whilst looking through each section
Evaluation session procedure	
1	Participants were shown a guided demonstration of the think aloud technique
2	Audio recording of the session was started
3	Participants were shown the prototype module evaluation tool and asked to think aloud whilst looking through each visualisation. They were asked to try and imagine that this was their module, and they were about to fill in a module evaluation report/form

Table 23.2 Number of respondents by university faculty/centre and discipline

University faculty/centre	School	Respondents
Foundation year	n/a	1
Humanities	Business	1
	History	2
	Law	2
	Politics	1
Natural sciences	Chemistry	6
	Computer Science	6
	Geography	1
	Mathematics	4
	Neuroscience	1

5 Results from Initial User Research Sessions

5.1 Respondent Profile

There were twenty-five respondents with the majority currently teaching within one of the two main university faculties, shown in Table 23.2 below.

5.2 Thematic Analysis

To identify patterns and themes, all sessions have been transcribed verbatim and imported into NVivo 12 and a Thematic Analysis undertaken, following the process outlined by Braun and Clarke (2006) and the guidance provided by NVivo (QSR International, 2019) for coding and mapping. This has included both authors familiarising themselves fully with the transcripts; the generation of a combined set of codes by each looking at a subset of the transcripts (13/12 split); searching for common themes within the list of codes; and then reviewing them by discussing and identifying coherent patterns. A set of 16 themes have then been named and defined (from an initial set of 28 created by both authors) and are outlined in Table 23.3, along with a brief description to clarify meaning.

The following sections describe four themes examined in more detail that are relevant to dashboard design (i.e. data sources) and use (i.e. its purpose and the process it supports).

Table 23.3 Main themes identified from thematic analysis

Theme	Description
Impact on staff	Negative impacts on staff due to the review process
Analysis/statistics	Questions people want to ask of the data
Challenges	Issues that impede the review process
Data	Potential sources of information to inform the review
Design and usability	Suggestions for design of the system and usability issues with the current/prototype system
Ethics	Ethical issues or concerns identified
Good practice	Examples of good practice seen at other institutions
Graphics/ representation	Methods of visualisation of data or analysis
Interventions	Potential uses of data and subsequent interventions for students
Pedagogy	Specific mentions of pedagogy/theory
Process	The review process and how it fits into other university processes
Purpose	Comments related to the purpose of the review process
Reflection	Reflections on data and changes to curriculum based on the review
Student feedback	Comments related to student feedback on modules
Timing	Issues related to the current timing of the review process or suggestions for improvements

Table 23.4 Key data sources used for curriculum reviews

Data type	Description
Module outcomes/ marks	For some respondents (such as chemistry and history), module marks and in particular the mean/median mark and the distribution were the focus and driver for reflection. If marks were too high, the lecturer would reflect on the level of challenge, if too low, on the content, delivery, and suitability of assessment
Attendance	A general impression of attendance levels was mentioned as a proxy for levels of engagement. If the engagement was poor, then changes to delivery would be considered or whether any external factors contributed, e.g. timing of sessions
Intangibles	Several people relied on their own memory of what happened and how delivery went, combining things like their own sense of student engagement and perception of the quality of the work students produced
Reports/ feedback from externals	For some disciplines, the feedback provided by the external examiner for their degree programmes was considered, e.g. comments made on exam scripts or marking
Student voice meetings	There are several meetings during the year where students are asked to bring up issues they are having related to their studies. If specific issues were raised about modules, this feedback would be taken on board by the lecturer during delivery but also at the module review stage
Feedback from teaching team	Where modules are taught in teams, informal feedback would be collated by the module lead and feed into the review process. This, however, was not an official requirement and was mainly done ad hoc

Table 23.5 Key data sources currently unavailable for curriculum reviews

Data type	Description
Entry grades and types of qualifications	Some respondents wanted to be able to combine things like attendance and module marks with the entry qualifications students came to the university with. This could then identify potential gaps in students' prior knowledge/experience and provide appropriate support
Components	The ability to view assessment component mark breakdowns (and potentially who marked them) was mentioned by several staff (some create this manually themselves already). This would indicate which specific components of assessment, e.g. exam or coursework, might need reviewing
Benchmarking	Almost all respondents were keen to be able to know how students were performing on their module compared to the others they were taking. It was noted that there were potential issues with this related to ethics and the effect on staff
Resource usage	Some respondents mentioned that they try and infer some usage of online materials, but it is currently often guesswork. Respondents were very interested though in being able to see how the digital materials they made available, e.g. lecture slides, lecture capture and things like library books, were being used. It was also suggested that as certain sessions and resources were more important than others, there should be some way of highlighting these to analyse their usage and impact on outcomes. Interestingly, although these data are seen as standard in the learning analytics community, the term "learning analytics" was not mentioned by any respondents
Student feedback on assessment	Several respondents spoke about issues with the timing of the student feedback collection process and suggested that they would want some student feedback on the assessment itself by students once completed and they have their marks
Comparison to previous years	Interestingly, very few people spoke about referring to the previous year's reports, but the majority mentioned that more longitudinal data was needed to be able to infer whether changes worked and to determine issues such as cohort effects
Other issues	Extenuating circumstances requests, how many cases of plagiarism, incidents in the exam hall, timetabling/rooming and assessment deadlines were all mentioned as useful bits of information that may affect delivery
Pool of good practice	One respondent mentioned that it would be useful to have examples of good practice available, embedded somehow within the module evaluation form itself so that they could judge their own practice and to also find possible alternatives that could be used to tackle the issues they had identified
Directions of travel	Again, although only mentioned by one respondent and not a specific form of data, an interesting point was raised regarding the importance of trying to keep in mind the university vision and strategies when reviewing the curriculum

5.2.1 Data

All participants reported they focused on certain data types during module reviews. Student feedback (discussed in the following section) was the primary source of information to support reflection and inform module changes; however, there were several other sources of data that people relied on to determine how well delivery had gone and what could change for future instances. Table 23.4 sets out key data types. There were also several sources of data that people mentioned that would be useful but currently do not have access, see Table 23.5.

5.2.2 Student Feedback

Unsurprisingly student feedback in a variety of forms was talked about by all respondents as a key influence on the module review process and subsequent changes to module design and delivery. This ranges from the required survey-based student feedback on each module (using mostly standard questions across the university) to more informal student feedback in the form of individual "chats" with students (either in tutee meetings or in labs/after lectures). Respondents stated that the feedback helps them understand problems and survey questions which ask students to specify specific suggested improvements are the most useful. It was also mentioned that bad scores on certain questions feed reflection and subsequent changes. Even though student feedback was deemed as very important, there were however a number of criticisms related to response rates; self-selecting samples meaning the feedback was not representative, i.e. the students that had "survived" the module were the ones giving feedback; potential bias; questions do not get at the appropriate level of detail and therefore not helpful; all happens at a similar time of the semester and so students get survey fatigue; 12 weeks being condensed into one survey; not knowing which member of staff it is referring to (in team-taught modules); and whether students understand the question in the first place and know what is "good", summarised by one respondent in the following quotation:

> The way that students rationalise why they think something's good is even worse than the way we rationalise it.

5.2.3 Ethics

The ethics theme emerged explicitly and implicitly with the focus on data emphasising the need to consider both its collection and potential for misuse. Data collection beyond student attendance data raised concerns with some respondents. One respondent described in detail their ethical concerns when asked about data use beyond student attendance data:

> Students can reasonably expect to have their attendance recorded, and coursework marks and so on…. If one attempts to monitor their use of the library, VLE, then I think it becomes rather intrusive.
>
> And I think I wouldn't countenance that unless the students have specifically opted into that diagnostic tool. For their benefit.

In contrast, others were open about data availability and use but did not seem to consider the potential ethical implications. Many respondents wanted an ability to anonymously link current disparate information together, for example, module marks, attendance and module evaluation responses. A typical response was:

> it would be nice to know how much of the negative feedback comes from poorly performing students' or that the data should be anonymous, but joined together.

Such responses map onto a desire to create a rich cohort picture, but there is a lack of awareness regarding the ability to use this picture and the "metadata" it provides to determine student identities. The main cause of this appears to be frustration with the ability to contextualise student module feedback and the inability to engage in constructive dialogue with a specific student (who may have given a negative response or has demonstrated a clear misunderstanding). However, it is irrelevant how the desire to create a clear picture arises, it is more important to recognise the ethical considerations this brings.

5.2.4 Purpose

Respondents spoke about the purpose of module evaluation. Several felt they were completing it because they had to, but they did not know how their responses were used and the outcomes. One respondent's comments emphasised a juxtaposition between the reviews they completed as part of the curriculum review process and their actual reflections on their modules. A typical response to the formal process is "Why should I complete this form?" compared to how they "tend to do personal reflection over the summer, rather than in the form". The lack of purpose and isolated nature of each module review creates a feeling that this is just a process that needs completing:

> I don't take it seriously…. I don't have a clear picture of where the information's going… there isn't any year-on-year kind of feeling about it. So, each one feels quite kind of isolated, it's just something that you get out the way some time after you finished teaching the module

Despite this lack of clear purpose, these views were supported even by respondents with responsibility for utilising this information as part of the curriculum review. One commented on the outcome:

> … all this paperwork, it goes into a big folder, it never really gets used again. Some of it gets pasted into the annual [curriculum] review reports. I feel like we do generate a lot of paper that we don't ever really use in any useful kind of way.

This view was further emphasised by the utility of the process: "thousands and thousands of…. Word documents that can contain all of this data is probably not that useful". The importance placed on this review process is therefore undermined by a lack of knowledge and clarity around its purpose.

5.2.5 Process

The final theme discussed here highlights the bespoke processes created to implement module reviews. Schools create their own review processes, but the role and responsibilities of staff varied with some respondents highlighting the role of their administrators: “our administrator on the programme fills in that part for us, and she generates these graphs, mean module marks, the distribution in the different categories”. In contrast, other staff had to organise meeting with their teams, synthesise data and then comment. The processes’ bespoke nature meant significant time is spent on tasks that could otherwise be automated. Many commented that current processes lack of continuity between years: with one commenting that the reviews “focused… experience within that year”. This is emphasised by respondents that took on new modules: “I also would want to look at, where we were last year, and any information that the previous module leader has used to develop the module”. The ability to monitor the impact of changes across year is important, for example: “proposed actions, how did they work?” It was felt that the focus on in-year experience and lack of continuity mean that the curriculum-level reviews are utilitarian and cannot be used to drive long-term developmental change. Some respondents knew the process did not support long-term action planning but did not know how to resolve the problem:

> … some sort of… not a calendar function, but some sort of system where you got an email that said, … please make sure you complete these changes by a certain date.

There was consensus regarding the flaws with current processes and how they related to the overall aim to improve programmes, some suggested the use of a “dashboard” that is automatically populated as the module progress to provide a real-time process, rather than annual process:

> some sort of a dashboard so people can quickly sort of go through, find out what’s going well and what’s going wrong would be a good thing… can you remember what happened before Christmas? No.? So, it’s almost a pointless system doing it like that.

This resonates with the general feeling that the entire process is rushed and thus lacks effectiveness and that current bespoke processes fail to create space and opportunity to deliver meaningful longitudinal module and programme reflection.

6 Tool Implementation

Following the first round of user sessions, we analysed the feedback related to the analysis/statistic; data; design and usability; and graphics/representation themes and formulated some specific requirements for analytics and visualisation including:

- Summary statistics and visual representation for each individual assessment component

- Module benchmark chart (plot average grade over all modules vs the current module for each student)
- Learning analytics data showing VLE click data, absences, and lecture capture data over a semester
- Comparison chart for the learning analytics data to show relationships with student (e.g. absences vs grade, lecture capture views vs grade etc.)
- Method for highlighting students on learning analytics comparison chart so they can track them for different learning analytics features
- Show the relationship between scores and free-text comments for each question on the student feedback.

6.1 Technical Architecture Overview

The curriculum analytics dashboard consists of an analysis module and a web/interaction module. The analysis module (written in Python) takes assessment grades, student feedback ratings/comments and learning analytics data in CSV format and produces histograms and simple analytic charts as well as summary statistics. All

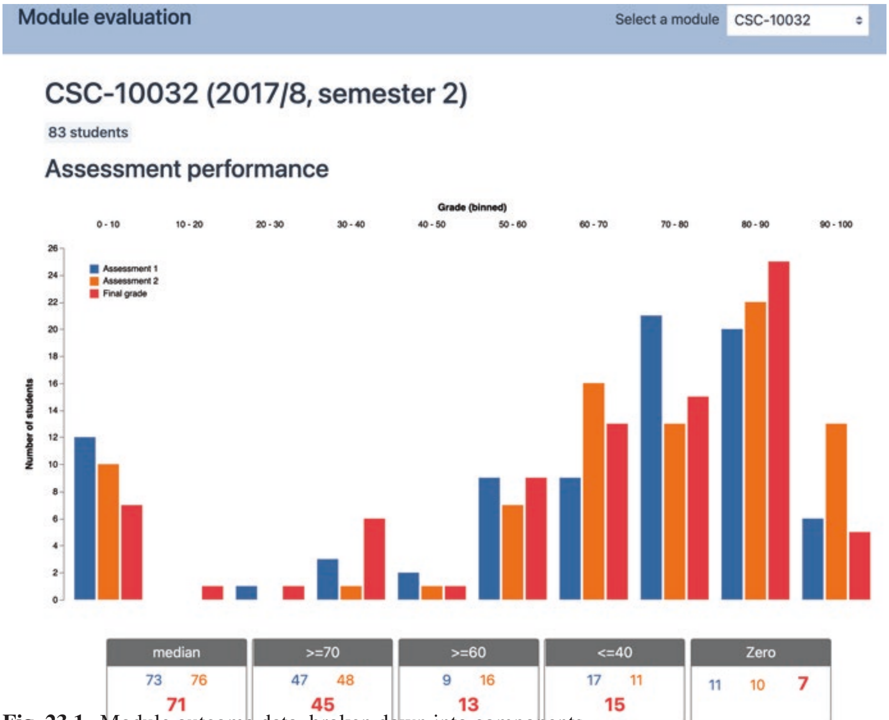


Fig. 23.1 Module outcome data, broken down into components

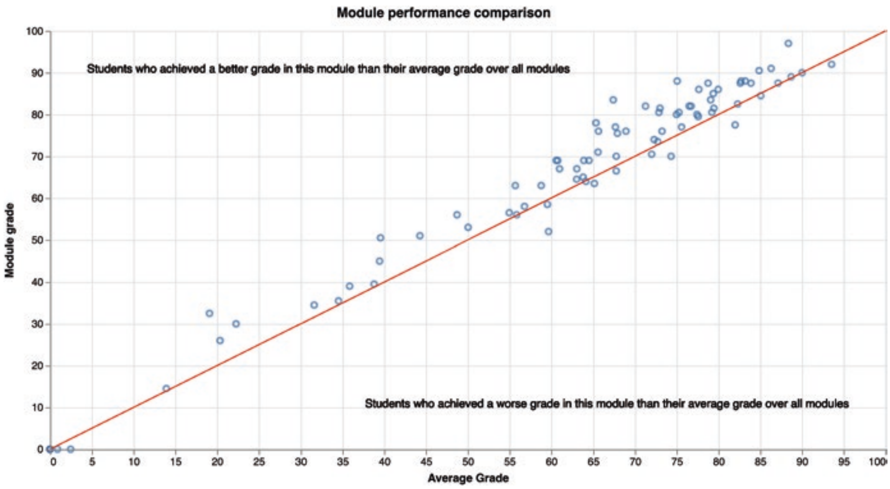


Fig. 23.2 Module performance comparison chart

charts are formatted according to the Vega specification. All the statistics and charts from the analysis module are output in JSON format. The web module is a simple single-page web application built using HTML5 and JavaScript that shows the charts and the summary statistics for the assessment data and learning analytics data.

6.2 Curriculum Analytics Dashboard Overview

The screenshots below show the version of the curriculum analytics dashboard that was shown to participants in the evaluation sessions. In this version of the dashboard, users are shown a succession of visualisations in one "document".

Figure 23.1 shows a representation of student performance for a module, with individual components and overall outcomes included. Below this are summary statistics including the median mark and the number of students in different mark categories (these categories were based on feedback from the initial user sessions).

Figure 23.2 shows the module performance comparison chart which supports benchmarking of modules across a cohort. On the X-axis is the average grade for a student for all modules (not including the one currently being viewed) and on the Y-axis is the student's grade for this module. If a student is above the red line, their module mark is higher than their average mark on other modules.

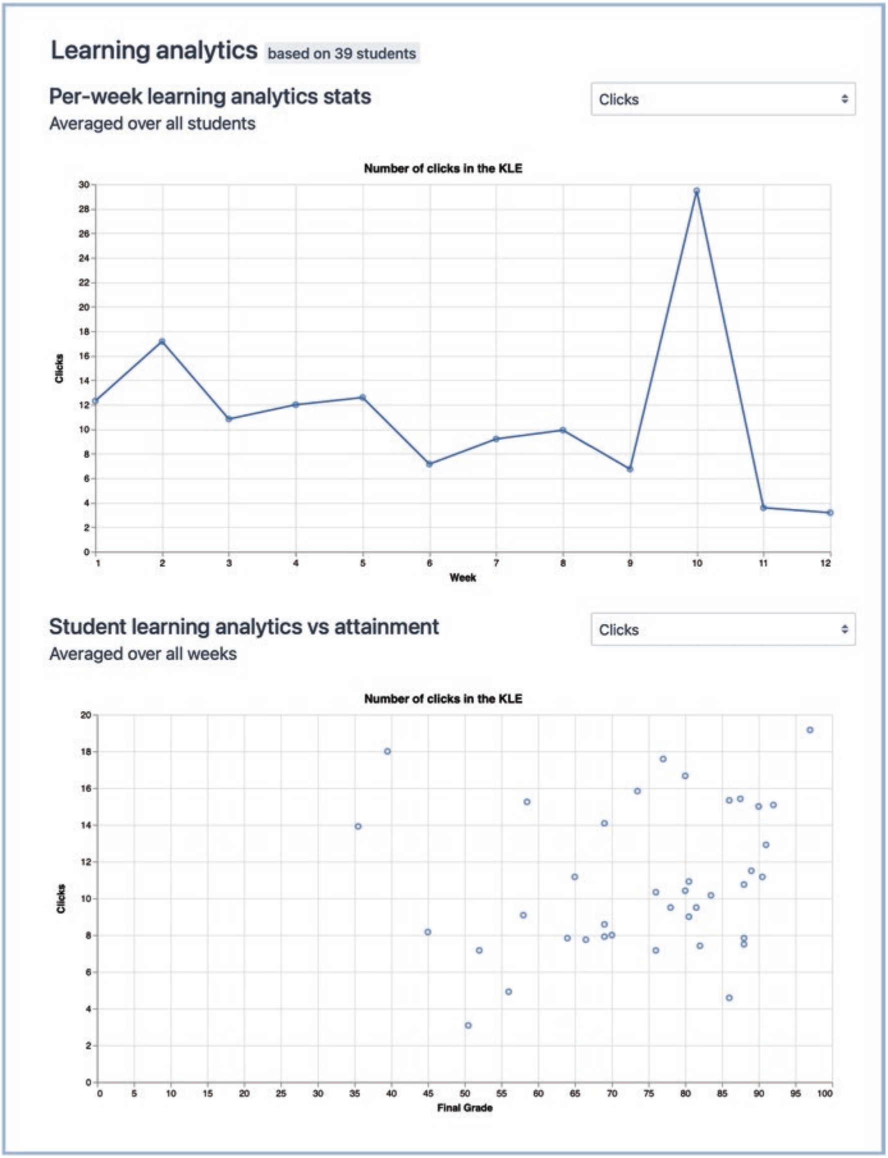


Fig. 23.3 Learning analytics data charts

Figure 23.3 shows the learning analytics data charts. The first one shows the distribution of certain learning analytics features of a semester. Users can access each feature by using the drop-down menu shown in Fig. 23.4 below.

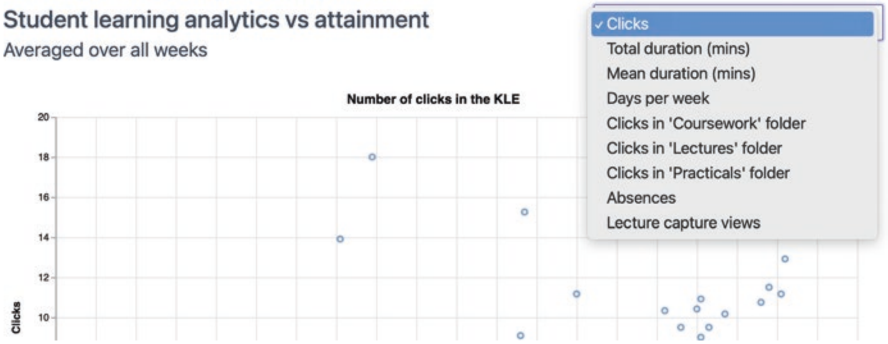


Fig. 23.4 A dropdown menu showing the different features users can view

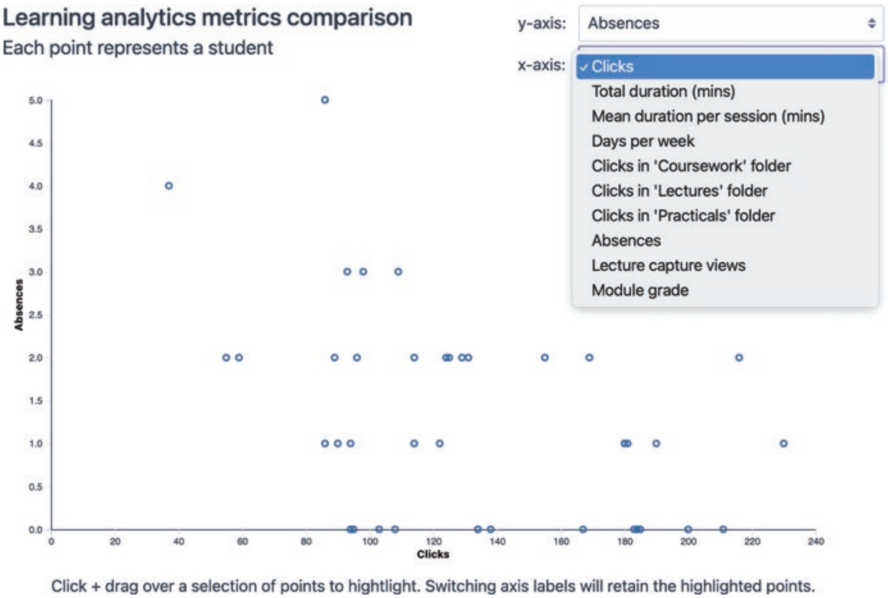


Fig. 23.5 Comparison functionality for all learning analytics features

The second chart allows for comparison of each learning analytics feature against the student grade. This is so the user can start to explore potential correlations/relationships between activity and attendance and student outcomes.

Figure 23.5 shows how a user can also select any of the learning analytics features to compare against each other. This then enables users to look for relationships beyond just with the grade, e.g. comparing absences and lecture capture views.

Figure 23.6 shows how individual or groups of students can now be highlighted (see red circle) so that when switching between features, they can still be identified.

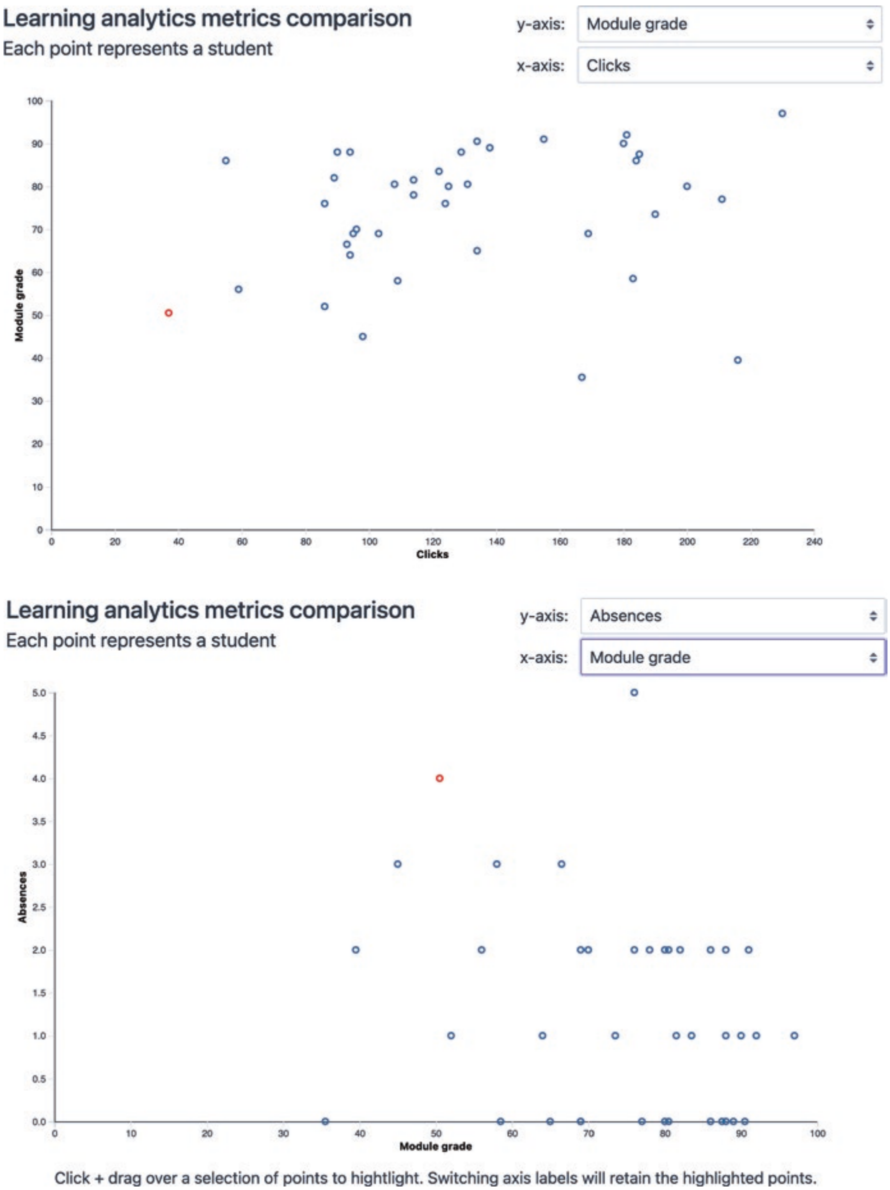


Fig. 23.6 Highlighting students for each feature

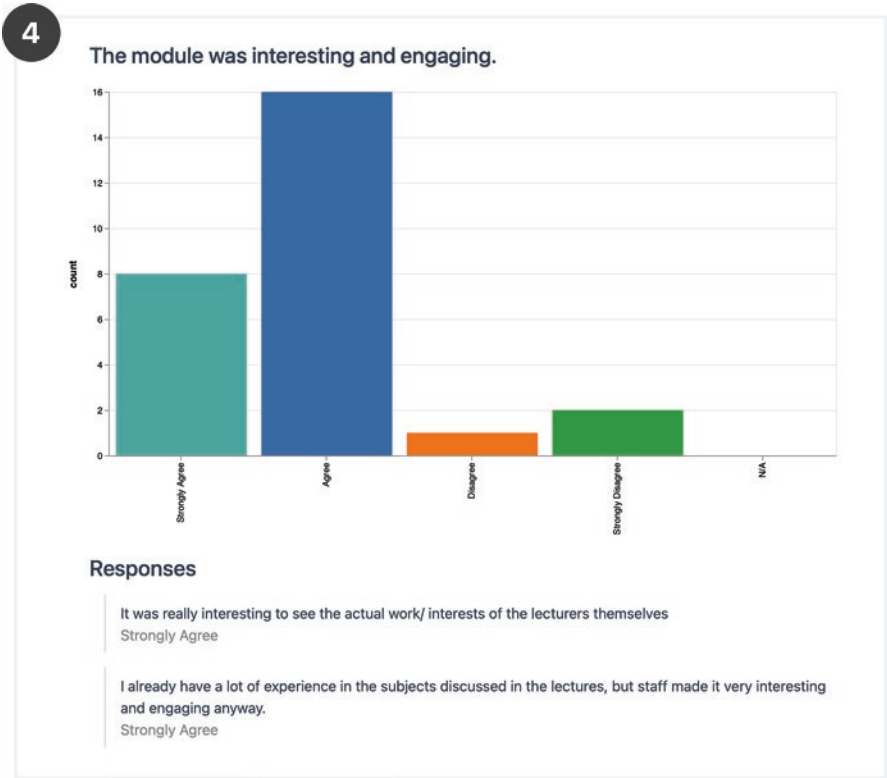


Fig. 23.7 Example results for a single question from student module feedback

Table 23.6 Number of respondents by university faculty/centre and discipline

University faculty/centre	School	Respondents
Foundation year	n/a	1
Humanities	Business	1
	Politics	1
Natural sciences	Chemistry	5
	Computer Science	3
	Geography	1
	Mathematics	3
	Neuroscience	1

This is so the user can view how an individual or group of students behave across a variety of different metrics, for instance, do some types of students (e.g. those who fail) have different attendance and engagement characteristics?

Figure 23.7 shows an example of the summary results for a single question from the student module feedback questionnaire (currently collected via Google Forms, a CSV of which is then used to create the summary by the tool). Under each free-text response is the score that the student who wrote the response gave for this question. This was mentioned by several people as being important due to the need to try and infer what was meant by some of the more obtuse responses. Showing the score then gives context to the reply.

7 Curriculum Analytics Dashboard Evaluation

As described in Sect. 3.1, the evaluation of the module evaluation tool was conducted using the same method as the initial user research sessions, but with the focus being on the version of the tool described in Sect. 5.1.

7.1 Respondent Profile

It was decided to recruit participants for the evaluation from the original 25 people who took part in the initial user research sessions. Although we appreciate that there are disadvantages to this related to potential biases respondents may have, we felt that due to the qualitative and iterative nature of our approach and the fact that it was clear that for some areas (relating to learning analytics) they had little pre-existing knowledge or opinions, this would be appropriate.

Sixteen participants were recruited from across three faculties shown in Table 23.6 below.

7.2 Results

The results described in this section are based on a thematic analysis of the recordings of each session following the process outlined by Braun and Clarke (2006). Nine main themes were identified and are outlined below.

7.2.1 Module Outcome Data

There was discussion related to whether a single chart was best for representing the different assessment components or whether this should be split into separate charts. The universal opinion though by all respondents was that a single chart including assessment components and the overall grade was preferred as this would enable immediate trend comparison (even though there were some comments that it may become too crowded with lots of assessment components). Some respondents asked about how “hidden” assessments would be considered, e.g. when a portfolio containing several individual assessments is recorded as one final mark in the university student records system. The colour scheme chosen to depict components and overall grade needs to be clearer so that users can focus more clearly. Some form of interactive UI design or shading was suggested to highlight a particular area.

The overall positive opinion though regarding this feature is exemplified by the following quote:

> So, this is the data that I need to create for myself using my CSV file. Having this upfront is very useful and a time saver.

7.2.2 Previous/Longitudinal Data

Like the initial sessions, there were some comments about wanting to compare to past data and the ability to measure change (3 years was commonly mentioned although it is not clear why this number is chosen). This is a key requirement for a system like this, but for some forms of data, currently we do not have access to these, or they may not exist.

7.2.3 Values and Measures

A common theme related to the choices of measures we had chosen and how best to represent them. For example, there was confusion in the summary statistics related to whether numbers represented percentages or number of students. Similarly, in the learning analytics data, averages for some of the measures were not useful, e.g. what does 0.25 of an absence mean? What does 0.28 of a lecture capture mean? “Clicks” were whole numbers so were clearer and it was suggested that totals were used for measures like absences, rather than averages.

7.2.4 Benchmarking

The consensus was that the module performance comparison chart was incredibly useful. Interestingly, during the initial user research sessions, a mocked-up version of this required explanation in all sessions. After some additional explanatory wording was added (relating to what above and below the line means), this did not require any explanation this time. This could be because they had seen this form of representation in the previous sessions, but as this was 8 months later, it is promising that this was now clear as to how to interpret it. Like comments made in the initial user research sessions, it was noted that this should not be used for staff performance management.

For data where people had no prior access or experience with, e.g. VLE usage data, it was mentioned by several respondents that some sort of baseline is needed to inform comparison/reflection. For module marks, respondents would confidently talk about grade distributions they would expect to see but for the other sources of data; this “expectation” is absent due to not having the opportunity to view it before and to build up experience of what is “normal”. This was highlighted by one respondent asking, “What is a virtual absence?”, i.e. what is the virtual equivalent of a student not attending a session (trying to relate their experience of absence in the classroom to online and what that would look like)? One suggestion to build this initial baseline would be to create something like the module performance comparison chart but for the learning analytics data.

7.2.5 General User Interface

Although there were few issues with people navigating and interpreting the information/layout of the page, there were some specific potential improvements noted:

- People often missed the drop-down menu to select the features of the learning analytics data. Whether this is because people are used to static views of this kind of information or this is down to inexperience with this kind of system needs further investigation and refinement.
- The student feedback is currently displayed as seven different charts, one under another. It was mentioned that this was a lot of scrolling and so potentially a tab interface could be used instead and is more in line with a traditional dashboard representation.

7.2.6 Analysis/Statistics

Some additional forms of analysis that people mentioned included:

- If students miss a class, then detect how long it is until they watch the corresponding lecture capture material.
- Ability to create testable predictions.

- Significance (both in the statistical sense and more generally) and wanting to try and quantify some of the relationships between factors and automatically highlight significant issues, e.g. What is the most important factor that could be affecting the grade? Does lecture capture intervention make a difference?

7.2.7 Additional Data

Interestingly, when asked about additional sources of data, most respondents were not able to suggest many others. Those that were mentioned were:

- Timetabling and temporal information were mentioned as being important as this would affect the distribution of activities over a semester (for some subjects not all weeks have the same timetable). Similarly, the ability to slice the data between different types of session, e.g. lab, lecture and workshop. This context is needed to inform the analysis of things like absences and VLE interaction.
- Engagement with feedback on Turnitin (so a comparison between viewing feedback and grade could be made).
- Engagement with the reading list and associated materials.

7.2.8 Embedding into Practice

There were several suggestions as to how this tool could be used to then inform module evaluation reports. These related to embedding the form that lectures fill in when evaluating their modules, within the tool itself so that people are asked to comment on each individual section of the report. This would then be seen as an interactive document that leads people through the data, asking them to reflect on specific areas (perhaps with significant issues/successes being automatically highlighted by the tool itself).

Although not an explicit way of embedding this into practice, several people mentioned that just because of the significant amount of individual effort and time this process currently takes would mean that there is a clear reason for people to use this and so uptake would occur naturally.

7.2.9 Supporting Reflection

All respondents were clear in their belief that it would help reflection with them all wanting to use it. Several respondents whilst using the prototype tool in the analytics section gave oral reflections on the module data and began interrogating and generating hypotheses that they wished to test, developing new analytics requirements, e.g.

> We have the lecture capture data for each lecture, we know if an individual was absent, so for a given absence, was the corresponding lecture capture viewed?

The general level of feeling can be best summed up by this respondent when asked whether they felt this tool would help support them reflect more objectively:

> Oh, 100%. Absolutely, yeah, yeah. This would be pretty transformatory. Making sure first of all that all the information is clearly illustrated and presented to you in one particular place. I think at the moment you get bits of information all over the place. You need to go to this Google Sheet to get this particular bit of information, or this bit of paper. To have all of the information that you need to prompt module reflection in the one spot would be really useful. I think it would help me as a consequence be more clear and systematic in terms of my appraisal of the performance of that module. Then as you end up moving through the University structure, at Programme level, School, Faculty then University, then that's when it becomes particularly powerful. It would provide you with an opportunity to get a full sense of what is going on, instead of a list of random modules where we are concerned about the module average. That doesn't really tell you anything, whereas if you have the opportunity to go into that module and find out what the real issue is, you'd be able to build up a picture of what the issues might be.

8 Discussion and Conclusion

Fundamentally, curriculum reviews are processes that require appraisal of disparate data sources with the aim of enhancing programmes of study, with many countries setting minimum quality assurance standards for such processes (QAA, p. 4, 2018a). With the emphasis on data, learning analytics should be central to this process. Our respondents' current practice though challenges this assumption. Although some data sources are available, they are often poorly presented and available in a manner that prevents comparative analysis, or the means to achieve such an analysis are so time-consuming that can be viewed as impossible. For example, a simple comparison between mark data and attendance data is universally absent but desired by all respondents. A key barrier is one system records marks and an entirely separate system records attendance. Thus, a simple comparison requires time-consuming manual user intervention. Significantly the rich potential that learning analytics presents are all but absent in the curriculum review's analysis phase.

Confronting the key curriculum review aim, our study raises fundamental questions for those interested in educational process management and data-informed curriculum design and enhancement. Whilst universities may feel their processes are clear, articulate and serve a clear purpose, our participants' experiences emphasise that current practices fail to create long-term strategic plans that enhance educational value. Criticism focused on both the absence of apparent purpose and the underlying processes. It appears that process management is delegated to individual schools and that data processing is often delegated further to individuals. Although respondents were clear in their aims, the disparate processes did not support their aims. More holistically, the delegation means the curriculum review's purpose is opaque, and significant work is undertaken with an apparent outcome that states little more than the process has been completed. There is, therefore, a need for better data management tools that are suitable for a wide and varied audience and support clear strategic planning and monitoring, generating long-term value.

When asked about their data needs in the first set of user research sessions, respondents listed few data sources, but more importantly little consideration was initially given to how to present this data to generate the greatest potential for deep analysis. In many cases, respondents simply stated that they didn't know what they wanted. Examining this more deeply, they wanted a process and system that met their needs and facilitated their reflection, but they did not know in what form. Returning to aim (1) in Sect. 2, our respondent data illustrates a lack of clarity around the questions staff and programme leads want to answer. Similarly, aim (2) (relating to forms of visualisation and representation to support review and reflection) demonstrates a knowledge gap, where the respondents did not know what they needed or how it might be presented. It is apparent that many respondents wanted the ability to create a clear "picture" of their "students' journey". Until such a "picture" is available though, surface analysis will prevail. This raises a design issue that the respondents are from a diversity of disciplines and any learning design tool must provide the flexibility for respondents to create this "picture" in a manner that makes the "student journey" self-evident to them.

The respondent data did raise some underlying tensions. Firstly, the lack of purpose meant some respondents were uneasy with providing open and honest reflections fearing that such reflections could provide management leverage against them. Secondly, and potentially related to the first, there appeared to be an underlying need to relate negative student responses with poor student performance. It is possible that there is a similar desire with positive comments, but the respondents were clear in their focus on areas where they could face criticism. It is unclear how respondents would feel and act if the data did not reveal a clear relationship. Within this discussion, it is important to recognise the ethical implications raised and the potential for data misuse.

Research often shows the benefits of learning analytics; however, a contribution of this study is that, at present, learning analytics is poorly utilised, if at all, within the curriculum and development process. Staff desire learning analytics type information, but as learning analytics is not part of the operational processes, the entire curriculum review has limited business purpose. The lack of focus on business purpose means data use is surface level and lacks a longitudinal view, fundamentally impacting the curriculum review's value in strategic and evidence-based reflection and subsequent learning (re)design. With these observations in mind, it is clear there is a need to invest and understand how to utilise and embed, through appropriate processes, learning analytics for operational productivity that creates self-evident business purpose in curriculum review and curriculum development. Without this, the state of learning analytics and its benefits may well be best summed up by the following quote:

> I'm sure that there are [benefits], but that's because I don't know what I don't know.

Table 23.7 User-centred guidelines and metrics to support the design of curriculum analytics dashboards

Theme	Principle
Assessment and grades	Assessment components should be included in any module outcome charts and summary statistics
	Present components and overall module outcomes on one chart
	Provide the ability to compare module performance across a cohort
Data	Provide context for data include timetabling information so that patterns can be linked with activities
	Do not assume that people understand the term learning analytics or are aware of the production/collection of usage data. Until you show people, they do not know what can be done
	The numeric representations of data need to relate to people's understanding of them. Averages are appropriate for some measures, but totals are better for others. It needs to be made clear what values mean, for example, is a higher number a "good" or "bad" indicator
	Provide the ability to compare data to previous years to infer whether changes worked and to determine issues such as cohort effects
	Provide indications of significance/confidence level for data where appropriate
Benchmarking	Benchmarking is important when including new sources of data that people might not be experienced with or have a mental model of, e.g. VLE usage
	However, academics can create their natural baselines which create a bias that might be invalid and should be questioned, e.g. an "appropriate" distribution of module marks
Required data	Attendance is seen as a proxy for levels of engagement and should be included
	Provide details about online resource usage such as views of lecture slides and lecture capture and whether library books are being used
	Provide the ability to consider the greater importance of some sessions and resources to analyse their usage and impact on outcomes.
	Student feedback is the main driver of reflection, but it is important to supply context for free-text responses
	Student feedback, although useful, is contentious due to issues such as the timing of collection, the representativeness of the sample and the ability of students to rationalise the delivery of a module
	Other forms of feedback could be considered such as from externals examiners, student voice/rep meetings and other members of the teaching team
	Entry grades and types of qualifications could be used in combination with other metrics to identify potential gaps in students' prior knowledge/experience and provide appropriate support
	Other issues should be considered for inclusion such as extenuating circumstances requests, how many cases of plagiarism, incidents in the exam hall, timetabling/rooming and assessment deadlines

(continued)

Table 23.7 (continued)

Theme	Principle
Curriculum review	Provide the ability to explore relationships between measures such as grades, attendance, VLE usage, lecture capture views, etc.
	Recommended good practice/interventions could be embedded within the module evaluation form/system itself to tackle the issues identified
	Embed the review process within the data itself. Make reports interactive documents that lead people through the data, asking them to reflect on highlighted/benchmarked/significant issues and successes
	Encourage people to make testable interventions and supply data to evaluate their impact. Ensure these actions are embedded in the following year's report to encourage further reflection on the impact

Table 23.8 Guidelines for embedding curriculum analytics dashboards into curriculum and module review

Theme	Principle
Ethics	Module reports and associated data should not be used as part of staff performance review but could be used to identify training needs
	The process must be developmental and not considered by either the university or staff as potentially punitive. For this reason, universities must make clear how staff reflections and data are used at all institutional levels
	Module reports and associated data could be used as evidence for promotion cases and applications for awards such as HEA fellowship. The types of questioning embedded in the form must elicit reflections and responses that naturally align with future staff development
	Ethical use of data must be considered at all stages and guidance provided (or access limited) as not all staff appreciate the issues with data aggregation
Process	The review process must be operational rather than management based where staff are clear how their reflections and feedback are used and acted on at all university levels. Staff must see the value in the process through subsequent actions and developments arising from the process
	Real-time access to data may negate the need for annual review processes and may provide more effective interventions and developments
	Bespoke processes create a significant amount of manual effort and should be replaced where possible with automated/digital methods of data collection and aggregation. Staff must be engaged at the start of this process to ensure the outcomes have value, promote deep reflection and reduce staff workload, providing time and space where staff focus entirely on educational development
	Facilitate longitudinal review though datasets that permit interrogation of a cohort's journey through their programme

What is promising though is the response of academics in the evaluation sessions. When presented with a fuller "picture", and with examples of data that they previously "didn't know", they were then able to start to see the advantages and benefits of having access to this information. What was even more pleasing was the level of reflection that was shown, as respondents started to realign their opinions and generate new lines of questioning and reasoning. For example, there is a feeling that academics create a natural baseline against which they judge various measures and calibrate their reflection, e.g. an academic might know when overall module marks are "good" or in need of consideration. These baselines are often not informed by anything more than "personal" judgement or inherited by their community of practice where expectations are passed on to newer staff by mentors. The result is the previous mentioned and ill-informed comments about a "cohort effect".

This is, however, an opportunity. As new metrics and sources of data emerge, with which people have no previous experience in analysing or reflecting on, pre-existing "baselines" and potential biases can be challenged. Academics will have to start to formulate data-informed baselines to create meaning in relation to their practice. An example of this behaviour is the question one respondent posed "What is a virtual absence?", that is, what is the virtual equivalent of a student not attending a session. These new lines of questioning demonstrate the benefits of not only a tool that aggregates and represents data but also an iterative user-centred design process which has effectively also acted as training in learning analytics for the respondents.

With regard to how learning analytics in this form can be embedded within module and curriculum evaluation and design, respondents were clear that a module evaluation tool must include questions that promote reflection as they engage with the data. In certain cases, a dashboard-like tool might tailor questions to encourage reflection around a particular piece of data, for example, successes in terms of outcomes, engagement with groups of students or where the results are particularly out of line with other modules. The tool then becomes an interactive document and future resource for academic discussion and development. In cases where a module is transferred to another or new academic, they have an immediate resource that contextualises past student journeys through the module.

8.1 Guidelines

From analysing the results of all user sessions and the production of the tool itself, we are proposing the following sets of guidelines for other researchers in the area, developers of learning analytics services that support learning design and curriculum review and universities who are trying to implement and embed similar tools and reflective review processes into their modules and programmes. Table 23.7 sets out user-centred guidelines and metrics (potential sources of data and representations) that should be implemented in dashboards to support curriculum review and reflection. Table 23.8 sets out guidelines for embedding curriculum analytics dashboards into curriculum and module review.

8.2 Conclusion

The research's outcomes signal the significant benefits of engaging academics in a partnership to design curriculum analytics dashboards and visualisation types that are centred around their needs. It is important however for the design of these dashboards and visualisations to not only be driven by users and the questions they want to answer but also to be embedded within appropriate processes that have their purpose made clear. This combined approach can bring about transformational engagement with learning analytics, generating a novel approach to deep reflection and decision-making around positive programme development and curriculum review. It is here where we see a key future research direction in learning analytics, with the process and purpose of its use being recognised as important as its visual and technical design.

Acknowledgements We would like to thank Chris Briggs for helpful conversations and his work constructing the dashboard tool. We also thank Theo Kyriacou for help conducting some interviews. This work was funded by a Jisc Learning Analytics Research Group grant.

References

Advanced HE. (2018). *Curriculum review and development*. https://www.heacademy.ac.uk/curriculum-review-and-developmenttargeting-student-success-through-future-proofed-curricula#section-4

Assistant Secretary for Public Affairs. (2018a, November 20). *User-centered design basics*. Useability.gov. https://www.usability.gov/what-and-why/user-centered-design.html

Assistant Secretary for Public Affairs. (2018b, November 20). *Contextual interview*. Useability.gov. https://www.usability.gov/how-to-and-tools/methods/contextual-interview.html

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. In Proceedings of the sixth international conference on Learning Analytics & Knowledge (LAK '16). *Association for computing machinery*, New York, NY, USA, pp. 329–338. https://doi.org/10.1145/2883851.2883944

Berrett, D. (2011). *Program reviews lead to 'Death spirals' – And a few happy endings*. The Chronicle of Higher Education, Vol: 58, Issue 3.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Burgos, D. (2010). What is wrong with the IMS learning design specification? Constraints and recommendations. In M. Atzmüller, D. Benz, A. Hotho, & G. Stumme (Eds.), *Proceedings of LWA 2010 – Workshop-Woche: Lernen*. Wissen & Adaptivitaet. https://www.kde.cs.uni-kassel.de/wp-content/uploads/conf/lwa10/papers/abis8.pdf

Charleer, S., Klerkx, J., Duval, E., De Laet, T., & Verbert, K. (2016). Creating effective learning analytics dashboards: Lessons learnt. In K. Verbert, M. Sharples, & T. Klobučar (Eds.), *Adaptive and adaptable learning. EC-TEL 2016* (Lecture Notes in Computer Science) (Vol. 9891, pp. 42–56). Springer. https://doi.org/10.1007/978-3-319-45153-4_4

Chugh, R. (2015). Do Australian universities encourage tacit knowledge transfer? In *Proceedings of the 7th international joint conference on knowledge discovery, knowledge* *engineering and knowledge management – Volume 1*: KMIS, (IC3K 2015), pp. 128–135. ISBN:978-989-758-158-8. https://doi.org/10.5220/0005585901280135

de Quincey, E., Briggs, C., Kyriacou, T., & Waller, R. (2019). Student centred design of a learning analytics system. In *Proceedings of the 9th international conference on Learning Analytics & Knowledge (LAK19)* (pp. 353–362). Association for Computing Machinery. https://doi.org/10.1145/3303772.3303793

European Association for Quality Assurance in Higher Education (ENQA) (2015). *Standards and guidelines for quality assurance in the European higher education area*. Brussells, Belgium.https://www.enqa.eu/wp-content/uploads/2015/11/ESG_2015.pdf

HESA. (2011, December). *What is a Course?** (**or Programme or Route or Pathway or Learning Opportunity…?*). Retrieved from: https://www.hesa.ac.uk/files/What-is-a-course_2011.pdf

Jessop, T. (2012). *TESTA (2009-12). Transforming the experience of students through assessment* (NTFS Project Final Report). Retrieved from: https://www.academia.edu/15601506/NTFS_Project_Final_Report_TESTA_2009-12_Jessop

Koper, R. (2005). An introduction to learning design. In R. Koper & C. Tattersall (Eds.), *Learning design* (pp. 3–20). Springer. https://doi.org/10.1007/3-540-27360-3_1

Maina, M, Craft, B and Mor, Y. (Eds.) 2015. Art & science of learning design. Sense Publishers, . https://doi.org/10.1007/978-94-6300-103-8.

Mangaroska, K., & Giannakos, M. (2017). Learning analytics for learning design: Towards evidence-driven decisions to enhance learning. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data driven approaches in digital education* (EC-TEL 2017. Lecture Notes in Computer Science) (Vol. 10474, pp. 428–433). Springer. https://doi.org/10.1007/978-3-319-66610-5_38

Matcha, W., Uzir, N. A., Gašević, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 13*(2), 226–245. https://doi.org/10.1109/TLT.2019.2916802

Nielsen, J. (2014, January 15). *Thinking aloud: The #1 usability tool.* Nielsen Norman Group. https://www.nngroup.com/articles/thinking-aloud-the-1-usability-tool/

Persico, D., & Pozzi, F. (2015). Informing LD with LA to improve teacher inquiry. *British Journal of Educational Technology, 46*, 230–248. https://doi.org/10.1111/bjet.12207

QSR International. (2019). *Nvivo, How to approach thematic analysis*. https://www.qsrinternational.com/nvivo-qualitative-data-analysis-software/resources/resource-library/how-to-approach-thematic-analysis

Quality Assurance Agency. (2018a, November 29). *UK quality code, advice and guidance: Monitoring and evaluation*. https://www.qaa.ac.uk/en/quality-code/advice-and-guidance/monitoring-and-evaluation

Quality Assurance Agency. (2018b). UK quality code for higher education, Part B: Assuring and enhancing academic quality. Chapter B8: Programme monitoring and review. https://www.qaa.ac.uk/docs/qaa/quality-code/chapter-b8_-programme-monitoring-and-review.pdf?sfvrsn=f402f781_8

Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior, 60*, 333–341. https://doi.org/10.1016/j.chb.2016.02.074

Rodríguez-Triana, M. J., Martínez-Monés, A., Asensio-Pérez, J. I., & Dimitriadis, Y. (2015). Scripting and monitoring meet each other. *British Journal of Educational Technology, 46*, 330–343. https://doi.org/10.1111/bjet.12198

Rugg, G., D'Cruz, B., Foreman-Peck, L., Grimshaw, E., Guilford, S., Roberts, D., & Tonglet, M. (2008). Selection and use of elicitation techniques for education research. *International Journal of Information and Operations Management Education, 2*(3), 235–254. https://doi.org/10.1504/IJIOME.2008.019648

Siemens, G., & Gašević, D. (2012). Guest editorial – Learning and knowledge analytics. *International Forum of Educational Technology & Society, 15*(3), 1–2. https://www.jstor.org/stable/jeductechsoci.15.3.1

Ed de Quincey is a Professor of Computer Science at Keele University, the Director of Education for the School of Computing and Mathematics and Senior Fellow of the Higher Education Academy (SFHEA). He has researched and taught in the area of online human behaviour for 16 years, looking into the usability and impact of digital products as well as uses of the information that they collect. This has included investigations into the potential of Twitter to detect disease outbreaks such as swine flu and other health-related issues such as hay fever and psychosis. This work is continuing with an AHRC-funded project investigating new strategies for combating online hate speech, and he is also working with medical practitioners at the University Hospitals of North Midlands looking into interface design guidelines for mobile applications. He has combined his research interests with his teaching and has explored the uses of Web 2.0 tools in learning and teaching and is now looking at how learning analytics can be used to improve student outcomes and curriculum design (funded by HEFCE and Jisc). He has previously worked as an eHealth Researcher at City, University of London and as a Principal Lecturer at the University of Greenwich.

Martyn Parker is a Senior Fellow of the Higher Education Academy (SFHEA) and a Fellow of the Institute for Mathematics and its Applications (FIMA) and is currently the programme director for Mathematics and Statistics and Director of Student Experience at the University of Warwick. He has extensive teaching and scholarly experience working on the transition from school to university mathematics. This work has led to innovations in programme and modules design and delivery. He works with national organisations to encourage and facilitate participation in higher education.

Chapter 24
Learning Analytics Dashboards in Educational Games

Seyedahmad Rahimi and Valerie Shute

1 Introduction

Digital games, including educational games, can be suitable vehicles for assessing and improving students' knowledge, skills, and other attributes (Clark et al., 2016; Gee, 2003; Shute & Ke, 2012). For instance, Clark et al. (2016) conducted a meta-analysis to investigate the effects of playing digital games on K-16 students' learning. Results from that meta-analysis (69 studies and collectively 6868 participants) showed that digital games significantly improved students' learning compared to nongame conditions with a moderate to strong effect size. However, despite the empirical evidence for digital games being useful for students' learning, the use of educational games in classrooms is still low (Chaudy & Connolly, 2018; Papadakis, 2018). One missing piece of the puzzle could be explicitly connecting gameplay and learning and making that visible for various stakeholders (e.g., students, teachers, parents) (Alonso-Fernández et al., 2019; Calvo-Morata et al., 2018; Chaudy & Connolly, 2018). Such visual representations of gameplay and learning are important parts of learning analytics (LA) dashboards in educational games.

According to the Society for Learning Analytics Research, the LA field is shaped around "…the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Gasevic, 2012, p. 1). LA dashboards are useful tools—for both teachers and students—as they summarize

S. Rahimi (✉)
University of Florida, Gainesville, FL, USA
e-mail: srahimi@ufl.edu

V. Shute
Florida State University, Tallahassee, FL, USA
e-mail: vshute@fsu.edu

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_24

students' complex learning-related data. There is ample research done regarding LA dashboards used in online learning platforms (e.g., MOOCs, learning management systems). However, little is known about the design and effects of LA dashboards in educational games. Our chapter addresses this issue. In this chapter, we (1) define LA dashboards and discuss who can benefit from them, (2) review the relevant literature and theories about LA dashboards in general, (3) discuss recommendations about the design of LA dashboards based on the literature, (4) present examples of LA dashboards in some educational games, (5) detail the design of a particular LA dashboard in an educational game called *Physics Playground*, and (6) conclude with suggestions for future research regarding the LA dashboard in *Physics Playground*.

1.1 What Is an LA Dashboard and Who Can Benefit from It?

LA dashboards are useful tools that include visual elements (e.g., graphs, colors, and charts) generated from students' interactions in the digital environment. The data can be presented at various grain sizes and relate to different stakeholders' needs (e.g., teachers and students). According to the literature, students can benefit from LA dashboards by allowing them to set personal goals, see progress toward their goals, obtain feedback about their learning, become motivated by receiving immediate feedback, and make decisions about what to do next (Bodily et al., 2018; Jivet et al., 2017; Schumacher & Ifenthaler, 2018; Sedrakyan et al., 2020). The type of feedback that LA dashboards provide to students can be seen as formative. Decades of research on formative feedback show that it is crucial to improve students' learning (Black & Wiliam, 1998; Shute, 2008). Through formative feedback, LA dashboards can help learners make better decisions in the learning process themselves in contrast with environments where computers make the decisions for learners (e.g., via adaptive learning environments). Such environments can help learners take ownership of and consequently improve their learning via the formative feedback within LA dashboards (Charleer et al., 2016; Shute et al., 2008; Shute et al., 2020).

In some cases, dashboards permit learners to compare their progress to other students (currently in their class or historical data). Thus, LA dashboards can either show progress relative to oneself or relative to others (i.e., intrapersonal vs. interpersonal frames of reference, respectively). Choosing an appropriate frame of reference depends on a student's particular learning goal orientation. Generally, there are two goal orientations: performance orientation which refers to norm-referenced comparisons (i.e., when students compare their performance to other students) and mastery orientation which refers to criterion-referenced comparisons (i.e., when students compare their performance against a certain level of mastery) (Dweck & Leggett, 1988). Research on various LA dashboards shows that including a norm-referenced (interpersonal) frame of reference should be used cautiously. In contrast, criterion-referenced (intrapersonal) dashboards consistently show positive impacts on students' motivation and learning (e.g., Jivet et al., 2018). We discuss these frames of reference in more detail later in this chapter.

Besides students, teachers can also benefit from LA dashboards by monitoring their students' progress and evaluating the effectiveness of the learning resources they use (i.e., learning supports and materials) and their instructional methods (e.g., Alonso-Fernández et al., 2019; Calvo-Morata et al., 2018). As a result, teachers may decide to change their teaching strategy (e.g., when they see most of their students struggling on a topic) or replace some learning resources that appear ineffective. Moreover, LA dashboards can help automate various types of feedback that teachers like to provide to their students in real-time, thus saving time and effort for teachers in large classes. Importantly, dashboard data can help teachers quickly identify and help students who are struggling and intervene accordingly.

The foregoing research relates to LA dashboards that currently exist within learning environments (e.g., MOOCs or LMSs). However, our focus is on educational games as effective environments that can also benefit from rich LA dashboards. Designing such dashboards in educational games can benefit from the research done in other learning environments. To understand where these benefits are rooted, we discuss the theories behind LA dashboards next.

1.2 Theories Behind LA Dashboards

Research on LA dashboards occurs at the intersections of various disciplines, including the learning sciences, information science, learning analytics, educational data mining, psychology, and data visualization (Schwendimann et al., 2017). Therefore, LA dashboards should be designed based on the theoretical foundations from these disciplines to achieve the optimal outcomes for students and teachers (Sedrakyan et al., 2020). The following are the most important theories related to the design of LA dashboards.

According to the literature (Jivet et al., 2017, 2018; Kim et al., 2016; Sedrakyan et al., 2020), the most common learning theory underlying LA dashboards is *self-regulated learning theory* (SRL; Zimmerman, 1990). SRL refers to the metacognitive processes and strategies that a learner adopts to maximize and optimize their learning. These strategies include planning, goal setting, organizing, self-monitoring, reflecting, and adapting at various stages of learning. A self-regulated learner is self-aware, knowledgeable, and decisive in their approach to learning (Zimmerman, 1990). Learners who are self-regulated report high levels of self-efficacy and intrinsic motivation—i.e., doing something because it is internally rewarding and satisfying (e.g., Borkowski et al., 1990). One approach to help students become self-regulated learners is to teach them about strategies they can adopt (e.g., goal setting, time management, resource management). However, Zimmerman (1990) asserts that only knowing a particular strategy is not enough for a long-lasting impact of those strategies. Instead, self-regulated learning strategies should be facilitated. LA dashboards are suitable tools that can facilitate self-regulated learning (Jivet et al., 2018; Sedrakyan et al., 2020).

Similarly, LA dashboards align with the *self-determination theory* (SDT; Black & Deci, 2000). According to SDT, people feel intrinsically motivated when they gain a perception of competence, autonomy, and relatedness. Using LA dashboards, learners can monitor their progress and strategically march toward their goals, leading them to achieve high levels of competence in the targeted skills they need. Through self-awareness about their learning progress, learners can decide what to do next and gain high levels of autonomy through various choices coupled with the high level of control available in the learning environments (e.g., educational games or MOOCs). Therefore, LA dashboards can enable, rather than inhibit, student autonomy and enhance learners' intrinsic motivation.

If LA dashboards are poorly designed, learners will not (or very seldom) use them, and thus, none of the positive effects of LA dashboards will be achieved. One reason given for not using LA dashboards is the perception that they are too cluttered, confusing, and hard to understand (Jivet et al., 2017). Theories from the fields of information and communication can help make LA dashboards easier to understand. For example, sense-making theory (Dervin, 1998) indicates that "knowledge is the sense made at a particular point in time-space by someone" (p. 36). Moreover, Weick, Sutcliffe, and Obstfeld (2005) note that "sense-making involves turning circumstances into a situation that is comprehended explicitly in words and that serves as a springboard into action" (p. 409). If the information provided to the learners through LA dashboards does not make sense to them, no proper action (e.g., working more on the skill or knowledge they lack) will occur. Another example of poor design of LA dashboards is when poor computational processes lead to information that the learners disagree with. It does not make sense to them (e.g., the learners feel competent in a given skill, but the LA dashboard shows otherwise). This discrepancy can make learners lose trust in what they see on their dashboard and stop using it (Jivet et al., 2018). Therefore, it is essential to conduct various usability studies and work closely with the target audience of LA dashboards to ensure that what is presented to learners makes sense (e.g., Bodily et al., 2018; Schumacher & Ifenthaler, 2018). The application of various theories and the associated research provides the basis for various recommendations relative to designing high-quality LA dashboards.

1.3 Recommendations for LA Dashboard Design

Although these recommendations come from LA dashboard design research within online learning environments, they may be useful for LA dashboard design in educational games, as educational games can also be considered learning environments. However, students might be more intrinsically motivated to play an educational game compared to completing an online course containing the same content. Therefore, the effects of the recommendations we propose here on students' learning should be examined when used in educational games. We discuss how each recommendation relates to educational games at the end of each part and begin with choosing the appropriate frame of reference.

1.3.1 Choose the Frame of Reference Thoughtfully

Research has shown that learners need at least one of the following frames of reference to be able to interpret the LA they see in a dashboard: (1) *social*, which allows comparisons with peers (e.g., comparing one's own score with the average score of the class); (2) *achievement*, which indicates one's distance from their goals; and (3) *progress*, which allows visual self-comparison over time using their data history (Jivet et al., 2017). LA dashboards can include all three frames of reference and allow students to choose the frame in which they feel most comfortable. Providing a frame of reference by force should be done cautiously as different learners (e.g., high-achievers vs. low-achievers) may react differently to various frames of reference. Specifically, Jivet et al. (2018) reported in their literature review that low-achieving students who used a social frame of reference often became demotivated (i.e., stopped using the LA dashboard) when they saw that they were behind other students. Similarly, some high-achieving students who used the social frame of reference could become demotivated and stop working if they felt that they were better than others and did not need to do more. However, other high-achieving students found that the social frame of reference was motivating, as it provided for healthy competition. In contrast, low-achieving students who did not know how other students were doing (i.e., they were using an intrapersonal frame of reference) reported that using LA dashboards was motivating. Consequently, one recommendation from this literature is to permit learners to choose the frame of reference where they feel most comfortable and motivated. For example, students can choose to compare themselves with their classmates' average scores (i.e., social) or completely deactivate that feature and compare current performance/learning with that from an earlier stage in their learning (i.e., progress). This recommendation about using a frame of reference comes from the literature on LA dashboards in online learning environments. One could argue that using a social frame of reference could be a natural decision as games already have a competitive nature. Alternatively, since we are talking about educational games, an achievement or progress frame of reference could be helpful to students with a goal orientation, permitting them to focus on their own learning. Clearly, more research is needed to evaluate this recommendation in the context of educational games.

1.3.2 Remember that LA Is About Learning

LA dashboards use various data sources (e.g., log data from learners' interactions with a learning environment). Usually, LA dashboards visualize the data related to those interactions without emphasizing how learners are doing regarding their learning goals. These LA dashboards focus more on progress made (e.g., the number of learning modules completed in a MOOC or the number of game levels completed in an educational game) rather than learning (Gašević et al., 2015). There is a need, especially in educational games, to include psychometrically sound assessments of students' learning in educational games. The idea of LA dashboards focusing on learning relates to the open learner model (OLM) (Bull et al., 2013). By visualizing the inferences about students' learning and showing the learning analytics to the stakeholders (i.e., students and teachers), metacognitive behaviors (e.g., reflection, planning, self-awareness, self-monitoring) can be enhanced. Therefore, visualizing students' performance analytics from their interaction data is not enough—inferences about students' knowledge, skills, and other attributes are also needed. Moreover, information is needed that provides clear suggestions about how students can do better. LA dashboards in educational games, like in commercial games, tend to focus on the analytics (e.g., displaying information from log data such as minutes spent per game level). But educational game designers and researchers also need to pay close attention to the *learning* part by linking students' behavioral data to specific and pre-identified competencies (i.e., knowledge, skills, and other attributes).

1.3.3 Include "How Can I Do Better?" Functionality

Most LA dashboards focus on the "how am I performing?" question rather than "how can I do better?" (Sedrakyan et al., 2020). After a successful sense-making (or "aha!") moment when using an LA dashboard, the student will then need to take some action (Weick et al., 2005). For example, based on an analysis of a student's current understanding of Newton's first law of motion, a learning environment (e.g., an educational game) can provide behavioral instructions (e.g., "You need to solve five levels with Newton's first law as their primary concept") if the LA show that the student has not played enough Newton's first law levels. Alternatively, the game can suggest cognitive supports (e.g., "You need to watch this video explaining Newton's first law") if the player played enough targeted levels but his or her estimates are low. Providing the right formative feedback can help learners find the LA dashboard effective in which case they would use the dashboard more frequently (Kim et al., 2016).

1.3.4 Seek Feedback from Stakeholders Throughout the LA Dashboard Design Process

The main stakeholders of LA dashboards in educational games that we are focusing on in this chapter are students (or learners in general). According to the literature, conducting usability and evaluation studies when designing LA dashboards is infrequently done (Jivet et al., 2018; Sedrakyan et al., 2020). As LA dashboard designers and researchers, we need to include what learners need and expect to see in LA dashboards (Schumacher & Ifenthaler, 2018). Moreover, we need to make sure that the content in LA dashboards makes sense to the students. In this vein, some researchers have suggested including mechanisms in the learning environment to collect data about students' opinions on elements included in the LA dashboard (Jivet et al., 2018). For example, a rating system can be employed that quickly allows learners to provide feedback about various aspects of the LA dashboard in use. This recommendation can be used in educational games as well. For example, after including students throughout the design process, educational game designers and researchers can embed quick rating questions about different parts of the LA dashboard. The questions would seek input on whether students understood the information provided to them and if there were alternative formats that should be used. Next, we briefly discuss some examples of LA dashboards in educational games.

1.4 LA Dashboards in Educational Games

Most of the studies that we reviewed have focused on LA dashboards for teachers, not students (e.g., Alonso-Fernández et al., 2019; Martínez-Ortiz et al., 2019). Although some of those findings may be used to design student-focused LA dashboards in educational games, there is a gap in the literature related to studies focusing explicitly on students-aimed LA dashboards. The issue discussed earlier (i.e., collecting and reporting performance data rather than learning-related data and inferences) also exists in LA dashboards in educational games. For example, Chaudy and Connolly (2018) conducted a review on game-based learning analytics. They reported that the type of data collected in the studies they reviewed (most of them created for teachers) were time-related data, counts, game actions, scores, and player data (e.g., demographic and academic). One could argue that game performance and learning are positively related; however, we would expect to see much stronger effects on student learning if the LA in educational games were more focused on learning than performance.

We reviewed several studies that detailed the design, development, and testing of LA dashboards in educational games for students. Here we describe two of these studies. Seaton, Chang, and Graf (2019) created a game (the name of the game was not mentioned in the article) to improve students' skills (i.e., problem-solving, associative reasoning, organization and planning, and monitoring work for accuracy). This game included ten sub-games targeting the cognitive and metacognitive skills mentioned above. Each sub-game generated a score for the targeted skills in percentages based on the players' performance. There were also multiple opportunities for earning game money, badges, and points. The LA dashboard employed in this game used line graphs to visualize skill scores over time (i.e., progress), and scatterplots to visualize the relationship between performance scores and time of the day. The LA dashboard was interactive and allowed players to select a particular skill and a specific time of day or a specific sub-game to see their data visualizations. These visualizations could help players understand how their playing habits impacted their performance (e.g., using the scatterplot, the players could see how playing a sub-game at different times of the day could positively or negatively affect their performance). Also, the players could identify their strengths and weaknesses. The authors conducted a proof-of-concept evaluation using gameplay data collected over 3 months from four players. The authors claimed that the LA dashboard did provide useful information to the players. However, these results need further investigation as only four players participated in the evaluation study. Also, this evaluation study examined if what was shown to the players was meaningful and useful to them. We can argue that the LA in this study was based on performance data rather than inferences about learning. Moreover, based on what the authors provided, there were no instructions available for the students on how to interpret the line charts and scatterplots, potentially causing extraneous sense-making issues. Therefore, more rigorous studies are needed (with larger samples) to make valid conclusions about the usefulness and effectiveness of the LA dashboard in this game relative to learning.

Another example of an LA dashboard for students was developed in a game called *Selene* (Reese, 2016) about the Earth and space. In this game, players get to create their Moon by simulating an accretion process (i.e., causing collisions that can produce space debris, and then the particles would accumulate to create a massive object—a Moon). Not all types of collisions can create moons in space. Players must learn how to create collisions that include a careful balance among velocity, heat, density, and radioactivity proportions. After players learn how to create a Moon, they can then try to replicate the surface of our own Moon (created over about 4.5 billion years) by colliding meteors and flooding the Moon's surface with lava. Reese (2016) indicated that *Selene* was designed after detailed cognitive task analyses completed by subject-matter experts and then cognitive science structure mapping (Gentner, 1983). Reese claimed that "the game is the procedural analog of what is invisible inside experts' heads" (p. 236). This approach is very similar to the evidence-centered design (ECD; Mislevy et al., 2003) approach for designing an assessment. In ECD, a competency model is elaborated first (answering the question of "what is it that we want to assess?"). Then, the environment in which we can elicit evidence for the competency model is designed and developed (we will discuss ECD in more detail later in this chapter). Following this approach, students' performance data, shown on the LA dashboard, were directly linked to their mastery of the knowledge represented in the game (Reese, 2016). On *Selene's* LA dashboard, players could see their achievements (i.e., when a player completed a game level and met certain criteria), progress, and highest game score.

In both of these examples described above, players could see leader boards and compare their performance to other students (i.e., the social frame of reference), which may lead to competition rather than knowledge and skill mastery (Alonso-Fernández et al., 2018). In the next section, we discuss an example of a student-focused LA dashboard in an educational game called *Physics Playground*, which uses an achievement frame of reference and focuses on mastery, not competition.

2 Physics Playground

Physics Playground (*PP*; Shute et al., 2019a) is a 2D web-based game created to help middle- and high-school students learn Newtonian physics (e.g., Newton's laws of force and motion, energy, linear momentum, and torque). For all the game levels, the goal in this game is to direct a green ball to hit a red balloon. There are two level types: *sketching* and *manipulation* (Fig. 24.1).

To solve sketching levels, students draw simple machines (i.e., ramps, levers, pendulums, and springboards) to guide the ball to the target balloon (Fig. 24.1a). To solve manipulation levels, students interact with various sliders to change physics parameters (i.e., gravity, air resistance, mass, and bounciness of the ball) and also manipulate external forces exerted from puffers or blowers to hit the balloon—no drawing is allowed in manipulation levels (Fig. 24.1b). *PP*'s number of game levels is dynamic—we have created about 150 game levels covering nine physics competencies (Fig. 24.2). We can add game levels to the online version of *PP* at any time using the game's level editor.

2.1 Stealth Assessment

To assess students' physics understanding in real-time for each of the nine competencies, *PP* employs stealth assessment (Shute, 2011). Specifically, *PP*'s stealth assessment machinery gathers student-gameplay data in log files, automatically scores and accumulates the collected data using statistical methods (e.g., Bayesian networks), and makes real-time inferences about the current level of students' targeted competencies related to understanding Newtonian physics (see recommendation 1.3.2). Then, *PP* uses those estimates to (a) adapt game level challenges to fit a student's current competency level (for the adaptive version of the game), (b) provide appropriate learning supports to students, and (c) inform students of their progress in the game and relative to targeted physics concepts via an LA dashboard called *My Backpack* (discussed in more detail later).

Stealth assessment is based on the evidence-centered design framework of assessment (ECD; Mislevy et al., 2003). ECD's primary purpose is to structure the

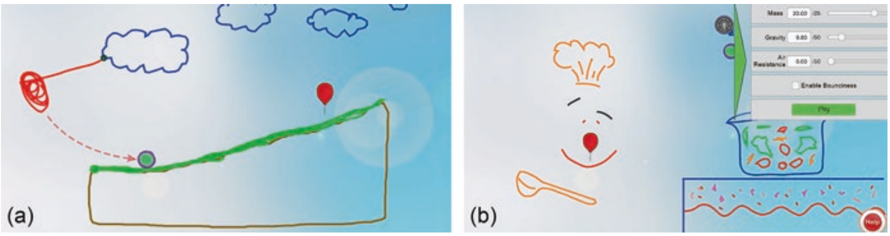


Fig. 24.1 Sketching level (**a**) and manipulation level (**b**)

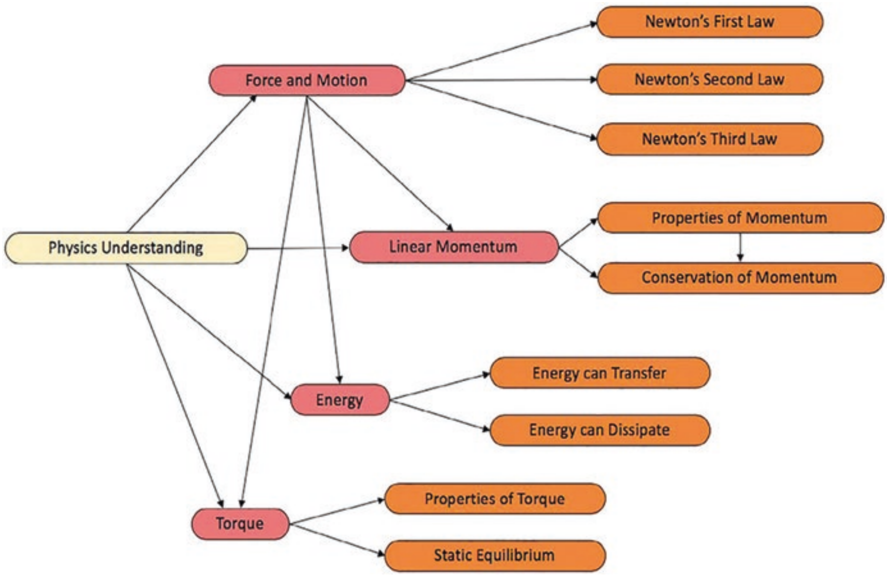


Fig. 24.2 Physics understanding competency model in *PP*

collection of evidence needed to make valid claims about students' competencies (i.e., knowledge, skills, and other attributes). ECD includes a framework of conceptual and computational models that work in harmony. The three core ECD models are the following: (1) the competency model (CM), operationalizing the construct we want to assess (e.g., conceptual physics understanding) and defining the claims to be made about student competencies; (2) the evidence model (EM), automatically scoring and accumulating valid evidence (i.e., observables) of a claim about student competencies (i.e., unobservables); and (3) the task model (TM)—detailing the nature and form of the tasks (e.g., game levels) that will elicit the evidence needed for the EM.

In stealth assessment, specific gameplay behaviors are dynamically linked to the CM. As students interact with the game environment, they generate a continuous stream of data captured in the game's log files. Then, the stealth assessment tools identify and extract evidence related to the CM—in real-time—i.e., the evidence identification (EI) process. The EI's output is the input data (e.g., scores, tallies) for the evidence accumulation (EA) process, which statistically updates the claims about relevant competencies in the CM (e.g., the probability of a student being low, medium, or high on a given competency; see Almond et al., 2020 for more detail on these processes). The more evidence a student generates during gameplay, the more accurate the estimates of competency levels. As mentioned, competency-level estimates can be used for various purposes (e.g., adaptive delivery of game levels, targeted feedback, relevant learning supports, and updating the LA dashboard—*My Backpack*). We have reported the design, development, and evaluation of various aspects of *PP* in other papers (e.g., Kuba et al., in press; Rahimi et al., 2021; Shute

& Rahimi, 2020; Shute et al., 2019b, 2020). Next, we discuss the features of the LA dashboard in *PP—My Backpack*.

2.2 My Backpack*: PP's LA Dashboard for Students*

We designed a multipurpose dashboard in *PP* called My Backpack where students can see their progress—shown at the top part of Fig. 24.3 (i.e., the number of levels they solved, the number of gold or silver coins they collected, and the amount of money they earned). Each gold coin (given for an elegant solution for a game level) earns the student $20, and each silver coin (given for a solution that did not meet the criteria needed for a gold coin) earns $10. Students can use their game money to purchase items and customize features of the game in *PP*'s store.

In addition to showing game progress (e.g., 6 out of 22 sketching levels solved), students can monitor their level of physics understanding (Fig. 24.3) based on the current stealth assessment estimates. These estimates are for (a) each of the specific nine competencies (shown in Fig. 24.3 with the orange bar charts) and (b) their overall physics understanding (shown at the bottom of Fig. 24.3 in green). *My Backpack* also includes a store (see Fig. 24.4) where students can spend the game money they earned through gameplay to customize their game by "buying" new background music, background images, and different ball types. We designed *My Backpack* through an iterative process considering various design decisions that we mentioned in the introduction.

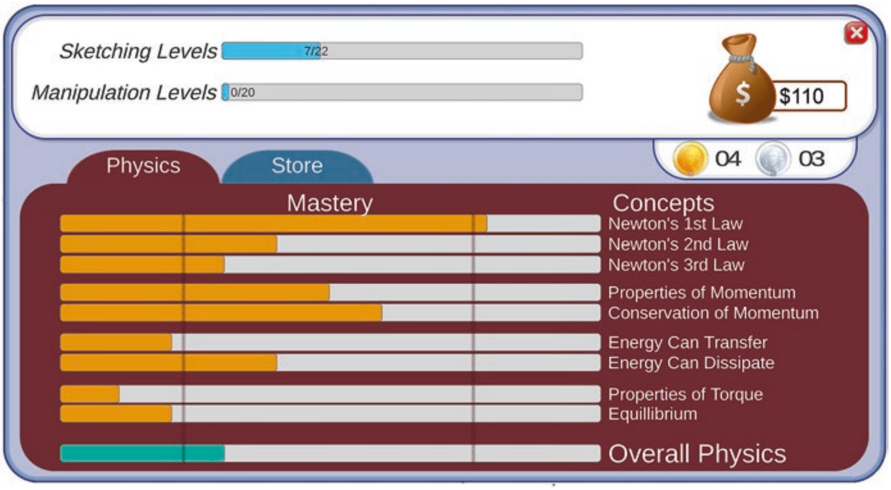


Fig. 24.3 *My Backpack*'s physics tab with indicators of student's level of competency

Fig. 24.4 Game store in *My Backpack* which includes music, background, and ball stores

2.2.1 Design Decisions Behind *My Backpack*

The first decision we needed to make was regarding the frame of reference (see recommendation 1.3.1)—social, progress, or achievement. For this version of *PP*'s LA dashboard, we decided to include an achievement (intrapersonal) frame of reference. Students can monitor their gameplay progress through the progress bars, the number of coins, and the amount of money earned (note that this is also an achievement frame of reference since students do not have access to their data history to see progress over time). Moreover, using bar charts for the nine physics competencies—the most commonly used data visualization in LA dashboards (Jivet et al., 2018; Schwendimann et al., 2017)—students can see how close they are to mastery per competency. We specifically used the word "Mastery" on top of the bar charts related to physics understanding estimates to emphasize that students should have a mastery goal (i.e., complete the bar charts) rather than a competition goal with other students. Also, because the BN estimates are dynamic (they can go up and down), students learn that if they provide negative evidence for one concept (e.g., perform poorly on a game level related to the concept that Energy Can Transfer, ECT), their level of understanding related to that particulate concept decreases. This functionality helps students build a type of mindset that they need to keep learning and doing well throughout gameplay. Consequently, they may be motivated to revisit some concepts to deepen their knowledge and achieve mastery (i.e., to complete the bar charts).

To provide various opportunities for the students to visit *My Backpack*, we made it easy to access (i.e., at the end of each game level, they would see a summary pop-up window indicating what money they earned in that particular level and an option to click on and visit *My Backpack*). In addition, we provided other reasons to visit *My Backpack* besides monitoring progress or achievement (i.e., we included the store that could incentivize students to use *My Backpack* more frequently). These decisions align with the principles underlying self-determination theory—i.e., providing opportunities for building competence and achieving autonomy.

We needed to translate the Bayes net estimates to a form that was understandable to students (so they can make sense of the information and then take proper actions; see recommendation 1.3.4). Consequently, we simplified the estimates. That is, instead of using three probabilities (associated with being high, medium, or low) per competency, we computed a single number (i.e., the expected a posteriori, or EAP value) ranging from −1 (low) to 1 (high) and presented that data in a bar chart (see Fig. 24.3). The EAP value for a competency is expressed as $P(\theta_{ij} = \text{High}) - P(\theta_{ij} = \text{Low})$, where θ_{ij} is the value for student i on competency j, and $[1 \times P(\text{High})] + [0 \times P(\text{Med})] + [-1 \times P(\text{Low})] = P(\text{High}) - P(\text{Low})$. Finally, to make this value even more understandable, we normalized it on a scale ranging from 0 to 1 (using this formula: $(\text{EAP} + 1) \div 2$) and showed it to the students using the orange bar charts. In our usability studies, students found *My Backpack*'s design intuitive and easy to use. Also, by providing the EAP estimates (computed via the stealth assessment machinery) to the students, we addressed the issue that LA should also be about learning—not just performance (Gašević et al., 2015). The stealth assessment process and updating of *My Backpack* is possible via *PP*'s complex architecture—discussed next.

2.3 PP's Architecture

A full explanation of *PP*'s architecture is outside of the scope of this chapter. Therefore, we only focus on the parts related to the stealth assessment processes and how *My Backpack* gets updated during gameplay. *PP* uses two separate servers: the *PP Server* (shown in Fig. 24.5 on the left) which hosts the game engine and the *Assessment Server* (shown in Fig. 24.5 on the right). The Assessment Server has two main components: (1) the *Dongle* component which is responsible for providing a student's prior data and their latest statistics per competency (i.e., EAPs) and (2) the assessment engine which includes two processes: evidence identification (EI) and evidence accumulation (EA).

The Dongle includes the following: (1) Proc 4 MongoDB (see Almond et al., 2020 for more details) is a filtered version of the log data, which is stored in the Learning Locker MongoDB (i.e., raw log files with much information that requires filtering; discussed below); (2) PlayerStart.php which is PHP code responsible for providing the student's previous data (i.e., levels played, coins collected, and money balance for the student) in a JSON format and interacts both with the Proc 4 MongoDB and the game engine via a POST request coming from the game engine; and (3) PlayerStats.php which is responsible for providing the student's EAPs for the nine physics competencies and overall physics understanding. These estimates are the output of the assessment engine.

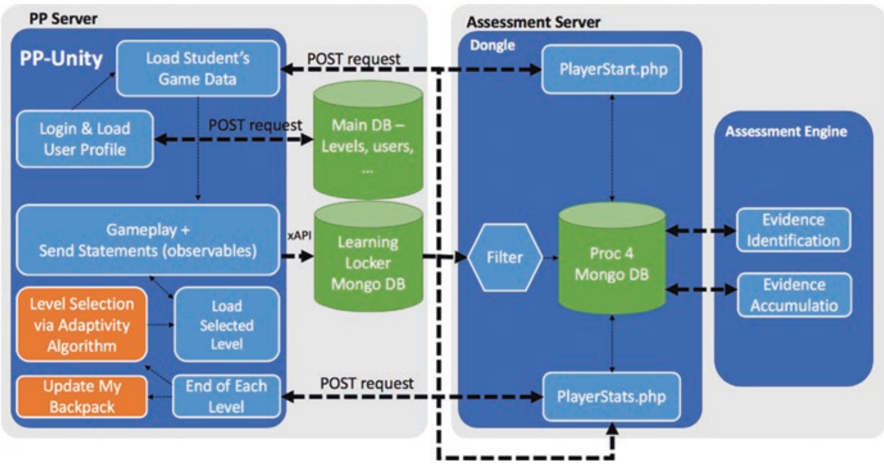


Fig. 24.5 *Physics Playground* architecture

The assessment engine has two components: (1) evidence identification (EI) whose goal is to find relevant, useful evidence in the stream of events coming from the Learning Locker and transform them into a few key observable outcomes (e.g., the coin a student received when playing a level—gold, silver, or none) and (2) evidence accumulation (EA) which is responsible for scoring the stream of observables coming from the EI process (using a Bayes net-based system) and importantly, updating the student's competency model. Using the physics understanding estimates, an adaptive algorithm in the adaptive version of *PP*—written in the game engine—selects the next level for the student (see Shute et al., 2020 for a full report about the effect of adaptivity on students' learning) and updates the student's LA output in *My Backpack*.

Learning Locker is a Learning Record Store (LRS) that stores statements generated by the xAPI-based learning activities (in this case, gaming interactions). We first specified the events or activities we needed to send to the Learning Locker. Next, we wrote various xAPI-compliant functions in the game engine when those events occurred in the game (e.g., when a level was solved and a coin was achieved). These events were sent in the form of xAPI statements to the Learning Locker. An xAPI statement consists of *actor* (i.e., user), *verb* (i.e., event), *object* (i.e., an object that the event is linked to), and *extensions* (which is a place for inserting extra data related to the event at hand—e.g., the level's name in which a particular event occurred). Learning Locker uses MongoDB, which is a document database storing data in JSON format. The Assessment Server copies and filters the raw data stored in Learning Locker—filtering out some of the xAPI metadata—for assessment purposes. Next, we discuss our plans regarding improving the LA dashboard in *PP*.

3 Future Directions for *PP*'S LA Dashboard

We envision *PP* as an engaging educational game used in classrooms (or at home) worldwide, to measure and support the learning of Newtonian physics. In one future version of *PP*, a teacher would be able to independently (without the need of possessing programming skills) create as many versions of the game with as many levels as desired for their students to play individually or collaboratively. This particular feature of *PP* (i.e., its modularity, which refers to its dynamic design capabilities) can address one of the main hurdles for using educational games in classes. That is, too often, educational games are viewed as unmodifiable black boxes that do not allow teachers to change any aspects of the game they want to use in their classes (Chaudy & Connolly, 2018). When teachers have this level of control over the game, that will instill some sense of ownership toward the game (Chaudy & Connolly, 2018), leading to more use and a higher impact on student learning.

Another logical next step with the game will entail building a dashboard for teachers to monitor their students' progress with the possibility of intervening in real time (e.g., sending feedback to students if needed). The dashboard for teachers can contain various learning analytics that can further help the teachers monitor their students' progress and learning. For example, teachers will be able to monitor progress of students individually as well as at the classroom level. Moreover, teachers could receive analytics about the effectiveness of the game resources (e.g., the efficacy of various learning supports and specific game levels). This future version of *PP* will allow teachers to dynamically add or remove any resources to and from the game based on the LA about the resources. The teacher's LA dashboard will be accessible outside of the game via an admin website to independently monitor their students' learning and progress.

To make the dashboard interpretable for teachers, we need iterative usability and experimental studies. We recommend following the suggestions from the literature about how to make LA dashboards in educational games understandable for teachers. For example, Calvo-Morata et al. (2018) suggested to (1) make LA dashboards simple rather than complex, (2) involve teachers in the dashboard design process, (3) add pop-up descriptors for complex data visualizations, and (4) add supports that can make teachers aware of undesired situations (e.g., use of alerts for statistical deviations of students from a baseline).

We also envision an advanced version of the current student dashboard in a future version of *PP*. Specifically, the student dashboard could be made to be customizable and personalized, to some extent. For example, a written interpretation/summary of the bar charts can be generated in the future to help students interpret their progress toward mastery (see recommendation 1.3.1). These features can give freedom to the students regarding their goal orientation (performance or mastery), leading to higher levels of autonomy and internal motivation (Black & Deci, 2000). To address the "how do I do better?" question (see recommendation 1.3.3), we will provide recommendations for the competencies under a certain threshold. For instance, if a student was estimated as being below some threshold relative to a concept (e.g., the EAP of ECT was less than 0.2), a pop-up menu could direct the student to either play a prescribed set of levels to enhance their knowledge about ECT or watch a targeted learning-support video about ECT before playing their next level.

Any of these future features would need to be subjected to rigorous usability and experimental testing to show relative effectiveness toward learning and performance before applied at scale. To date, testing the efficacy of the LA dashboard in *PP* has not been a primary goal. Therefore, despite following most of the recommendations about LA dashboard design, we have not collected data on the effectiveness of the LA dashboard in *PP* in terms of enhancing learning. However, we plan to conduct such studies in the future, which are intended to further help students become aware of and maximize their learning. For example, we plan to include in-game collections of usability data from students (see recommendation 1.3.4)—as suggested by Jivet et al. (2018). That is, using a simple five-star rating system, we can ask students what they think about the LA dashboard's features as they interact with each one. We will also investigate the relationship between time students spent viewing the dashboard and their motivation and learning. These investigations can shed light on how LA dashboards should be designed in educational games. In addition, in future versions of *PP*, we plan to follow the four recommendations we discussed in Sect. 1.3.

4 Conclusion

Educational games are promising tools for assessment and learning. Currently, little is known about the optimal design and effects of LA dashboards in educational games. Typically, the dashboards in educational games provide visual and textual information about learners' game performance rather than their learning. LA dashboards are tools that can help learners become aware of their learning progress and monitor their goals. There is much research around LA dashboards in online learning environments with many lessons that educational games developers and researchers can learn from. However, we need more research in this area. We addressed this issue in this chapter by reviewing theories related to LA dashboards, discussing recommendations that can be used when designing LA dashboards for educational games, reviewing LA dashboards in educational games, and finally, walking through an example of a LA dashboard in *Physics Playground*. The gap in research about LA dashboards in educational games—mainly for students—is still fairly wide. We believe that the return on investment for investigating how LA dashboards can affect students' learning in educational games will be large. Therefore, we invite our colleagues in both LA and game-based learning research areas to come together and fill this gap.

Acknowledgements This work was supported by the US National Science Foundation (award number #037988) and the Institute of Education Sciences (award number #039019). We also would like to acknowledge Russell Almond, Fengfeng Ke, Ginny Smith, Renata Kuba, Chih-Pu Dai, Curt Fulwider, Zhichun Liu, Xi Lu, and Chen Sun for helping in different phases of this project.

References

Almond, R., Shute, V., Tingir, S., & Rahimi, S. (2020). Identifying observable outcomes in game-based assessments. In *Innovative psychometric modeling and methods* (pp. 163–192). Information Age Publishing.

Alonso-Fernández, C., Cano, A. R., Calvo-Morata, A., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2019). Lessons learned applying learning analytics to assess serious games. *Computers in Human Behavior, 99*, 301–309. https://doi.org/10.1016/j.chb.2019.05.036

Alonso-Fernández, C., Pérez-Colado, I., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2018). Improving serious games analyzing learning analytics data: Lessons learned. In M. Gentile, M. Allegra, & H. Söbke (Eds.), *International conference on games and learning alliance* (pp. 287–296). Springer. https://doi.org/10.1007/978-3-030-11548-7_27

Black, A. E., & Deci, E. L. (2000). The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self-determination theory perspective. *Science Education, 84*(6), 740–756.

Black, P., & Wiliam, D. (1998). Assessment and classroom learning. *Assessment in Education: Principles, Policy & Practice, 5*(1), 7–74. https://doi.org/10.1080/0969595980050102

Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., & Verbert, K. (2018). Open learner models and learning analytics dashboards: A systematic review. In *Proceedings of the 8th* *international conference on learning analytics and knowledge* (pp. 41–50). ACM. https://doi.org/10.1145/3170358.3170409

Borkowski, J., Carr, M., Rellinger, E., & Pressley, M. (1990). Self-regulated cognition: Interdependence of metacognition, attributions, and self-esteem. In B. F. Jones & L. Idol (Eds.), *Dimensions of thinking and cognitive instruction* (pp. 53–92). Lawrence Erlbaum Associates.

Bull, S., Kickmeier-rust, M., Vatrapu, R., Johnson, M. D., Hammermueller, K., Byrne, W., … Meissl-egghart, G. (2013). Learning, learning analytics, activity visualisation and open learner model: Confusing? In *European conference on technology enhanced learning* (pp. 532–535). Springer.

Calvo-Morata, A., Alonso-Fernández, C., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2018). Making understandable game learning analytics for teachers. In G. Hancke, M. Spaniol, K. Osathanunkul, S. Unankard, & R. Klamma (Eds.), *Advances in web-based learning – ICWL 2018* (pp. 112–121). Springer. https://doi.org/10.1007/978-3-319-96565-9_11

Charleer, S., Klerkx, J., Duval, E., De Laet, T., & Verbert, K. (2016). Creating effective learning analytics dashboards: Lessons learnt. In K. Verbert, M. Sharples, & T. Klobučar (Eds.), *Adaptive and adaptable learning* (pp. 42–56). Springer. https://doi.org/10.1007/978-3-319-45153-4_4

Chaudy, Y., & Connolly, T. (2018). Specification and evaluation of an assessment engine for educational games: Empowering educators with an assessment editor and a learning analytics dashboard. *Entertainment Computing, 27*, 209–224. https://doi.org/10.1016/j.entcom.2018.07.003

Clark, D. B., Tanner-Smith, E. E., & Killingsworth, S. S. (2016). Digital games, design, and learning: A systematic review and meta-analysis. *Review of Educational Research, 86*(1), 79–122. https://doi.org/10.3102/0034654315582065

Dervin, B. (1998). Sense-making theory and practice: An overview of user interests in knowledge seeking and use. *Journal of Knowledge Management, 2*(2), 36–46. https://doi.org/10.1108/13673279810249369

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256. https://doi.org/10.1037/0033-295X.95.2.256

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

Gee, J. P. (2003). *What video games have to teach us about learning and literacy* (Vol. 1). Palgrave/Macmillan.

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy*. *Cognitive Science, 7*(2), 155–170. https://doi.org/10.1207/s15516709cog0702_3

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data driven approaches in digital education* (pp. 82–96). Springer. https://doi.org/10.1007/978-3-319-66610-5_7

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40). ACM. https://doi.org/10.1145/3170358.3170421

Kim, J., Jo, I.-H., & Park, Y. (2016). Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement. *Asia Pacific Education Review, 17*(1), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Kuba, R., Rahimi, S., Smith, G., Shute, V., & Dai, C.-P. (in press). Using the first principles of instruction and multimedia learning principles to design and develop in-game learning support videos. *To Appear in Educational Technology Research and Development (ETRD).*

Martínez-Ortiz, I., Freire, M., Pérez-Colado, I., Fernández-Manjón, B., & Rotaru, D. C. (2019). From heterogeneous activities to unified analytics dashboards. In *2019 IEEE global engineering education conference (EDUCON)* (pp. 1108–1113).

Mislevy, R. J., Steinberg, L. S., & Almond, R. G. (2003). Focus article: On the structure of educational assessments. *Measurement: Interdisciplinary Research & Perspective, 1*(1), 3–62. https://doi.org/10.1207/S15366359MEA0101_02

Papadakis, S. (2018). The use of computer games in classroom environment. *International Journal of Teaching and Case Studies, 9*(1), 1–25. https://doi.org/10.1504/IJTCS.2018.10011113
Rahimi, S., Shute, V., Kuba, R., Dai, C.-P., Yang, X., Smith, G., & Alonso Fernández, C. (2021). The use and effects of incentive systems on learning and performance in educational games. *Computers & Education, 165*, 104135. https://doi.org/10.1016/j.compedu.2021.104135
Reese, D. D. (2016). Dashboard effects challenge flow-learning assumption in digital instructional games. In *Emotions, technology, and digital games* (pp. 231–287). Academic. https://doi.org/10.1016/B978-0-12-801738-8.00011-7
Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030
Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., … Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522
Seaton, J. X., Chang, M., & Graf, S. (2019). Integrating a learning analytics dashboard in an online educational game. In A. Tlili & M. Chang (Eds.), *Data analytics approaches in educational games and gamification systems* (pp. 127–138). Springer. https://doi.org/10.1007/978-981-32-9335-9_7
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512. https://doi.org/10.1016/j.chb.2018.05.004
Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189. https://doi.org/10.3102/0034654307313795
Shute, V. J. (2011). Stealth assessment in computer-based games to support learning. In S. Tobias & J. D. Fletcher (Eds.), *Computer games and instruction* (pp. 503–524). Information Age Publishers.
Shute, V. J., Almond, R., & Rahimi, S. (2019a). *Physics Playground (Version 1.3)*. Tallahassee, FL. Retrieved from https://pluto.coe.fsu.edu/ppteam/pp-links/
Shute, V. J., Hansen, E. G., & Almond, R. G. (2008). You can't fatten a hog by weighing it – Or can you? Evaluating an assessment for learning system called ACED. *International Journal of Artificial Intelligence in Education, 18*(4), 289–316.
Shute, V. J., & Ke, F. (2012). Games, learning, and assessment. In D. Ifenthaler, D. Eseryel, & X. Ge (Eds.), *Assessment in game-based learning: Foundations, innovations, and perspectives* (pp. 43–58). Springer. https://doi.org/10.1007/978-1-4614-3546-4_4
Shute, V. J., & Rahimi, S. (2020). Stealth assessment of creativity in a physics video game. *Computers in Human Behavior, 116*, 106647. https://doi.org/10.1016/j.chb.2020.106647
Shute, V. J., Rahimi, S., & Lu, X. (2019b). Supporting learning in educational games: Promises and challenges. In P. Díaz, A. Ioannou, K. K. Bhagat, & J. M. Spector (Eds.), *Learning in a digital world: Perspective on interactive Technologies for Formal and Informal Education* (pp. 59–81). Springer. https://doi.org/10.1007/978-981-13-8265-9_4
Shute, V. J., Rahimi, S., Smith, G., Ke, F., Almond, R., Dai, C.-P., … Sun, C. (2020). Maximizing learning without sacrificing the fun: Stealth assessment, adaptivity and learning supports in educational games. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.12473
Siemens, G., & Gasevic, D. (2012). Guest editorial-learning and knowledge analytics. *Journal of Educational Technology & Society, 15*(3), 1–2.
Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science, 16*(4), 409–420. https://doi.org/10.1287/orsc.1050.0133
Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist, 25*(1), 3–17. https://doi.org/10.1207/s15326985ep2501_2

Seyedahmad Rahimi is an assistant professor of educational technology in the School of Teaching and Learning at the University of Florida. Previously, he was a postdoctoral researcher at the Department of Educational Psychology and Learning Systems at Florida State University. He worked with Dr. Valerie Shute on several of her research projects. His research focuses on assessing and fostering students' 21st-century skills (focusing on creativity) and STEM-related knowledge acquisition (focusing on physics understanding) using educational games. Seyedahmad is also actively researching various aspects of educational games (e.g., game mechanics, game difficulty, cognitive and affective supports, dashboard design, and incentive systems) and how they affect students' motivation, performance, and learning. His research resulted in multiple book chapters, journal articles, and conference presentations. This chapter was written when Seyedahmad was a postdoctoral researcher at FSU.

Valerie Shute is the Mack & Effie Campbell Tyner Endowed Professor in Education in the Department of Educational Psychology and Learning Systems at Florida State University. Before coming to FSU in 2007, she was a principal research scientist at Educational Testing Service, involved with basic and applied research projects related to assessment, cognitive diagnosis, and learning from advanced instructional systems. Her general research interests hover around the design, development, and evaluation of advanced systems to support learning of knowledge, skills, and dispositions. Her research has resulted in numerous research grants, journal articles, chapters in edited books, a patent, and several recent books.

Part V
Future Directions of Visualization and Dashboard

Chapter 25
Maximizing Student Achievement Through the Collection and Visualization of Assessment Data

Creating an Equitable Learning Opportunity for Underrepresented Populations

Tandra Tyler-Wood and Deborah Cockerham

1 Introduction

High-stakes testing continues to serve as the primary criteria for admission into special education classes, gifted education classes, college programs, and many career opportunities. Often, students either doubt their ability to succeed on a test or lack confidence because of previous test challenges. These factors may cause stress and anxiety that impact test performance, limit opportunities, and disrupt future educational planning. In addition, if tests are scored at a distance, test scores may not be received until weeks or months after testing. With such a delay, students and teachers have little opportunity to receive feedback and make critical changes in learning.

Technology-based dashboards that can monitor progress and provide immediate access to detailed information can offer immediate feedback from a broader perspective. With data visualization through dashboards, students can receive timely and understandable insights into their learning. This information can support appropriate modifications for addressing learning deficits and provide information for tailoring instruction to the student's learning needs. Students receive feedback on an ongoing basis, so scores on high-stakes testing do not come as a surprise. Because multiple points on student achievement can be obtained, ongoing formative assessment provided through dashboards has the potential to provide a more accurate and well-rounded picture of a student's

T. Tyler-Wood (✉) · D. Cockerham
University of North Texas, Denton, TX, USA
e-mail: tandra.wood@unt.edu; deborah.cockerham@unt.edu

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_25

true academic ability. The stress associated with using a single test to determine a student's future can be minimized.

2 Assessment in Education

2.1 A Brief History of Uses of Assessment

As humans, we instinctively conduct informal assessments. Informal assessments such as observations have most likely been around since humans dwelled in caves. Surely, early individuals noticed differences in skill sets such as hunting, building fires, and constructing dwellings.

In contrast, formal assessments are more structured and are designed to provide information on the attainment of skills or objectives. Around the turn of the twentieth century, Alfred Binet worked to identify children who had difficulties learning in the Paris, France school system. Although his goal was to identify children who might need assistance in school, the intelligence test he developed had far-reaching effects, and the assessment began to take on a life of its own as it became the foundation for the construct of "intelligence" (Carson, 2014). Binet's vision for the test was positive, but the test was soon used to categorize individuals, which led to granting and denying opportunities. In the United States during World War I, Binet's intelligence test was used to identify individuals who might become officers. Those who received lower scores on the test were deemed to be less intellectually capable and were often sent to the "front line" (Schlenoff, 2015).

Through the years, Binet's construct of intelligence has played a major role in society. Intelligence tests were used at Ellis Island to either admit or deny entry to individuals who hoped to immigrate to the United States (Schlenoff, 2015). Because intelligence tests were administered in English rather than in the individual's native language, those from English-speaking countries such as England, Scotland, and Ireland attained the highest scores. From its earliest days, assessment seemed to veer from supporting individual needs to influencing societal policy.

Hernstein and Murray's Herrnstein & Murray, 1994 "Bell Curve" asserts that there are quantifiable differences among the intellectual abilities of groups from different regions and races. Interestingly, this theory takes little notice of the tendency for test takers who resemble the test creators to score higher. Even with this gap, Hernstein and Murray's (Herrnstein & Murray, 1994) book provides evidence of measurable differences between the scores of subgroups in our population. For example, Herrnstein and Murray report that Asian Americans have a higher mean IQ than white Americans, who in turn outscore black Americans. Categorizations such as this, which determine an individual's potential by a single high-stakes intelligence test, lack equity and have been a source of strife among the American people. Well-documented examples of differences in income and opportunity within subgroups of our population abound. It is difficult to say what role history, opportunity, and income play in the scores obtained by students on assessments.

2.2 Common Uses of Assessment

While the overarching goal of educational assessment is to strengthen student learning (Baroudi, 2007), assessments are prepared for a wide variety of purposes. The design of an effective assessment reflects its particular purpose, with most assessments aimed at helping teachers, administrators, students, policy-makers, and other educational stakeholders involved in the learning process to understand current student learning and make decisions for future learning (Broadfoot & Black, 2004; Crisp, 2012; Pellegrino, 2012).

Assessments may be used to measure student progress or determine the need for student intervention. In the K-12 classroom, assessment often addresses specific academic areas such as math, reading, or science. Classroom assessment is usually administered by teachers and may influence student learning more than any other type of assessment (McMillan, 2013). Both formative and summative assessments are frequent, and teachers may invest up to 50% of their work hours in assessment preparation, implementation, and analysis (Fives & Barnes, 2020). Mavrommatis (1997) suggests that classroom assessment consists of a four-step sequential process that is developed as teachers and/or researchers (1) gather information, (2) interpret results in the light of testing standards, (3) respond to students based on interpretations, and (4) observe impacts of the responses on students. The results of classroom assessments not only provide the teacher with information on individual student comprehension and mastery of skills but also suggest if student intervention is needed and may offer insights on how to improve the learning experience.

Standardized testing that is administered within K-12 classrooms or in university settings often involves high stakes for either students or schools. For example, state-required tests that assess grade-level proficiency through the use of knowledge-based questions may impact school status and funding opportunities. While such standardized tests can keep learning focused on relevant standards and necessary skills, an overemphasis on test results and norms may move instruction from activities that build the twenty-first-century skills such as higher-order thinking and creativity to worksheets that drill students on test-like items (Herman & Golan, 1993).

In addition, the use of high-stakes standardized testing to raise school standards often becomes competitive as schools try to match or exceed minimum standards. A punitive testing approach may result, interfering with the ability of assessments to empower students in taking charge of their own learning (Airasian & Gregory, 1997; Firestone, 1998, cited in Broadfoot & Black, 2004). Often referred to as "teaching to the test," such a strategy makes a student's immediate and temporary performance on standardized tests the educational focus, disrupting the opportunity to enhance learning and prepare students for future success (Herman & Golan, 1993). This "teaching to the test" effect appears to be much more pronounced in schools with high proportions of disadvantaged students (Herman & Golan, 1993).

The student selection process for many universities and colleges is based upon standardized tests such as the American College Test (ACT) or Scholastic Assessment Test (SAT). Results from these tests are used to determine which applicants may be the most promising students. Both the ACT and the SAT appear to be highly related to general intelligence, and both have been shown to predict first year college students' grade point averages (Coyle & Pillow, 2008). However, the tests only provide a one-time assessment of a student's potential, similar to a snapshot. Unexpected test day circumstances such as illness, anxiety, or family issues are not considered in determining test scores and may limit the accuracy of results. Overall performance in high school has been suggested as a more accurate measure for selecting incoming college students, since the national standardized tests add little information to the high school record (Rooney & Schaeffer, 1998). When colleges depend on national tests to determine the best student candidates, high schools who try to prepare students often overemphasize the importance of multiple-choice tests, diluting the quality of high school educational programs. In addition, using the tests as primary admission criteria limits equity for students who struggle with test-taking or understanding the culture, leading to a less-diversified student population (Rooney & Schaeffer, 1998).

2.3 Self-monitoring Behavior

Self-monitoring skills are often weak in students with disabilities, and assessments that function as interventions have been used successfully to support development of these skills (Briesch et al., 2019). Self-monitoring has been considered an assessment process, as it requires an individual to observe personal actions and note progress related to the targeted behavior or skill (Korotitsch & Nelson-Gray, 1999). Around 90% of psychologists report that they have implemented self-monitoring interventions (Briesch et al., 2014). However, intervention strategies vary widely. A meta-analysis of self-management strategies (Briesch et al., 2019) found that prompted self-monitoring is the most frequent intervention approach. In prompted self-monitoring, students receive a signal that reminds them to take action toward the desired behavior. For example, Rosenbloom et al. (2019) used a smartphone app, I-Connect, to improve on-task, disruptive, and task completion behaviors in four adolescent boys with autism spectrum disorder (ASD). While the sample size was small, the authors note improvements in on-task and task completion behaviors for the boys. Authors suggest that the I-Connect app may increase task accomplishment when used by individuals with ASD.

In another study (McDougall et al., 2012), students with attention-deficit/hyperactivity disorder and emotional disorder used tactile-cued self-monitoring (TCSM) to improve academic productivity. The TCSM mechanism was a device similar to a pager, which the student kept in his pocket. Each day during a 10-min classwork period, the device, called a MotivAider, vibrated every 90 s. At this signal, the student assessed if he was focused or not and marked the answer on a self-recording form placed near his worksheet. Work output improved significantly for students involved in the study.

Assessments integrated with interventions have also been used successfully for building academic skills such as reading comprehension (Kim et al., 2012).

Self-monitoring is considered an important source of information related to diagnosis, assessment, and intervention for individuals with disabilities. The level, types, and speed of feedback to students with disabilities can be greatly enhanced through appropriate data visualization.

3 Technology in Education

3.1 Learning with Technology

Technology plays a more integral role in current K-12 education than it has for any previous generation. The heavy infusion of technology into education supports opportunities to collect ongoing data documenting students' learning knowledge, strengths, and weaknesses (National Research Council, 2000). As teachers learn to use data to enhance and improve student learning, they can visualize and chart progress toward learning goals. Individual academic plans that previously were only provided for students with special needs can now be constructed for any student.

Technology supports the identification of data sources that can be used for developing an individual educational plan (IEP) for any student. Ultimately, the data collected on student achievement could be used to provide IEPs for all students, preventing the stigmatizing impact of labeling for those who receive IEPs (Citizen Contributor, 2017). In addition, individual goals allow students to move through the curriculum at a faster or slower pace than their classmates. Technology-based learning utilizing collected data has the potential to maximize learning opportunities for all students.

3.2 Technology-Based Environments and Data Visualization for Teachers

Today's classroom teacher is often under pressure to justify instruction (Berliner, 2018). Scores from state-mandated tests are publicly accessible, and schools are ranked on the outcomes of these assessments. Administrators, legislators, and parents demand accountability not only for the test scores but also for instructional practices that may impact test scores. In addition, parents and other stakeholders seek assurance that each student is receiving a high-quality education.

Technology-based data collection displayed through dashboards offers an opportunity to document comprehensive student progress with minimal effort. Using data-driven educational decision-making, educators can examine assessment data to identify student strengths and deficiencies and can better understand and adapt instructional approaches to meet student needs (Mertler, 2007). The process of critically examining curriculum and instructional practices relative to students' actual performance on standardized tests and other assessments yields data that supports teachers in making more accurately informed instructional decisions (Mertler & Zachel, 2006). Many types of assessment (e.g., classroom tests, norm-referenced tests, criterion-referenced assessments, and formative assessments) can be used to inform instruction.

Information visualization allows users to view "computer-supported, interactive visual representations" that can clarify and increase understanding of data (Card et al., 1999). Whereas early definitions of information visualization noted that these graphics only represent abstract data (Card et al., 1999), more recent writings refer to visualizations of physical or material data (Sorapure, 2019). The unique perspectives offered by information visualization can assist the viewer in finding meaningful patterns and drawing insights from data (Sorapure, 2019). Using this theoretical framework, we can explore how data can be leveraged to support equal access and equal educational opportunities. The challenge remains to provide teachers with the knowledge and training needed to visualize and maximize data for appropriate instructional usage.

3.3 The Role of Dashboards in Teaching and Learning

Technological advancements have generated a strong interest in exploring learner behavior data through learning analytics. Based on these data, dashboards can provide learners and teachers with relevant formative feedback for meeting a variety of learning goals (Sedrakyan et al., 2020). While most dashboard feedback is based only on learner performance indicators, effective feedback should also include the self-monitoring skills underlying learning processes and an awareness of the student's learning goals. A dashboard design that visualizes the relationship between assessments and the learning sciences may enhance the cognitive and behavioral process-oriented feedback to learners and teachers (Sedrakyan et al., 2020).

Dashboards offer the opportunity to return assessment to its original goal: to provide individuals with information that offers timely insights into their own learning and skill sets. The ultimate goal is for students to use this knowledge to maximize career and life goals. Although the full range of learning support that dashboards can provide is still unknown, dashboards are already providing teachers with tools that can help maximize student learning potential (Ramaswami et al., 2019).

4 Benefits of Learning Dashboards

4.1 Increasing Test Scores Through Educational Programs

Data indicate that children living in poverty show progressively lower test scores as they get older (Campbell et al., 2002). However, with appropriate educational opportunities, children in lower-income subgroups have shown increases in test scores. Early childhood programs that provide preschoolers with appropriate, structured curriculum and services appear to support not only higher test scores but also stronger long-term educational outcomes (Barnett & Belfield, 2006). The Abecedarian Project (Goldstein et al., 2013) provides evidence of the positive long-term effects of high-quality **early** childhood education. In this project, at-risk preschoolers received nutrition, health care, social services, and opportunities to participate in high-quality educational games and activities from infancy to kindergarten. Measures of intelligence quotient and academic achievement were documented and compared between children who received preschool treatment and the control group of preschoolers who received no services. Goldstein et al. (2013) reviewed the project and noted that, at the beginning of the study, mean scores on many subtests were subaverage, indicating that the programs were reaching at-risk children. The preschoolers who received the preschool treatment significantly increased their standard scores in three areas: cognitive skills, receptive vocabulary, and social-emotional development. Findings suggest that the quality of the program greatly influences the children's progress. The researchers concluded that children who attend a structured, achievement-oriented, publicly supported, and community-based pre-K program could make notable gains in school readiness.

Clearly, preschool children may not be able to interpret the cognitive and achievement data that might be provided through a dashboard. However, as children progress through the curriculum, those who have developed the ability to self-monitor and self-assess, with support from visualizations and dashboards, might be able to avoid the "wash-out" effects one often sees as participants progress through school and benefits of the program recede (Cooper & Lanza, 2014).

4.2 The Teacher's Role in Data Interpretation

In today's information age, teachers are given a plethora of information, but not all information is pertinent or credible. Teachers can facilitate learning as they provide relevant data and guide students to critically evaluate information. Too often, data has been used to categorize students and to justify limiting student learning opportunities, a practice that has led to denied access to learning opportunities (Bainbridge, 2020). For example, a mathematics pre-test is often used in the United States and other countries to determine which students can take algebra at an early age and which students should remain in a general mathematics curriculum. Without the opportunity to take algebra, students' future educational opportunities are stifled. A comprehensive evaluation of a student's previous work, rather than information from a single test score, could support a more accurate determination of such high-stakes decisions.

Teachers may need support in their understanding of data visualization. Ratner et al. (2019) proposed a plan to assist teachers with understanding data visualizations as contingent, situated, and socio-material achievements that consider teachers as data users. When designers take the time to identify and understand teacher-user needs for data, they may be able to develop more usable data visualizations. Since visualizations shape teachers' interpretations of test data, it is equally important that teachers understand the capacities and limitations that impact the development of the visualization (Ratner et al., 2019).

Designers' representations of data do not ultimately determine the actual use of visualizations, since digital technologies may be reconfigured in unique or unusual ways. To provide appropriate and usable data to classroom teachers, designers and teachers need to work in a collaborative formative process to achieve data visualizations with needed and usable information about students' learning. Visualization design should not be a one-way process in which the power to shape the development of data visualizations is attributed only to experts in the field of data design. Instead, all stakeholders must collaborate when designing data visualization that abstracts, summarizes, or categorizes assessment data (Santen et al., 2020).

In a study that brought academics, researchers, software developers, and K-7 educators together, Carter and Crichton (2014) worked to better understand the impact of a suite of assessment tools upon the twenty-first-century K-7 classroom learning environments. The resources examined in this study provided educators with digital assessment and feedback tools for gathering, curating, and documenting meaningful learning artifacts from classroom activities. As researchers worked with data interpretation experts, they explored a participatory approach for developing data visualizations that helped map the twenty-first-century learning and assessment practices, tools, and technologies. Through professional collaboration, the team created a template for providing usable data that could impact classroom learning (Carter & Crichton, 2014).

In a Queensland, Australia study, issues with testing were seen after scores on a national assessment identified this location as "low-performing" (Hardy & Lewis, 2018). Project 600, an intervention designed to target and improve the scores of "invisible" students, was implemented to raise scores. "Invisible" students were defined as average students not typically warranting remediation or special attention to improve achievement. Average students were targeted for intervention because administrators believed that improving their scores was the easiest method for improving district scores. Project 600 sought to provide visualization of educational data in order to impact the learning of "invisible" or average students. The authors discussed the complex and contradictory ways in which so-called "invisible" students were made "visible" through data. Average students typically out-number other students in a school district, so increasing their scores could greatly improve the district's overall scores. The teachers indicated that the individual data visualizations of students' scores enabled teachers to see average students as individual learners, without pressure to enhance overall student results on standardized testing. The targeted "average" students became "visible" because of the potential to increase their individual test scores and thereby increase the overall standing of the school and district. Focusing upon particular students deemed worthy of attention through data, the researchers questioned whether these students were "visible" as learners in and of themselves rather than as mere "data points" amenable to further intervention for what their scores might contribute to overall state results. The study demonstrates the importance of remembering that students are individuals with a critical stake in their own successful learning and do not merely represent data points for providing program evaluation data.

4.3 Empowering Students Through Data Visualization

To provide valuable feedback obtained on pertinent educational data, many educational dashboards have been devised in recent years. For example, dashboards based on performance data have been used successfully to provide medical students with critical feedback to support informed self-assessment and ongoing learning (Hardy & Lewis, 2018). These individual student learning dashboards were found to deliver timely and continuous feedback on performance, accurate visualizations, and user-friendly interpretations of performance data.

Dashboards can also facilitate ongoing performance monitoring and personalized learning plans that help students move toward developmental milestones. The ongoing information they provide about skill attainment can support students in preparing for high-stakes, highly competitive testing. Dashboards can summarize and integrate data from multiple evaluation sources to provide insights into the student's targeted competencies and performance trajectory. When designing dashboards, Hardy and Lewis (2018) recommend that developers:

- Base the dashboard on standardized assessment data and up-to-date information.
- Include quantitative and qualitative data from a variety of sources.
- Consolidate key performance metrics using at-a-glance data visualizations with the capability to drill down for more detail.
- Identify and display performance benchmarks.
- Clearly display areas of concern and recommend resources for improvement.
- Provide ongoing coaching and support for learners on how to interpret and act upon information in the dashboard.

The appropriate use of learning dashboards can provide critical data that is needed for students to gain control and increase overall learning. When entrance into a field is based upon high-stakes testing, one poor assessment score can jeopardize continued pursuit of the career. Ongoing feedback on skills can be displayed though dashboards to provide a more valid evaluation of a potential student's skill set and overall competence.

4.4 The Role of Data Visualization in Behavioral Self-management

Shatri and Buza (2017) indicate that since the dawn of humanity, visual imagery has been an effective way to communicate both abstract and concrete information. In the early 1990s, Presmeg (1992) indicated that visualization facilitates understanding data. In addition, Gangwer (2015) suggests that data visualization can be a tool to help teachers make instructional decisions. Data visualization assists teachers in determining instructional approaches, strategies, and content. Visualization offers a method of bringing critical data reflecting academic progress into the forefront of learning and provides insight into the time required to master key concepts. Visualizations can also provide ongoing information as to what needs to be taught next. For the learner, appropriate visualizations of data can communicate insights into critical learning information that may be intuitive, but that is difficult to comprehend without an added visualization (Arcavi, 2003). Clarifying the relationship between visualization and mastery of content increases learning and creates opportunities for application of what is taught (Janitor et al., 2010).

Kanfer and Goldstein (1980) define behavioral self-management as a technique for shaping learned behavior. Behavioral self-management is the process of modifying one's own behavior by systematically managing cues, cognitive processes, and contingent consequences (Kanfer & Goldstein, 1980). When personal assessment data is provided to students through data visualization, a powerful teaching tool can be harnessed. Personal visualizations of current learning status can provide the data needed for acquiring new knowledge. Behavioral self-management is an approach to learning and behavioral change that depends on the individual taking the initiative to control the change process. Data visualization, used as a tool to provide individual achievement data, can provide ongoing information on cognitive processes such as efficacy in acquiring new information. Data visualizations can provide input for behavioral self-management.

Social cognitive theory (Bandura, 1989) provides a basis for behavioral self-management (BSM) as it emphasizes the dynamic interaction between people (personal factors), their behavior, and their environments. Self-regulation is a key component of social cognitive theory. Bandura (1989) indicates that self-regulation operates through a set of psychological subfunctions that must be developed and mobilized to implement self-directed change. Neither intention nor desire alone has much effect if people lack the capability for exercising influence over their own motivation and behavior (Bandura & Simon, 1977). When Bandura first discussed self-regulation, technology was not capable of providing the opportunity for ongoing feedback through the use of data visualizations. Currently, data visualizations can provide initial and ongoing information concerning the gains made in mastering the skill set that the learner seeks to master. Although similar to behavior modification, BSM differs in one important respect: there is a heavy emphasis on cognitive processes, reflecting the influence of Bandura's social cognitive theory and emphasis on the importance of self-regulation in the learning process. Through data visualizations students can develop a strong sense of learning their strengths and weaknesses. By providing easily interpreted and ongoing feedback, data visualizations of current levels of achievement can be used in a self-management approach for improving understanding of curricular materials.

Teachers play a critical role in the students' use of data visualizations for self-management of learning behavior. To implement an effective BSM, teachers must:

- Provide instruction in the use of both visualizations and the learning management system.
- Make sure that ongoing assessment data is available for each student as the student progresses through the curriculum.
- Ascertain that the data provided through visualizations is reflective of learning objectives.
- Facilitate students' understanding of the relationship between classwork and achievement gains reflected through the self-management system.
- Monitor student progress and provide assistance as needed.
- Determine the overall effectiveness of the self-management system as a teaching tool.

Teachers who are appropriately trained and have good understanding of both data visualization and BSM can eliminate the reliance many educational systems place on high-stakes testing. The data visualization/BSM approach suggested offers many advantages over high-stakes testing. Advantages include:

- Reliance on a comprehensive work record as opposed to one single data point (high-stakes test).
- Continuous and up-to-date information on each student's academic progress.
- A convenient method to provide acknowledgment of achievement to parents, institutions of higher learning, and other stakeholders.
- Less stress on teachers and students as they are evaluated on long-standing, comprehensive data that provides a thorough look at academic accomplishments as opposed to relying on data gathered during a single point in time that can be easily influenced by outside sources.

In order to implement a continuous assessment system within the classroom, educators will need to be provided with appropriate curricular resources, technology, and training. Initially, the move to the proposed system could prove time-consuming and expensive; however, the equity objectivity proposed by such a move far out-weights the initial inconveniences and time spent implementing a new system.

5 Conclusions

Research on data visualizations and dashboards has been available for over a decade. This chapter reviewed the use of these tools in the context of the impact they can make for providing equitable educational opportunities. Historically, high-stakes tests have been used to make life-changing decisions for students. Admission to academic programs, universities, and even careers has been governed by the outcome of a single test. This chapter suggests that an educational decision based on one test may not be as reliable or equitable as a decision based on multiple data points, particularly when these are available through data visualization. In many situations, information provided through high-stakes testing has been used to limit learning and career opportunities for some students. However, with data visualizations and dashboards, assessment data can be used to enhance learning and increase educational opportunities for all students.

In addition, self-monitoring behavior can be strengthened as data visualizations and dashboards increase available self-monitoring data and learning opportunities. Data visualizations and dashboards can be especially impactful in providing learning opportunities for students with special needs, as timely feedback supports these populations in understanding skill sets and developing self-awareness.

The use of dashboards and data visualizations offers unique technological opportunities to provide data that builds more equitable educational and job opportunities for all students. Through the use of these technologies, stressful high-stakes testing can become a remnant of the past. Immediate feedback can provide students with information on their ongoing progress, and students can have a "picture" of what needs to be learned each day. Specific learning and behavioral needs can be more thoroughly addressed through the use of self-monitoring behavior. Additional research in this area can provide insights into the effectiveness of dashboards and data visualizations for enhancing equitable educational opportunities.

Glossary

Assessment refers to the wide variety of methods or tools that educators use to evaluate, measure, and document the academic readiness, learning progress, skill acquisition, or educational needs of students.

Dashboards display concrete performance data with cutting-edge visualizations on a single platform, enabling users to access, monitor, and synthesize information efficiently for the purpose of performance improvement.

Evaluation is a systematic determination of merit, worth, or significance, using criteria governed by a set of standards. Evaluation can be used to determine the success rate or value of situations, individuals, or programs.

Formal assessments provide structured approaches to gathering information on the attainment of skills or objectives.

Formative assessments monitor and continuously evaluate student learning. Formative assessments provide ongoing feedback that can be used by students and teachers to facilitate and strengthen student learning. Formative assessments can help students self-identify their strengths and weaknesses. Such assessment targets areas that need work. A formative assessment refers to the continuous assessment of progress toward a long-term objective; therefore, it is ongoing and should be collected throughout the school year (Pemberton et al., 2006). In addition, formative assessments can help teachers recognize where students are struggling. As a conveyor of ongoing information about learning, the information gained through formative assessments can be summarized into an effective learning dashboard for both students and teachers. Formative assessments are generally low stakes. Few if any long-term educational decisions are based on a single formative assessment score. Low-stakes testing such as formative assessments can reduce the stress often associated with the assessment process.

Group test can be administered to a large group of individuals at one time or across settings and time. Group tests have the advantage of allowing comparisons of an individual's score to a group. In addition, smaller groups such as a classroom can be compared to a larger group such as all third graders who participated in the test. Group tests can provide valuable information on program assessment, but typically do not provide day-to-day information on an individual student's learning achievements and needs.

Group tests meet a pressing practical need. Because they can be administered to a large group at one setting, group tests are often preferred over individual tests. Group tests not only permit the simultaneous examination of large groups but also use simplified instruction and administration procedures. Less interpretation is needed on the part of the examiner, so less training is needed. As a rule, group tests are much less expensive when compared to individual tests. However, group tests are often considered less valid and reliable than individual tests.

High stakes indicates that major educational decisions such as passing a grade or admission into college are based on scores obtained by the student. In high-stakes testing, assessment results or outcomes are used to make decisions that have either a significant positive or negative impact on an individual's future opportunities.

Individual tests can be administered to only one person at a time. Many individual tests require oral responses and/or the manipulation of materials. Specific prompts and probes are administered to the test taker. Extensive training and certifications are required of the professionals who administer individual tests. Because of the need for training and the limited number of tests that one examiner can administer, individual tests are usually much more expensive to administer than group tests. However, individual tests are often preferred because they allow more interaction between the examiner and examinee. Examiners can evaluate behavior during the administration of the test. Scores on individual tests are often not as dependent on reading ability as group tests are, often resulting in a more accurate assessment of the construct being measured. Individual tests often measure constructs such as achievement, intelligence, and creativity.

Both individual and group tests can provide important information for a learner or an educator. Many testing companies offer information gathered from group and individual tests that can be accessed through a dashboard.

Informal assessment involves observations of a person's skill sets. Often rubrics or checklists are used in formative assessment so that a record of the data obtained during an observation can be made.

Normative data shows the average of a large representative group of assessment scores. Normative data is typically provided so that a student's scores can be compared against a group of students who have also completed the assessment.

Standardized test scores are metrics used to compare the distance of an observation (e.g., test score) from the population mean (or sample mean) measured in standard deviation units. Standard scores enable us to determine where a given score falls relative to the comparison sample.

Summative assessments typically are used to evaluate student learning at the end of an instructional unit. Student scores are often compared against a standard or benchmark (Pemberton et al., 2006). Summative assessments may be "high stakes," meaning that scores can play a major role in permitting or denying access to specific educational or career opportunities. Summative assessments can play a major role in program evaluations and, as such, can be very useful in decision-making concerning the worth of specific practices or programs. Providing summative assessment data through a dashboard could amplify critical decision-making data. However, such data may not facilitate the day-to-day learning needs of individual students because instructional objectives may not be provided.

References

Airasian, P. W., & Gregory, K. D. (1997). The Education Reform Act of 1988.

Arcavi, A. (2003). The role of visual representations in the learning of mathematics. *Educational Studies in Mathematics, 52*, 215–241.

Bainbridge, C. (2020). *The right scores for admittance to a gifted program*. Very Well Family. https://www.verywellfamily.com/whats-the-right-score-gifted-program-admittance-1449055

Bandura, A. (1989). Human agency in social cognitive theory. *American Psychologist, 44*, 1175–1184.

Bandura, A., & Simon, K. M. (1977). The role of proximal intentions in self-regulation of refractory behavior. *Cognitive Therapy and Research, 1*, 177–193.

Barnett, W. S., & Belfield, C. R. (2006). Early childhood development and social mobility. *Future of Children, 16*(2), 73–98. https://doi-org.libproxy.library.unt.edu/10.1353/foc.2006.0011

Baroudi, Z. M. (2007). Formative assessment: Definition, elements and role in instructional practice. *Post-Script (1444-383X), 8*(1), 37–48.

Berliner, D. C. (2018). *Education week*. https://www.edweek.org/education/opinion-response-the-role-of-student-test-scores-in-teacher-evaluations/2018/08

Briesch, A. M., Daniels, B., & Beneville, M. (2019). Unpacking the term "Self-management": Understanding intervention applications within the school-based literature. *Journal of Behavioral Education, 28*(1), 54–77. http://dx.doi.org.libproxy.library.unt.edu/10.1007/s10864-018-9303-1

Briesch, A. M., Swaminathan, H., Welsh, M., & Chafouleas, S. M. (2014). Generalizability theory: A practical guide to study design, implementation, and interpretation. *Journal of School Psychology, 52*(1), 13–35.

Broadfoot, P., & Black, P. (2004). Redefining assessment? The first ten years of assessment in education. *Assessment in Education: Principles, Policy & Practice, 11*, 7–26.

Campbell, F. A., Ramey, C. T., Pungello, E., Sparling, J., & Miller-Johnson, S. (2002). Early childhood education: Young adult outcomes from the abecedarian project. *Applied Developmental Science, 6*(1), 42–57. https://doi-org.libproxy.library.unt.edu/10.1207/S1532480XADS0601_05

Card, S. K., Mackinlay, J. D., & Shneiderman, B. (1999). Chapter 1: Information visualization. In S. K. Card, J. D. Mackinlay, & B. Shneiderman (Eds.), *Readings in information visualization: Using vision to think*. Morgan Kaufman.

Carson, J. (2014). Mental testing in the early twentieth century. *History of Psychology, 17*(3), 249–255. https://doi-org.libproxy.library.unt.edu/10.1037/a0037475
Carter, D., & Crichton, S. (2014). Empowering twenty-first century assessment practices: Designing technologies as agents of change. *Educational Media International, 51*(4), 295–309.
Citizen Contributor. (2017). *Why every student should have an IEP*, Citizen Ed. https://citizen.education/2017/09/20/every-student-should-have-an-iep/
Cooper, B. R., & Lanza, S. T. (2014). Who benefits Most from head start? Using latent class moderation to examine differential treatment effects. *Child Development, 85*(6), 2317–2338. https://doi-org.libproxy.library.unt.edu/10.1111/cdev.12278
Coyle, T. R., & Pillow, D. R. (2008). SAT and ACT predict college GPA after removing "g". *Intelligence, 36*(6), 719–729.
Crisp, G. T. (2012). Integrative assessment: Reframing assessment practice for current and future learning. *Assessment & Evaluation in Higher Education, 37*(1), 33–43.
Firestone, W. A. (1998). A tale of two tests: Tensions in assessment policy. *Assessment in Education: Principles, Policy & Practice, 5*(2), 175–191.
Fives, H., & Barnes, N. (2020). Navigating the complex cognitive task of classroom assessment. *Teaching and Teacher Education, 92*. https://doi.org/10.1016/j.tate.2020/103063
Gangwer, T. (2015). *Shifting to visual teaching, international conference of creativity, thinking & education*, April 18–20, 2015 at the University of St. Thomas in Minnesota, p. 4.
Goldstein, P., Warde, B., & Peluso, P. (2013). Children's readiness gains in publically funded community-based pre-kindergarten programs for 4 years olds and preschool for 3 year olds. *Child & Youth Care Forum, 42*(6), 507–523. https://doi.org/10.1007/s10566-013-9215-0
Hardy, I., & Lewis, S. (2018). Visibility, invisibility, and visualisation: The danger of school performance data. *Pedagogy, Culture & Society, 26*(2), 233–248.
Herman, J. , & Golan, S. (1993). "The Effect of Standardized Testing on Teaching and Schools," Educational Measurement: Issues and Practices, Winter, 20–25.
Herrnstein, R. J., & Murray, C. A. (1994). *The bell curve: Intelligence and class structure in American life*. Free Press.
Janitor, J., Jakab, F., & Kniewald, K. (2010). "Visual Learning Tools for Teaching/Learning Computer Networks: Cisco Networking Academy and Packet Tracer," 2010 Sixth International Conference on Networking and Services, 351–355, https://doi.org/10.1109/ICNS.2010.55
Kanfer, F., & Goldstein, A. (1980). *Helping people change: A textbook of methods*. Pergamon Press.
Kim, W., Linan-Thompson, S., & Misquitta, R. (2012). Critical factors in reading comprehension instruction for students with learning disabilities: A research synthesis. *Learning Disabilities Research & Practice, 27*(2), 66–78.
Korotitsch, W. J., & Nelson-Gray, R. O. (1999). An overview of self-monitoring research in assessment and treatment. *Psychological Assessment, 11*(4), 415–425.
Mavrommatis, Y. (1997). Understanding assessment in the classroom: Phases of the assessment process—The assessment episode. *Assessment in Education: Principles, Policy & Practice, 4*(3), 381–400.
McDougall, D., Morrison, C., & Awana, B. (2012). Students with disabilities use tactile cued self-monitoring to improve academic productivity during independent tasks. *Journal of Instructional Psychology, 39*(2), 119–130.
McMillan, J. H. (Ed.). (2013). *SAGE handbook of research on classroom assessment*. Sage.
Mertler, C. A. (2007). *Interpreting standardized test scores: Strategies for data-driven instructional decision making*. Sage Publications.
Mertler, C. A., & Zachel, K. (2006). Data-driven instructional decision making: An idea (and practice) whose time has come. *Principal Navigator, 1*(3), 6–9.
National Research Council. (2000). *How people learn: Brain, mind, experience, and school: Expanded edition*. The National Academies Press. https://doi.org/10.17226/9853
Pellegrino, J. W. (2012). Assessment of science learning: Living in interesting times. *Journal of Research in Science Teaching, 49*(6), 831–841.

Pemberton, J., Rademacher, J., Tyler-Wood, T., & Cereijo, M. (2006). Aligning assessments with state curriculum standards and teaching strategies. *Intervention in School and Clinic, 41*, 283–289. https://doi.org/10.1177/10534512060410050501

Presmeg, N. C. (1992). Prototypes, metaphors, metonymies and imaginative rationality in high school mathematics. *Educational Studies in Mathematics, 23*, 595–610.

Ramaswami, G. S., Susnjak, T., & Mathrani, A. (2019). Capitalizing on learning analytics dashboard for maximizing student outcomes. In *2019 IEEE Asia-Pacific conference on computer science and data engineering (CSDE)* (pp. 1–6). https://doi.org/10.1109/CSDE48274.2019.9162357

Ratner, H., Andersen, B. L., & Madsen, S. R. (2019). Configuring the teacher as data user: Public-private sector mediations of national test data. *Learning, Media & Technology, 44*(1), 22–35.

Rooney, C., & Schaeffer, B. (1998). *Test scores do not equal merit: Enhancing Equity & Excellence in college admissions by deemphasizing SAT and ACT results*. National Center for Fair and Open Testing.

Rosenbloom, R., Wills, H. P., Mason, R., Huffman, J. M., & Mason, B. A. (2019). The effects of a technology-based self-monitoring intervention on on-task, disruptive, and task-completion behaviors for adolescents with autism. *Journal of Autism and Developmental Disorders, 49*(12), 5047–5062.

Santen, S. A., Myklebust, L., Cabrera, C., Patton, J., Grichanik, M., & Zaidi, N. L. B. (2020). Creating a learner performance dashboard for programmatic assessment. *Clinical Teacher, 17*(3), 261–266.

Schlenoff, D. (2015). *Challenging the immigrant: The Ellis Island intelligence tests*. Scientific American, Challenging the Immigrant – Scientific American.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512.

Shatri, K., & Buza, K. (2017). The use of visualization in teaching and learning process for developing critical thinking of students. *European Journal of Social Sciences Education and Research, 111*(4), 71–73.

Sorapure, M. (2019). Text, image, data, interaction: Understanding information visualization. *Computers and Composition, 54*, 102519.

Chapter 26
Linking Assessment Results and Feedback Representations in E-assessment: Evidence-Centered Assessment Analytics Process Model

Sinan Keskin and Halil Yurdugül

1 Introduction

Observing an object, skill, or knowledge and showing the results of the observation with numbers or symbols are explained with the concept of measurement; and considering these numbers and symbols according to certain criteria and reaching a decision and judgment are explained by the assessment concept (Turgut & Baykul, 2012). Education and teaching activities have predetermined goals. Measurement and assessment are the process of measuring and making judgments to what extent these goals have been achieved for both learners and teachers. In the traditional approach, measurement results are usually presented to users using numerical values (exam scores). However, with the e-learning and e-assessment that are becoming widespread today, measurement results have begun to be presented to the users via analytics dashboards that contain easy to understand and meaningful information beyond simply displaying a numerical value. Analytics dashboards enable the visualization of the learning data obtained from the learning and assessment analytics. Assessment analytics refers to the generation of meaningful patterns from data based on students' interactions with assessment tasks or feedbacks in an e-learning system or e-assessment system and the use of these patterns in the context of assessment for/as learning. Thus, it provides learners and teachers to monitor and reflect on their online teaching and learning patterns. The prime purpose of this chapter is to linking e-assessment results with learning analytics dashboards. For this purpose,

S. Keskin (✉)
Computer Education & Instructional Technology, Van Yuzuncu Yil University, Van, Turkey
e-mail: sinankeskin@yyu.edu.tr

H. Yurdugül
Computer Education & Instructional Technology, Hacettepe University, Ankara, Turkey
e-mail: yurdugul@hacettepe.edu.tr

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_26

e-assessment, the assessment analytics framework, evidence-centered assessment analytics process model, measurement theories and analysis methods used in the assessment, and data visualization representations were explained in this chapter.

2 E-assessment

E-assessment can be defined as the implementation of information communication technologies in assessment applications to measure students' learning (Shute & Kim, 2012). With the implementation of information technology in the assessment, the e-assessment is conceptualized in different ways such as computer-based assessment, computer-assisted assessment, online assessment, and web-based assessment. The common feature of these different concepts is that they draw attention to the use of different digital technologies in the assessment. The technologies used in assessment have evolved because of advancements in information and communication technologies, and this development has resulted in the emergence of new concepts. In the literature, there are various classifications for assessment. One of these classifications is based on the purpose of the assessment. According to its purpose, it is addressed as a formative and summative assessment (TGAT Report, 1988). While formative assessment aims to shape and develop students' competencies; on the other hand, summative assessment aims to reveal the students' success status (Sadler, 1989).

To make literal assessments in e-learning environments, a flexible assessment approach is needed following the distance education approach rather than traditional approaches. In face-to-face teaching environments where traditional assessment approaches are adopted, learners are subjected to a midterm and a final exam. However, in distance education, multi-metric assessment frameworks should be used. When it comes to using conventional assessment methods in distance education, the measurements made fall short of producing reliable and valid results. Although assessment tasks are planned to measure learning performance, especially formative assessment tasks contribute significantly to students' learning processes. The main purpose of formative assessment is to improve learning performance. In formative assessment, learner performance is assessed, and assessment feedback is provided to learners in order to help them improve their performance (Clarke, 2001; Earl & Katz 2006; Sadler, 1989). Learners can only access information about their learning performance through well-structured system feedback because there is no direct learner-teacher interaction in e-learning environments (Vasilyeva et al., 2007). Feedback informs students about expected learning performance. Thus, feedback has a critical role in adaptive e-assessment and e-learning systems. Another argument worth mentioning at this point is that feedback should be directly related to learner performance (Mory, 2003). Accordingly, feedback should have an informative and motivating role regarding the learner's performance after a certain learning task.

Feedback types provided in adaptive systems differ in accordance with learner characteristics, learning goals, and types of knowledge (Shute, 2008). In terms of knowledge types, feedback in e-learning environments can be classified as cognitive and behavioral feedback. Cognitive feedback provides information on learners' understanding of the subject, while behavioral feedback provides learners with procedural information on organizing learning (Sedrakyan, 2016). Similarly, feedback differs based on learner characteristics including achievement and learning orientation (Narciss, 2008; Shute, 2008). Feedback can be presented immediately after each item or at the end of the test. Taking these various learner and task characteristics into consideration while giving feedback ensures that formative assessment systems are more adaptable. These characteristics are also important inputs for the assessment analytics. Dashboard components have an important role especially in the design of effective test-based feedback. In addition, process-oriented feedback created using process analytics has come to the fore today. Beyond providing summative knowledge to learners about their learning performance, it seeks to clarify the learning pathways, provide hints for smoother learning, and inform learners about procedural steps of the learning process (Sedrakyan et al., 2019).

3 Assessment Analytics

Assessment analytics is used to monitoring the learners and learning process, tracking, and recording assessment data, provide feedback, predict the future state of learners, and especially make progress in learning outcomes by using assessment data (Papamitsiou & Economides, 2016). During an e-learning process, learners leave different tracks by interacting with different activities such as learning, communication, and assessment. Assessment analytics are carried out using especially assessment data obtained from the e-learning process. Assessment data consists of the interactions of learners with assessment activities and the results (grades, points) they obtained from these activities. As in learning analytics, data are transformed into analytics based on a model (Nouira et al., 2017). In other words, analytics are performed by using an assessment modeling that includes assessment data, learner, and task characteristics. Consequently, assessment analytics may be described as an attempt to improve learner performance by utilizing learner psychometric data and assessment feedback (MacNeill & Ellis, 2013). Static data (user characteristics, features, stored data, etc.) as well as dynamic interaction data can be used in assessment analytics. In systems where dynamic data is used, feedback is also dynamically delivered to users.

Modeling in the assessment analytics is carried out with an analytics engine just as in the learning analytics process. Assessment activities and learner characteristics data are used as inputs to the assessment analytics engine. The metadata definitions determine the scope and detail level of these data. Unlike a basic learning activity, assessment activities have different properties such as assessment type, item type, item number, technique, feedback type, and task session. For this purpose, Nouira et al. (2017) proposed an ontological data model for assessment analytics as well as defined metadata properties for this model. Ontological modeling is used to define the concepts, relationships, and basic properties of a particular domain explicitly and formally (Guarino, 1995). In Fig. 26.1, we summarized the basic metadata classes and properties that an assessment activity should have according to the assessment analytics ontological model.

An e-assessment activity is expected to have seven basic data classes as seen in Fig. 26.1. Each data class has subclasses, properties, and attributes. For example, an assessment activity can be created in diagnostic, formative, and summative forms according to its purpose. Among these seven data classes, the statement and object classes provide the most important information for the assessment engine. A statement explains the student who is participating in an assessment activity, students' actions, and the outcomes of those actions. For example, the expression "John successfully completed quiz 2 with 80 points in 20 minutes" can be handled as a statement definition for an assessment task. The object class defines the properties and attributes of the assessment task objects. Assessment item author (creator), item subject (module), item difficulty level, and feedback messages are stored in this class. As can be seen, assessment activities have some metadata definitions different from other e-learning activities. In summary more complex and detailed data definitions are needed. Therefore, while defining e-assessment activities, it is recommended to create activities based on data models appropriate to their nature.

Assessment analytics is a system where different data sources described above are used as input, these data are processed with different approaches, and the results are presented to the users. In the next section, this system is discussed in detail with the assessment analytics process model.

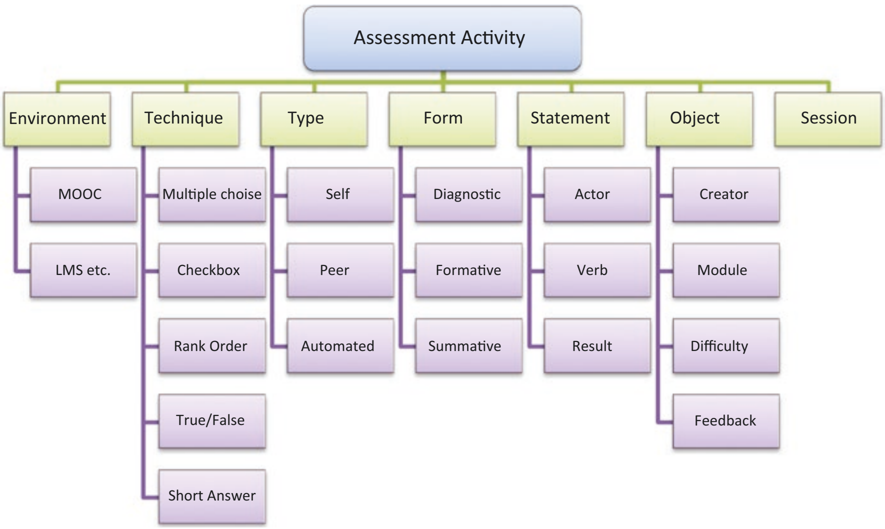


Fig. 26.1 Seven basic data classes of the assessment activities

4 Evidence-Centered Assessment Analytics Model

In e-learning or e-assessment, assessment analytics refers to the creation of meaningful patterns from data based on students' experiences with assessment tasks or feedbacks. If considering assessment analytics as a process, the ontological model proposed by Nouira et al. (2017) can be used to describe the process's inputs. In the next process stage, how analytics are to be carried out are discussed. In other words, the process stage can be named as the analytics engine where input data is processed and outputs are produced (Papamitsiou & Economides, 2016). In the final stage, the outputs of the analytics and the presentation method of the outputs are explained. Giving the patterns obtained as a result of the analytics to the instructor to improve the instructional design was expressed as the *assessment for learning*. Presenting analytics results to the students to increase their learning awareness and shape their learning experiences was expressed as the *assessment as learning* (Earl & Katz, 2006).

Various measurement models (IRT, CTT, SATO, etc.) have been developed to ensure that the assessment is carried out systematically. However, these models serve, especially for summative assessment purposes. Along with new assessment approaches, much more complex, diverse, and comprehensive data started to be produced. Mislevy, Almond, and Lukas (2003) developed the evidence-centered assessment design (ECD) model for the design of educational assessment (Fig. 26.2). Each component in the model defines the inputs, operations, and outputs of the assessment process. The student model describes what is to be measured such as learner knowledge, skills, and abilities. The evidence model explains how to make this measurement. That is, it defines the observable and latent variables related to learner performance. The task model defines the place (where?) of the measurement. The task definitions for measuring the performance indicators are determined with this component. With the assembly model, it is decided how many times the measurement will be made. In other words, it is the model that defines how the student, evidence, and task model will work together to create the psychometric structure of the assessment. The relationships between the three models are defined by

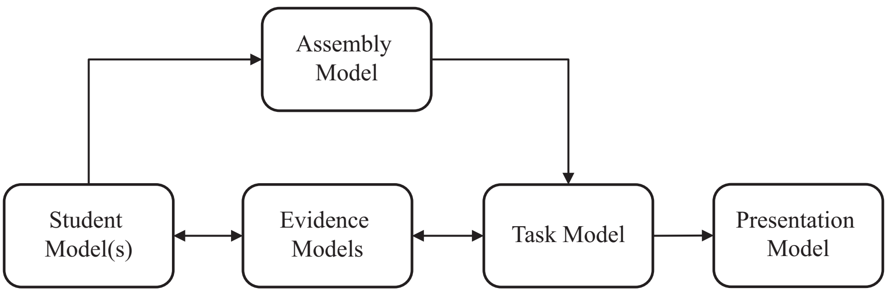


Fig. 26.2 Evidence-centered design model

the assembly model. Finally, the presentation model explains how the assessment will be delivered to the users.

In our research, we propose a new model called "evidence-centered assessment analytics process model." Based on the generic model proposed by Mislevy et al. (2003), this model aims to explain the process for current e-assessment designs. Our model outlines the technological developments observed in the e-assessment systems and the benefits of data analytics with an integrated process model.

Evidence-centered assessment analytics process model describes the adventure followed from the design of the assessment to the assessment analytics dashboard design (Fig. 26.3). The basic input to the assessment process is the student and competency model defined in the learning management systems (LMS). LMSs are web-based applications that bring together online learning activities such as content, discussion, and assessment. These systems keep records of students, instructors, and learning activities, ensuring that they are processed in an orderly manner. The student model includes psychometric, e-learning behaviors, and demographic data about students. On the other hand, the competency model explains what is expected from the student, the relationships between subject-competence, and acquisitions. The competency model defines the specific knowledge and skills required to succeed in a particular subject. Mislevy et al. (2003) explain the task model as the environment in which the assessment task is performed. Nowadays, e-assessment is carried out employing testing and learning tasks in LMS. Therefore, testing, assessment interactions, and learning tasks are taken into consideration while making measurements in the assessment analytics process. The evidence model can be used to make the assessment task definitions in accordance with the competency definitions. The information obtained so far is processed by using the assessment analytics engine. At the end of the assessment analytics process, feedback messages are given to learners regarding their performance. Interactions with these messages are also used as an input to this process. Therefore, feedback is both input and output of the process. Feedback is presented to users through a presentation model, directly through written messages, or through an assessment analytics dashboard.

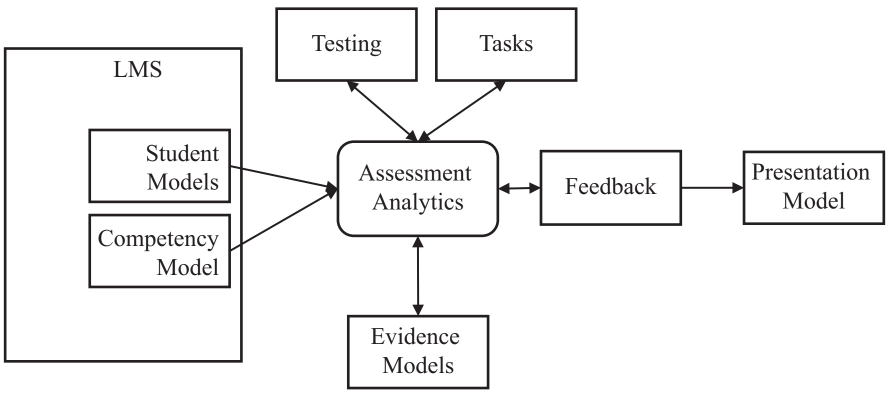


Fig. 26.3 Evidence-centered assessment analytics process model

In the next section, basic measurement theories, methods, and algorithms used in the analysis of educational data will be briefly explained to explain how to perform analytics. Then, in the last section, dashboard components that can be used to present meaningful information obtained from the process stage to users are explained.

5 Assessment Analytics Engine

In the previous section, the assessment analytics process, ontological model, and basic data sources are explained. In this section, data analysis approaches are discussed to explain how the obtained data sources will be examined. Sedrakyan et al. (2019) stated that three basic data analysis approaches are adopted in the learning analytics process. These are (I) summary representations based on statistics, (II) sequential representations based on process analytics, and (III) prediction algorithms for making future predictions (Sedrakyan et al., 2019). In line with this approach, we discussed statistical methods, measurement models, and algorithms frequently used in the analysis of e-assessment data in this section.

5.1 Basic Statistics Methods

E-learning and assessment behaviors are recorded as log data in the system. When the data of more than one learner comes together, a data set is formed. Descriptive statistics are used to summarize and organize the general characteristics of the numerous observations in the data set. Central tendency and distribution measures, frequency, percentage, and outlier detection can be given as examples of descriptive statistics. In summary, a diagnosis of the group is made with descriptive statistics.

Central tendency measures are used to determine the central value from which the variable values are collected. The most used measures for this purpose are mode, median, and mean. The mode is preferred for nominal and ordinal level measurements, the median for ordinal and ratio level measurements, and the mean for interval and ratio level measurements. The central distribution measures aim to reveal how much the measurements in a particular variable differ from each other. Variance and standard deviation can be given as examples of distribution measures. Standard deviation, the most used distribution measure, is used to show how far the observations deviated from the arithmetic mean.

The data sets where the mode, median, and mean values are equal and the observations accumulated close to the mean are normally distributed. Data represent behaviors, as they move away from the normal distribution; these data are called outliers (Keskin et al., 2019). These data may occur as a result of system errors, deliberate manipulation, or actual learner behavior. Especially detecting real learner behaviors as an outlier is an important data source for intelligent learning systems, because these outlier observations indicate students who are ahead or behind the

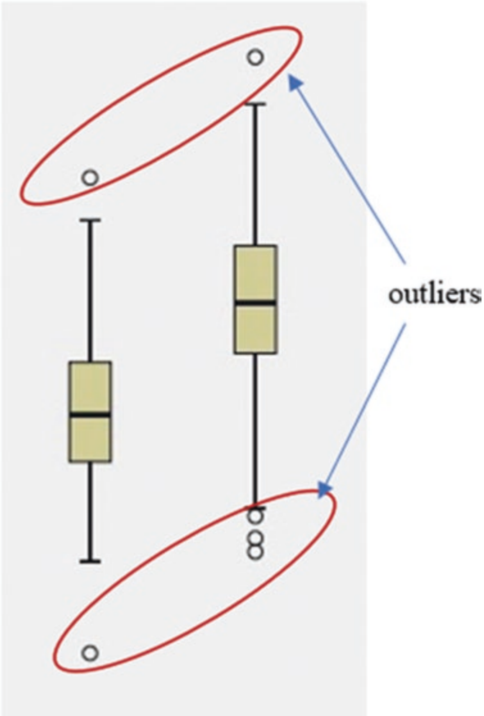


Fig. 26.4 Box plot graphs

group. Outlier analysis guides the practitioners in identifying the students who show a better learning performance than the group in general or who fall behind the class and who are likely to dropout the course. Z, Grubbs, Rosner, box plot, and Hampel methods can be given as examples of statistical methods used in determining outliers (Keskin et al., 2019). Among these methods, Z statistics are recommended to be used in e-assessment systems because it is relatively easy to calculate, and box plots are both an easy calculation method and produce easy-to-understand graphic outputs (Fig. 26.4).

5.2 Measurement Models

Measurement models are used to score psychological test results. We can use measurement models for scoring paper-pencil tests and contemporary e-assessment tasks. In this section, we presented classic test theory, item response theory, and SATO caution index.

5.2.1 Classical Test Theory (CTT)

Classical test theory is a measurement theory that aims to explain the relationship between the observed characteristics of the learners and their unobservable characteristics with a linear model (Lord & Novick, 1968). According to the classical test theory, observed features always contain some error. The true score can be obtained when this error is subtracted from the observed measurement. Since it is not possible to reduce the error to zero and directly measure the true score, CTT helps to predict true scores based on observed measurements.

CTT is often favored by practitioners because it is conducted using simple statistical methods. The test score of the individuals is obtained by adding the scores obtained from the items. Statistical calculations are carried out using the total score and item scores. While calculating the total score in CTT, the items are added up without weight. The most important disadvantage of CTT is that the calculated total score is affected by the difficulty level of the test. In CTT, four item statistics are used: item difficulty index, item discrimination index, item variance, and item reliability coefficient. The item difficulty index calculated for maximum performance tests is an item statistic calculated by dividing the number of people who answered an item correctly by the number of all people who took the item. As a result of the item difficulty index, it is decided the relevant item is difficult or easy. If the calculated difficulty index is close to 1, it is interpreted as the item is easy. The power of an item to reveal the difference between individuals in terms of its measured feature is expressed as item variance. Item variance is calculated by multiplying the item difficulty index (p) with the inverse of the item difficulty index (1–p). Item variance reaches the highest value for medium difficulty items. Accordingly, items with medium difficulty have high discrimination in achievement tests. Item validity, in other words, item discrimination index, expresses the power of an item to distinguish students with different knowledge levels (low/high) from each other. Finally, item reliability index is a parameter related to the contribution level of the item to explain the difference between ability levels.

5.2.2 Item Response Theory (IRT)

The item response theory (IRT) tries to explain the relationship between individuals' non-observable abilities and their responses to test items with a mathematical model (Hambleton et al., 1991). Unlike CTT, the test scores of the students depend on the characteristics of the item and the student (Yurdugül, 2010). The competencies of a student who answered an easy item and a student who answered a difficult item are not the same. For this reason, it is recommended to consider the item difficulty and discrimination parameters instead of scoring the items equally. The probability of each person responding correctly to one item in the test is independent of the other people taking the test. For IRT, item difficulty, item discrimination, and prediction parameters are used. The item knowledge function is used to explain the contribution level of an individual's performance on an item in determining his ability level (Crocker & Algina, 1986).

When compared to CTT, IRT has advantages such as item parameters are independent from the sample, responses to items can be in two or more categories, and item weights are taken into account when calculating the total score. The most important disadvantages of IRT are that it is relatively difficult to calculate and interpretation of results requires expertise.

5.2.3 Sato's Caution Index

Sato is a caution index that is used to diagnose students and aims to determine the learning status of students through their response patterns to items (Chen et al., 2005). By using this caution index, students' success and ability levels are tried to be determined. The total test score is calculated by coding the students' answers to the items as 1/0. Then the students are ranked according to their scores and the items according to their difficulty levels. A series of calculations are performed to obtain student and problem indexes. The calculated caution indexes are evaluated in six subclasses for students and in four subclasses for problems. Sato index makes a classification according to the performance of the student in the group. Accordingly, Sato caution index is a norm-referenced assessment. Çüm (2019), who analyzed Sato, CTT, and IRT psychometrically, revealed that Sato produced consistent, valid, and reliable results like other measurement theories. There are some studies using the Sato caution index in e-learning. For example, Şahin and Yurdugül (2019) used the Sato caution index in presenting the instructional feedback in the intelligent intervention system. Similarly, Bayrak and Yurdugül (2016) used the Sato caution index to classify students in a web-based self-assessment system. In summary, Sato is an alternative measurement model that can produce action-oriented outputs in the context of assessment analytics, and it generates valid and reliable result like other measurement theories.

5.3 Sequential Analysis

Sequential pattern mining is an approach that aims to reveal sequential patterns of user behavior recorded in the database (Mabroukeh & Ezeife, 2010). These analyses aim to discover sequential relationships between different objects by examining the frequencies of repeating patterns (Tarus et al., 2018). Sequential events are not independent of each other, and preliminary measurements affect the results of the final measurements (Gottman & Roy, 1990). When the data are analyzed sequentially, it is possible to better predict the events that will occur later. Various sequential analysis algorithms are utilized in the process of revealing sequential patterns. Markov chain, lag sequential analysis, and generalized sequential pattern can be given as examples.

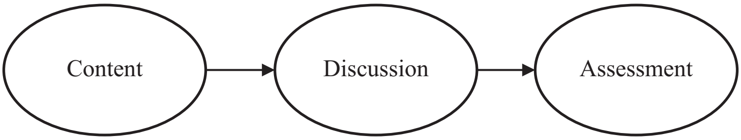


Fig. 26.5 Sample sequential pattern

An example sequential pattern is given in Fig. 26.5. To draw the arrows (➔) representing the transitions between the system components, the frequency of these transitions must have reached a certain density. Sequential analysis tests whether these densities are statistically significant. Significant transitions are shown with arrows as shown in Fig. 26.5. Another advantage of sequential analysis is that it can work with real-time data such as machine learning algorithms. Thus, decision-making processes based on real-time data can be supported. There are various studies investigating navigation patterns in e-learning environments with sequential analysis. For example, Şahin et al. (2020) revealed in their research that e-learning navigations differ based on learner characteristics. Fatahi, Fami, and Moradi (2018) showed that using sequential behavior patterns, learners' learning styles can be predicted with high accuracy. Tarus et al. (2018) utilized sequential pattern mining in context-sensitive recommender system design. Massa and Puliafito (1999) conducted a study to predict the dropout behavior of university students using Markov chains. When looking at the literature, it's clear that sequential analysis is a significant guide for practitioners in decision-making processes. Besides, feedback about the learning process and learning goals obtained from the sequential analysis are at least as effective as those that explain the learner's current performance (Sedrakyan et al., 2019). Process-oriented feedback presented as a result of the sequential analysis, enhancing teachers' and learners' engagement and achievement by helping the regulation of the learning process.

5.4 *Classification Algorithms*

Another approach that can be used in the analysis of e-assessment data in the context of machine learning is classification algorithms. Classification algorithms aim to make inferences by using a set of independent variables related to the target variable. In this section, naive Bayes, decision trees, K-nearest neighbor, and linear classification algorithms are briefly mentioned.

5.4.1 Naive Bayes

Based on basic probability principles, naive Bayes is an algorithm that can be easily created, is useful for large data sets, and can be applied without the need for complex iterative parameter estimates (Sayad, 2010). Naive Bayes is performed with two groups of data called training and test data. Probability calculations are performed over the training data that each observation belongs to a class and is categorical, and as a result of these calculations, the classification probability values for the categories are obtained. The process carried out so far is called training. The category of test data is tried to be determined by using the probability value obtained during the training process. The number of observations used in the training process has a significant effect on the accuracy of the predictions to be made during the test phase. Therefore, training data is expected to be as much as possible. The consistency of the analysis results performed on these two data sets increases the classification accuracy parameter, which shows the power of the classification.

5.4.2 Decision Trees

Decision trees are a widely used classification method to create classification rules in tree form, which are simple, understandable, and easy to use. It is used to create rule sets for the predefined target variable by using the independent variables. The variables included in the analysis can be continuous or discrete. When continuous variables are used, appropriate cut points are determined, and classes are created according to these cut points. These classes can consist of two categories or more. The obtained rule sets are used in the decision-making phase and to create recommender systems. Different algorithms such as ID3, C4.5 (j48), Gini, Sprint, CART, REP tree, and random forests are used in the creation of decision trees. Training and test data are needed as in naive Bayes. The tree structure is created using the training data and the classification accuracy of the tree is determined with test data.

5.4.3 K-Nearest Neighbor (KNN)

K-nearest neighbor (KNN) is a density-based classification algorithm in which the class of the new observation to be included in the data set is decided by looking at the nearest k neighbors. Observations take place on a plane according to their qualities. When a new observation is added to the data set, the distance between the new observation and the predetermined k closest neighbors is measured. This measurement is performed by using different distance measurement methods such as Euclidean, Manhattan, Mahalanobis, and Hamming distance. After the distance calculation, the class of the new observation is decided by looking at the nearest neighbors.

5.4.4 Linear Classification: Logistic Regression

Logistic regression is one of the methods commonly used to predict the dependent variable. When it comes to regression analysis (linear), the first thing that comes to mind is quantity estimation. However, a linear classification (attribute estimation) can also be made using regression analysis. The method used for this purpose is called logistic regression analysis. In logistic regression analysis, the dependent variable is a discrete class variable that can only take two values. Examples of two values that dependent variables can take are yes/no, successful/unsuccessful, complete/dropout, etc. Prediction of the dependent variable can be done with one or more independent variables. Considering that the data produced in e-learning environments are discrete, it's clear that logistic regression analysis is a good prediction solution.

6 Assessment Feedback

Feedback is the information about learner performance that is produced as a result of the interaction with learning and assessment task (Narciss, 2008). Feedback aims to reveal the real situation of the learning and direct the learning processes. With feedback, new teaching is provided to learners in a different form. To demonstrate learner performance, assessment feedback is delivered into two forms: test- and item-based. With the developing of e-assessment applications, feedback is offered to learners regarding their test performances and system interactions. Accordingly, in the context of assessment analytics, feedback can be explained in two basic categories, namely, experience and performance feedback (Fig. 26.6).

Performance-oriented feedback can be presented to learners immediately at the end of a task (item-based) or the end of a series of tasks (test-based). Item-based feedback can include messages about the performance of learners' response to an assessment item. Examples of item-based feedback are verification, correct response, topic contingent, response contingent, misconception, etc. (Shute, 2008). Verification and correct response feedback can be visualized using the dashboard. However, other elaborated feedback types such as topic contingent and response contingent are conveyed to learners directly through instructional and motivational messages. Topic contingent and misconception feedback is structured based on the competency model defined in the LMS. Another type of performance-oriented feedback is the test-based feedback that is presented after learners complete all subtasks within an assessment task. This kind of feedback provides information about learners' general test performance and learning deficiencies, prominent knowledge, and skills.

New types of feedback that provide information about learners' e-assessment experiences have emerged since the adoption of assessment analytics. Experience feedback is created by using data on assessment tasks and feedback interactions. This feedback focuses on the student's interaction with the assessment task rather than test performance. As seen in Fig. 26.6, there are two types of experience feedback, descriptive and predictive. Descriptive experience feedback is used to explain the current learning situations of learners by using basic statistical methods and measurement models. On the other hand, predictive feedback uses assessment interaction data for predicting learners' future learning situations. Data is processed

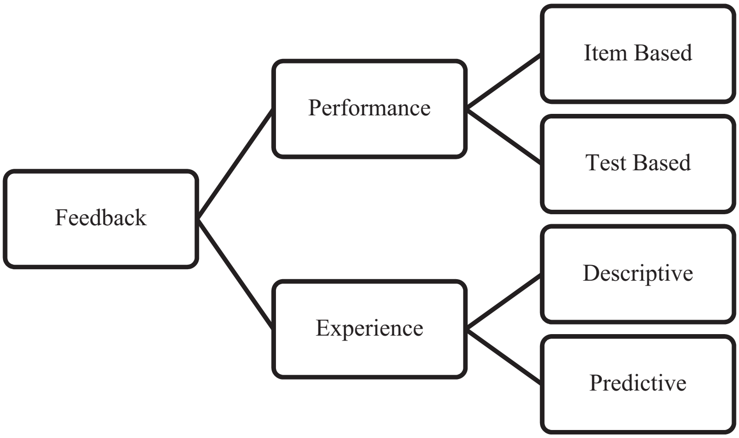


Fig. 26.6 Assessment feedback

using sequential analysis and classification algorithms, and predictive results are presented to users via dashboards and predictive experience feedback messages.

7 Assessment Analytics Data Visualization Options

Learning analytics are mostly presented to users through dashboards. Dashboards are designed to provide learners with various information and guidance about their current performance. In this context, cognitive and behavioral feedbacks are tried to be presented to users through self- or peer-regulated messages, the accuracy of learning, motivational/affective feedback, task completion rates, and user effort indicators to regulate the learning process of learners (Sedrakyan et al., 2019). The feedback frequently used in the e-assessment guides the learners in completing their cognitive deficiencies and in detecting errors in learning behavior. Analytics serve the purpose of learning regulation by visualizing learning goals and activities, directing them to cooperation between learners, and providing information on learning strategies and time planning.

As a result of applying the measurement theories and algorithms explained in the previous section to the assessment data, the analysis findings are mostly obtained in the form of numerical tables. Data visualization representations are used to present the findings in a comprehensible way to all users. With the visualization of data, the decision-making processes of learners, trainers, and managers are supported. Visualization makes it possible to easily monitor the learning process and to identify potential problems (Sedrakyan et al., 2019). Data visualization is expected to be understandable, simple, and catchy by the target audience (Sedrakyan, 2016). The right visualization representations should be used to ensure that the message reaches the target audience clearly and reliably. The purpose of the data visualization usually determines the visualization representations. Data are visualized to show comparison, relationship, distribution, and composition (Abela, 2020). Table 26.1 summarizes some data visualization options based on their purpose. Comparison charts serve the purpose of comparing observations, observing change over time, and comparing data sets. Relationship graphs are preferred to summarize the relationships and correlations between variables. Composition charts are used for visualization of part-whole relationships. Finally, distribution charts are used to determine the distribution of variables over time, trends in data, and outliers.

Table 26.1 summarizes the commonly used graphics and charts for visualizing the e-assessment results. Column, line, bar, pie, and Mekko charts are preferred for visualization of comparisons. Column, bar, and line charts are the simplest chart types used to visualize the distribution and comparison of data. Bar chart is used in analytics dashboard to visualize planned and actual students' achievements (Sedrakyan et al., 2019). They are also suitable graph types for observing changes over time. Bar and line charts visualize the change of a limited number of observations/variables over time or the distribution. In cases where the number of variables and time periods are many (if there is a transition toward a continuous variable), it is recommended to prefer a line chart instead. Such graphs showing the change over time offer clues to learners in managing and guiding the learning process (Sedrakyan et al., 2019). It is thought that it will significantly contribute to the early prevention of any adversities that may occur in the learning process. Besides, it is possible to present the average performance of the peers and make individual-group comparisons with a second variable to be added to the graphics. Thus, learners are provided with the opportunity to make a comparison with norm reference. In addition, these charts are an effective visualization representation tool for the purpose of comparing expected and observed performances of learners.

A composition chart is preferred to highlight proportions of parts within a data set (Wilke, 2019). For this purpose, stacked charts, pie chart, Mekko chart, and area chart can be used to visualize whole-part relations. The number of parts and whether observations have changed over time are considered when deciding the visualization option. For example, if there is a limited number of items (such as gender,

Table 26.1 Graphs and charts used in data visualization and their purpose

Type	Compare	Composition	Distribution	Relation
Column	+		+	
Stacked column		+		
Line	+		+	+
Bar	+		+	
Stacked Bar		+		
Pie	+	+		
Scatter plot			+	+
Bubble			+	+
Mekko	+	+	+	
Area		+		

education level), pie charts can be used. However, as the number of independent parts increases, it is not possible to visualize them clearly with pie charts. In a nutshell, it is appropriate to use pie charts to emphasize simple fractions such as quarters and half. Stacked charts are better suited to visualize trends over time. For example, a stacked bar chart can be preferred to visualize the change over time. In this case, time series presented on the x axis and relative proportion on the y axis. Area chart, a type of line chart, is another option used to visualize data composition. It serves to visualize part-whole relations like pie charts. While static data is visualized in pie charts, the area chart is preferred for displaying part-whole relations of the data that has changed over time. If the variables used are continuous, it is recommended to choose area graphs. On the other hand, when a continuous variable (age, exam grade, etc.) is used instead of gender, a switch from stacked charts to area charts is recommended. Area charts are usually preferred to emphasize the magnitude of change over time, compare expected and observed performances of learners, and draw attention to trends. In an educational context, these graphic types are suitable for visualizing completing portfolio tasks and monitoring progress. Using visualizations that provide teachers with general summaries about the classroom supports them in classroom orchestration (Charleer et al., 2017). For example, it can guide the instructors in determining the lagged students who need feedback. Regulation needs in the e-learning process can be easily captured through time-varying graphs (Sedrakyan et al., 2020).

Another important issue about a data set is how the observations are distributed in terms of a particular variable. Column, line, bar, scatter plot, and bubble charts are preferred to visualize the distribution of data. Managers and educators need distribution charts especially to understand and summarize the situation of the target audience. When it is necessary to visualize more than one distribution in a single chart, the stacked representation of the available chart types can be used. Finally, to visualize the relationships between variables, line, scatter plot, and bubble charts are used. While relation charts are better for visualizing structures that we assume to be linked, they can also help users to find unexpected patterns and group correlated structures. The scatter plot is mostly preferred to show the relationships of two variables and to visualize the distributions. It shows similarities and differences within the data set. Thus, outlier observations in the data set can be easily identified. Outliers represent extreme behaviors, so they can guide instructors to identify lagging or leading students (Keskin et al., 2019; Martinez-Maldonado et al., 2014). The relationship between the three variables can be visualized using a bubble chart. Observations are shown on a two-dimensional plane as in a scatter plot. Unlike the scatter plot, the observations are not simply represented by a point, but in circles (bubbles) of different sizes, parallel to the size of the third variable. It is an effective option that can be used to offer a quick glance to instructors or institution about learners (Martin & Ndoye, 2016). In addition to standard relationship graphs, modern graphic formats such as network diagrams, connection maps, brainstorm graphs, and tree diagrams can also be used to illustrate connections.

8 Conclusion

Assessment analytics aims to improve assessment process and student learning. The input of analytics process is data which is derived from student, competency models, and interactions with assessment tasks. The data pass through a process stage called the assessment analytics engine. In the assessment analytics engine, data are examined with descriptive, sequential, and predictive analysis. The outputs obtained from this stage mostly present to users through dashboards and instructional messages. As a result of assessment analytics, three different types of feedback classified as summative feedback, real-time feedback, and predictive feedback are presented to users (Schumacher & Ifenthaler, 2018a). Summative feedback can be explained as providing feedback on learning situations using previously recorded log data. Real-time feedback, on the other hand, are informing users instantly about their learning behavior. Finally, predictive feedback refers to the use of classification algorithms to predict future learning situations of learners based on current learner data. Studies in the literature indicate that only performance-oriented feedback decreases intrinsic motivation to learn, and learners should be supported with guiding feedback regarding the learning process (Lonn et al., 2015; Sedrakyan et al., 2019, 2020). In other words, assessment analytics dashboards should be designed for not only performance-oriented but also process-oriented and emotional support (Hassan et al., 2019; Schumacher & Ifenthaler, 2018b; Sedrakyan, 2016). It is clear that the assessment analytics process requires a complex interrelated process with many variables. In this chapter, evidence-centered assessment analytics process model has been proposed and explained in detail.

Data visualization representations are used to present the outputs of analytics engine. Data visualizations provide designing understandable messages, summarize complex and large amounts of findings, clarify the user behavior, and identify the issues that need attention. For the message to reach the target audience clearly and accurately, it is necessary to choose the right representations. The most important determinant in making this choice is the purpose of the visualization. Data are basically visualized to show comparison, relationship, distribution, and composition. As a result of analytics, users can be given action-oriented suggestions, visualized summaries, and interventions. These different outputs presented to learners affect cognitive, affective, and behavioral learning outcomes at different levels (Aguilar et al., 2021). It is recommended to conduct experimental evaluation that explain the relationship between different visualization options and learning outcomes.

In this chapter, an evidence-centered assessment analytics process model proposed and data visualization options that can be used in this process are presented with their purposes. Similarly, there are various studies in the literature to explain the learning analytics process (Chatti et al., 2012; Ifenthaler, 2017; Lal, 2014). The studies put forward on the assessment and learning analytics process dealt with analytics mostly in their context. In future research, there is a need for interface models that will connect two fields and define reciprocal linkages. Our study is limited to explaining how the assessment analytics process can be carried out.

Efforts need to be made to increase the accuracy of the analytics' predictions. For this purpose, studies can be conducted in which the most appropriate analysis approaches for different input data of the assessment analytics process can be determined. Adaptive assessment system designs require models that represent user preferences and behaviors. Determining learners' visualization preferences with various psychometric features will be a valuable source of knowledge for adaptive system designers. Finally, current dashboard research mostly focuses on presenting indicators related to learner performance (Sedrakyan et al., 2020). It is also known that providing continuous regulation messages to learners reduces their intrinsic motivation (Lonn et al., 2015). As a result, we invite further assessment analytics research to better understand and assist learners' emotional states.

References

Abela, A. V. (2020). *Chart chooser*. ExtremePresentation.com https://extremepresentation.typepad.com/files/chart-chooser-2020.pdf

Aguilar, S. J., Karabenick, S. A., Teasley, S. D., & Baek, C. (2021). Associations between learning analytics dashboard exposure and motivation and self-regulated learning. *Computers & Education, 162*, 104085.

Bayrak, F., & Yurdugül, H. (2016). Designing at the micro level learning analytics module for web based self-assessment system. *Educational Technology Theory and Practice, 6*(2), 85–99.

Charleer, S., Klerkx, J., Duval, E., Laet, T. D., & Verbert, K. (2017). Towards balanced discussions in the classroom using ambient information visualisations. *International Journal of Technology Enhanced Learning, 9*(2/3), 227. https://doi.org/10.1504/ijtel.2017.084501

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5–6), 318–331.

Chen, D., Lai, A., & Liu, I. (2005). The design and implementation of a diagnostic test system based on the enhanced S-P model. *Journal of Information Science and Engineering, 21*, 1007–1030.

Clarke, S. (2001). *Unlocking formative assessment: Practical strategies for enhancing pupils' learning in the primary classroom*. Hodder and Stoughton.

Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory*. Harcourt Brace Javanovich College Publishers.

Çüm, S. (2019). *A psychometric comparison of Sato test theory with classical test theory and item response theory.* Unpublished doctoral dissertation. Hacettepe University, Turkey.

Earl, L. M., & Katz, M. S. (2006). Rethinking classroom assessment with purpose in mind: Assessment for learning, assessment as learning, assessment of learning. *Manitoba Education, Citizenship & Youth*.

Fatahi, S., Shabanali-Fami, F., & Moradi, H. (2018). An empirical study of using sequential behavior pattern mining approach to predict learning styles. *Education and Information Technologies, 23*(4), 1427–1445.

Gottman, J. M., & Roy, A. K. (1990). *Sequential analysis: A guide for behavioral researchers*. Cambridge University Press.

Guarino, N. (1995). Formal ontology, conceptual analysis and knowledge representation. *International Journal of Human-Computer Studies, 43*(5–6), 625–640.

Hambleton, R. K., Swaminathan, H., & Rogers, H. J. (1991). *Fundamentals of item response theory*. Sage.

Hassan, L., Dias, A., & Hamari, J. (2019). How motivational feedback increases user's benefits and continued use: A study on gamification, quantified-self and social networking.

International Journal of Information Management, 46, 151–162. https://doi.org/10.1016/j.ijinfomgt.2018.12.004

Ifenthaler, D. (2017). Learning analytics design. In L. Lin & J. M. Spector (Eds.), *The sciences of learning and instructional design* (pp. 202–211). Routledge.

Keskin, S., Aydin, F., & Yurdugül, H. (2019). The determining of outliers on e-learning data in the context of educational data mining and learning analytics. *Educational Technology Theory and Practice, 9*(1), 292–309.

Lal, P. (2014). Online tutor 2.0: Methodologies and case studies for successful learning. In G. Alves (Ed.), *Designing online learning strategies through analytics* (pp. 1–15). IGI Global.

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior, 47*, 90–97.

Lord, F., & ve Novick, R. M. (1968). *Statistical theories of mental test scores*. Addison Wesley Publishing Company.

Mabroukeh, N. R., & Ezeife, C. I. (2010). A taxonomy of sequential pattern mining algorithms. *ACM Computing Surveys (CSUR), 43*(1), 1–41.

MacNeill, S., & Ellis, C. (2013). Acting on assessment analytics. *JISC CETIS Analytics Series, 2*(2).

Martin, F., & Ndoye, A. (2016). Using learning analytics to assess student learning in online courses. *Journal of University Teaching & Learning Practice, 13*(3), 7.

Martinez-Maldonado, R., Clayphan, A., Yacef, K., & Kay, J. (2014, June). Towards providing notifications to enhance teacher's awareness in the classroom. In *International conference on intelligent tutoring systems* (pp. 510–515). Springer.

Massa, S., & Puliafito, P. P. (1999). An application of data mining to the problem of the university students' dropout using Markov chains. In *European conference on principles of data mining and knowledge discovery* (pp. 51–60). Springer.

Mislevy, R. J., Almond, R. G., & Lukas, J. F. (2003). A brief introduction to evidence-centered design. *ETS Research Report Series, 2003*(1), i–29.

Mory, E. H. (2003). Feedback research revisited. In J. H. Jonassen (Ed.), *Handbook of research on educational communications and technology* (pp. 745–783). MacMillian Library Reference.

Narciss, S. (2008). Chapter 11: Feedback strategies for interactive learning tasks. In *Handbook of research on educational communications and technology* (Vol. 3, pp. 125–144). https://doi.org/10.4324/9780203880869.CH11

Nouira, A., Cheniti-Belcadhi, L., & Braham, R. (2017). An ontological model for assessment analytics. In *13th international conference on web information systems and technologies WEBIST* (pp. 243–251).

Papamitsiou, Z., & Economides, A. A. (2016). An assessment analytics framework (AAF) for enhancing students' progress. In *Formative assessment, learning data analytics and gamification* (pp. 117–133). Academic.

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science, 18*, 119–144.

Şahin, M., Keskin, S., & Yurdugül, H. (2020). Sequential analysis of online learning behaviors according to E-learning readiness. In *Online teaching and learning in higher education* (pp. 117–131). Springer.

Şahin, M., & Yurdugül, H. (2019). An intervention engine design and development based on learning analytics: The intelligent intervention system (in 2 S). *Smart Learning Environments, 6*(1), 1–18.

Sayad, S. (2010). An introduction to data science. http://www.saedsayad.com/data_mining_map.htm. Accessed 07.03.2020.

Schumacher, C., & Ifenthaler, D. (2018a). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407.

Schumacher, C., & Ifenthaler, D. (2018b). The importance of students' motivational dispositions for designing learning analytics. *Journal of Computing in Higher Education, 30*(3), 599–619.

Sedrakyan, G. (2016). *Process-oriented feedback perspectives based on feedback-enabled simulation and learning process data analytics*. PhD thesis, KU Leuven.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107*, 105512.

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages, 50*, 19–38.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189.

Shute, V. J., & Kim, Y. J. (2012). e-assessment. In N. Balacheff, J. Bourdeau, P. Kirschner, R. Sutherland, & J. Zeiliger (Eds.), *TEL thesaurus*. Stellar Initiative. http://myweb.fsu.edu/vshute/pdf/eassessment.pdf

Tarus, J. K., Niu, Z., & Kalui, D. (2018). A hybrid recommender system for e-learning based on context awareness and sequential pattern mining. *Soft Computing, 22*(8), 2449–2461.

TGAT Report. (1988). *National Curriculum Task Group on assessment and testing – A report*. Department of Education and Science.

Turgut, M. F., & Baykul, Y. (2012). *Eğitimde Ölçme ve Değerlendirme* (6. Baskı). Pegem Akademi.

Vasilyeva, E., Puuronen, S., Pechenizkiy, M., & Rasanen, P. (2007). Feedback adaptation in web-based learning systems. *International Journal of Continuing Engineering Education and Life Long Learning, 17*(4/5), 337. https://doi.org/10.1504/IJCEELL.2007.015046

Wilke, C. O. (2019). *Fundamentals of data visualization: A primer on making informative and compelling figures*. O'Reilly Media.

Yurdugül, H. (2010). Farklı madde puanlama yöntemlerinin ve farklı test puanlama yöntemlerinin karşılaştırılması. *Journal of Measurement and Evaluation in Education and Psychology, 1*(1), 1–8.

Sinan Keskin is an academic staff at Van Yuzuncu Yil University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education at Gazi University in 2010 and worked as a teacher for 1 year. He gets his Ph.D. degree in 2019. He has experience in distance education, e-assessment, instructional design, and programming teaching. His research interests relate to e-assessment, feedback design, instructional discussions, adaptive e-learning, learning analytics, and educational data mining.

Halil Yurdugül is a Professor at Hacettepe University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education in the Department of Statistics at Hacettepe University. He completed Ph.D. degree in 2003 at Hacettepe University. His research interests relate with psychology, psychometry, education, measurement and evaluation in education, statistic, assessment, e-assessment, learning analytics, educational data mining, and intelligent learning management systems.

Chapter 27
Visualization and Dashboards: Challenges and Future Directions

Muhittin Sahin and Dirk Ifenthaler

1 Introduction

Instructional technologies provide researchers with significant opportunities in order to facilitate learners' learning and design more effective learning environments. Nowadays, it is seen that especially digital learning environments are used intensively as instructional technology. Large amount of data about the learning experiences of learners are recorded in digital learning environments. Log data contains important information for learners, instructors, institutions, and decision-makers (Yoo et al., 2015). Thus, learning experience of learners in digital learning environments is being improved (Sin & Muthu, 2015). There are some major challenges in digital learning environments such as lack of quality log data, and analyzing, and understanding data (Kuosa et al., 2016). At this point educational data mining and learning analytics give researchers various opportunities. Educational data mining is a method used to discover meaningful structures and latent patterns in e-learning environments (Baker & Siemens, 2014). Educational data mining enables to discover meaningful patterns based on the system usage of learners, instructors, and administrators in order to increase the quality of online learning environments (Romero & Ventura, 2010). Learning analytics use dynamic data in

M. Sahin (✉)
Ege University, Bornova, Turkey

University of Mannheim, Mannheim, Germany
e-mail: musahin@mail.uni-mannheim.de

D. Ifenthaler
University of Mannheim, Mannheim, Germany

Curtin University, Perth, Australia
e-mail: dirk@ifenthaler.info

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5_27

digital learning environments and enable (a) real-time modeling about learners and learning, (b) estimation and optimization of learning processes, and (c) assessment, revealing, and analysis of data for learning environments and educational decision-making (Ifenthaler, 2015). Analyzing of log data can present some opportunities as supporting self-regulation, more effective learning experience with personalized learning, and increasing awareness of the learning process (Drachsler et al., 2014). The aim of learning analytics is to present highly adaptable and personalized learning environments (Ifenthaler & Widanapathirana, 2014).

One of the important issues in digital learning environments is visualization of the patterns in a way that learners or instructors can understand it (Duval, 2011). Patterns which are related to the learning experiences of learners in digital learning environments are presented via dashboards. A dashboard is a learning analytics application that used to support learning processes of learners by providing information about learning experiences (Yoo et al., 2015). Most of the studies about dashboards aim to (i) support awareness and reflection, (ii) self-regulation, and (iii) monitoring (Jivet et al., 2017). Expectations of learners from dashboard system which are based on learning analytics include (a) support planning and organization, (b) adaptive recommendation, (c) individual analysis of learning process, and (d) providing self-assessment opportunity (Schumacher & Ifenthaler, 2018).

On the other hand, many studies have been mentioned that there are deficiencies in the field of visualization and dashboard (Bodily et al., 2018; Sarikaya et al., 2018; Sedrakyan et al., 2019). Within the scope of this chapter, (a) detailed information about visualization and dashboard is given, (b) researches in the field of literature in the context of visualization and dashboards are examined, (c) design principles are introduced, and (d) visualization and dashboard existing challenge and its future directions are discussed.

2 Background

2.1 Visualization

Looking into the history of visualization, it is possible to see that it is expressed as "information visualization." "Information visualization is the use of computer-supported interactive visual representations of abstract data to amplify cognition" (Card, Mackinley, & Shneiderman). The aim of information visualization helps to discover relations among data via visuals (Herman et al., 2000). In other words, information visualization aims to present unstructured information in databases/data warehouses with various visual techniques in a way that individuals can understand. Nowadays ICT can facilitate visualization but the activity that happens in the mind (Mazza, 2010). The important factors of visualization effectiveness are data, task, internal representation, and cognitive ability (working memory capacity, domain knowledge, etc.) (Zhu, 2007). As can be seen, visualization is related to many fields. Many principles should be taken into consideration when selecting and presenting visualization techniques. Visualization should be familiar and interesting to the learner in order to help learners to understand and interpret data (Kuosa et al., 2016). Within the scope of this research, visualization is discussed in the context of digital learning environments. Having a visual overview about the learner's learning experience can be useful for instructor and learners (Duval, 2011). Visualization helps to promote not only problem-solving but also reflection (Rieber, 1995). In addition, learners' awareness of the learning process increases through visualization (Khan & Pardo, 2016). It is easy to use visualizations in digital learning environments for students who have knowledge of visualization techniques (Sedrakyan et al., 2017). The use of these visualization techniques in digital learning environments has become widespread especially with learning analytics. Learning analytics use algorithmic analysis or information visualization in order to increase self-awareness and reflection based on tracking learning activities (Duval et al., 2012). Information of learners' learning experiences and learning performances in digital learning environments are presented to stakeholders via dashboards.

2.2 Dashboard

Dashboard is a rich computer interface with reports, visual indicators, and warning mechanisms that gather information dynamically in the field of business (Malik, 2005). Technologically, dashboards are multilayered applications built on business intelligence and data integration infrastructure (Lempinen, 2012). In this section, it is handled as the learning analytics application for the learning experiences of learners in digital learning environments. Dashboards that used in digital learning environments are structured based on three research areas as information visualization, learning analytics, and educational data mining (Schwendimann et al., 2016). Latent learning patterns of learners in e-learning environments can be discovered with educational data mining algorithms, and these patterns are presented to learners using visualization techniques and dashboards through learning analytics. In this way, e-learning environments can be improved and made more effective. Dashboard presents visual representation of the learner's or course's current and historical status for flexible decision-making in learning environments (Few, 2006). Thus, dashboard research aims to identify which data is meaningful to different stakeholders in education and how the data can be presented to support meaningful processes (Schwendimann et al., 2016).

In addition, through information on the dashboard, students' performance patterns can be explored, problems can be estimated and focused on this problems, and motivational structures can be identified (Podgorelec & Kuhar, 2011). Dashboards provide learners with real-time feedback, suggestions, and/or visualizations in order to support student reflection and knowledge awareness (Bodily et al., 2018). In the literature, dashboards were presented to the learners for comparison with peers, monitoring achievement of learning outcomes, and self-monitoring (Jivet et al., 2017). The benefits of dashboards in digital learning environments are summarized below (Yoo et al., 2015):

- Allow teachers to know students' learning situations in a real-time and scalable way.
- Improve student's self-knowledge levels.
- Make more intelligent decisions with the help of data mining algorithms.
- Help students improve their motivation and self-directed learning ability and achieve their learning goals.

Initial examples of research studies are *Course Signals* (Arnold & Pistilli, 2012) and *GLASS (Gradient's Learning Analytics System)* (Leony et al., 2012). *Course Signals* is a system that can give appropriate feedback to students and provide information about students' performance via signal lights. The other example is *GLASS* and it was developed so that learners can compare themselves with the peers with visualization of the learners' performance. In addition to these studies, SAM (Student Activity Meter) (Govaerts et al., 2012) visualization tool for awareness and self-reflection, LOCO-Analyst (Ali et al., 2012), and eLAT (Dyckhoff et al., 2012) can be given as examples of initial studies of dashboards. It is possible to see that many studies on dashboard have been conducted after these years. The purposes of the dashboard studies in the literature are presented below (Sedrakyan et al., 2019):

- Increase awareness about the learning process.
- Support cognitive process.
- Identify the student at risk.
- Provide immediate feedback.
- Monitor achievement status.
- Provide procedural information.
- Support decision-making.
- Inform.
- Display learner relations.
- Compare.
- Reflect.

Frequent visualization techniques utilized in dashboard studies are bar charts, line graphs, tables, pie charts, indicators, alert mechanisms, and network graphs (Podgorelec & Kuhar, 2011; Schwendimann et al., 2016). Frequent studies focus on learners (Arnold & Pistilli, 2012; Jin, 2017; Khan & Pardo, 2016; Papanikolaou, 2014; Park & Jo, 2015; Şahin & Yurdugül, 2019), instructors (Ali et al., 2012; Dyckhoff et al., 2012; Mottus et al., 2015; Van Leeuwen et al., 2015; Zhang et al., 2018), both learners and instructors (Sedrakyan et al., 2018; Kuosa et al., 2016; Govaerts et al., 2012; Leony et al., 2012), and other stakeholders, such as administrators (Rienties et al., 2016). In addition to these studies, it is seen that there is also research conducted in mobile dashboard design (Fulantelli et al., 2019; Kuhnel et al., 2018; Seiler et al., 2019).

For determining how and to what extent dashboard information will contribute to stakeholders, a benefits matrix may help as suggested in Table 27.1. The individual cells may be completed from individual perspective and provide a first decision point for implementing dashboard features (Ifenthaler, 2020).

Table 27.1 Dashboard benefit matrix

Dashboard goal/stakeholders	Learner	Instructor	Administrative	Researchers
Increase self-awareness				
Support cognitive process				
Determine dropout learner				
Instant feedback				
Display achievement status				
Present procedural knowledge				
Support decision-making				
Reflection				
Comparison				
Participant relations				
Increase participation				

3 Challenges and Future Directions

Learning analytics were presented as an emerging topic for adoption within 4–5 years in the 2011 Horizon Report prepared by the New Media Consortium (Johnson et al., 2011). Learning analytics are still part in the 2020 Horizon Report as "Analytics for Student Success" (Brown et al., 2020). Dashboards are used in order to support decision-making and increase awareness, motivation, and learning (Sarikaya et al., 2018). Graphics, tables, and visuals on the dashboards can be configured through visualization techniques. However, inappropriate designs and digital learning environments can negatively affect the learning processes of the learners. There are also findings that visualization techniques can produce undesirable effects or strengthen negative beliefs about learning and teaching (Gašević et al., 2015). In order to prevent undesirable effects, appropriate visualization techniques and dashboard designs should be developed. In this context, there are some difficulties in visualization and dashboard design. The difficulties encountered about visualization and dashboard design in the literature are presented in Table 27.2.

As can be seen in Table 27.2, some difficulties were expressed by different researchers. These difficulties and some solution proposals are as follows.

3.1 Linking Learning Theories

In the literature there is a gap between dashboard design and learning sciences (Sedrakyan et al., 2016; Sedrakyan et al., 2019). Several research related to dashboards consider a final design evaluation of the dashboard, while the design and development process is ignored (Bodily et al., 2018). In order to make dashboard designs more effective and to improve digital learning environments, dashboard

Table 27.2 Challenges of visualization and dashboards

Challenges	Research
Linking learning theories	Bodily et al. (2018), Sedrakyan et al. (2016), Yoo et al. (2015)
Determining effective metrics and effective visualization techniques	Ahn et al. (2019), Sarikaya et al. (2018), Sedrakyan et al. (2018), Yoo et al. (2015)
Data security and privacy	Sarikaya et al. (2018), Dabbebi et al. (2017)
Adaptive dashboard design	Schumacher and Ifenthaler (2018)
Amplifies cognition	Ahn et al. (2019), Yoo et al. (2015), Card et al. (1999)
Acceptance structures	Sedrakyan et al. (2018)

designs should be associated with learning theories, instructional design, and learning design (Ifenthaler et al., 2018). Learning theories are important in order to explain learning phenomenon and also help to design principles for learning environments, content, and tasks (Ertmer & Newby, 1993). In addition, more appropriate instruction and learning design can be structured through linking between learning analytics and learning theories (Ifenthaler et al., 2018; Wong et al., 2019).

3.2 Determining Effective Metrics and Effective Visualization Techniques

Another challenge in dashboard design is which visualization techniques to be used and which learner metrics to show. It is important to identify which metric from students' data is valuable to show (Yoo et al., 2015). A large amount of data about learners are stored unstructured in digital learning environments. However, it is necessary to determine which of these metrics are effective on the learner performance and present them to the learners. In order to determine these metrics, feature selection algorithms used in the pre-process stage of educational data mining can be utilized. Feature selection contributes to reducing the number of metrics/variables (Şahin et al., 2017). It is important to identify the metrics that are important for learners' learning experiences or learning performances, as well as presenting them with appropriate visualization techniques and visuals. In this context, the most important question is which visualization techniques are more appropriate and can be utilized. For this purpose, it is necessary to conduct research on which of the visualization techniques are more appropriate for students and to examine this situation (Sedrakyan et al., 2018). In order to make an effective dashboard design, a theoretical link should be established with human cognition and perception, situation awareness, and visualization technologies, and it should be structured based on this theoretical framework (Yoo et al., 2015). In addition, contextually appropriate presentations, visual language, and social framing issues should be taken into consideration in dashboard design (Sarikaya et al., 2018).

3.3 Data Security and Privacy

The other issues that should be discussed in the design of the dashboard are data design, sharing, security, reliability, and confidentiality (Sarikaya et al., 2018). This issue appears to be discussed not only in dashboard designs but also in learning analytics (Mah et al., 2019) and in related fields (Bertino & Ferrari, 2018; Chen & Zhao, 2012; Song et al., 2012). Which information will be used for learners, who will be enabled to access, and obtaining the permissions of the users can be given as examples which should be discussed under this topic (Ifenthaler & Schumacher, 2019).

3.4 Adaptive Dashboard Design

Dashboards shall be configured to allow a high level of customization (Schumacher & Ifenthaler, 2018). In other words, dashboards that are appropriate for the needs and characteristics of learners should be presented to the learners. For example, comparison with the group to the learners who have high external motivation and the learners who have high internal motivation can be presented with their daily individual performance. However, in order to develop adaptive designs, learning patterns, profiles, or preferences should be discovered based on the individual characteristics of the learners. Personality types, motivation sources, learning strategies, etc. could be indicators for individual characteristics of learners. In addition, adaptive dashboard designs can be structured specific to individual or to groups.

3.5 Amplifies Cognition

Cognitive concepts such as paying attention to cognitive load, human perception, and data literacy, avoiding visual clutter, and dividing data into interpretable sections have direct effects on design (Ahn et al., 2019). Therefore, the visuals and graphics that are presented should amplify the cognition of the learners. (a) Increasing resources, (b) reducing search, (c) enhancing recognition of patterns, (d) perceptual inference, (e) perceptual monitoring, and (f) manipulable environment amplify cognition (Card, Mackinley, & Shneiderman). In this context, it is necessary to develop designs such as presenting information related to each other together, presenting both visual and textual notifications, meaningful information, presenting different visuals and information according to the learners, and presenting graphics that are easy to use by the learners. It is possible to say that the visualization principles of proximity, similarity, enclosure, closure, continuity, and connection introduced by Gestalt in the dashboard designs still remain valid (Few, 2013). Concepts such as ease of use or perceived usefulness are within acceptance structures, and information on this concepts are included under the next topic. The presentation of different visuals or information to the learners is part of the adaptive dashboard.

3.6 Acceptance Structures

The structures in the technology acceptance models should be taken into consideration in the dashboard designs (Sedrakyan et al., 2018). The findings about why stakeholders use the developed e-learning environment or why they do not use it can be revealed through their acceptance structures. By determining these reasons, it will shed light on more appropriate environment designs. The important point is not only to develop a learning environment but also to use the developed environment by its stakeholders in accordance with its purpose. Davis (1989) defined these structures "perceived usefulness" and "perceived ease of use" in the context of *Technology Acceptance Model (TAM)*. Vankatesh et al. (2003) defined "unified theory of acceptance and use of technology (UTAUT)" as "performance expectancy," "effort expectancy," "social influence," and "facilitating conditions." The learning environments should present some features to the learners such as being easy to use, having high-level perceived usefulness, increasing learners' performance, etc. from this perspective. These models can guide researchers as to which visualization techniques can be utilized or what information will be presented to the learners. In addition to these, present sequential pattern via dashboard, intervention design, and dashboard interaction as an interaction type can be shown as future directions of the dashboard. Monitoring learners their own sequential behavior or the behavior of successful students can guide what they should do in the next step. The ultimate purpose of the intervention is to increase student achievement or improve students' learning experience (Pardo & Dawson, 2016). A structured intervention model that developed with learning analytics to support learning and teaching process can improve the learning performance of learners (Wu et al., 2015). At this point, intervention design and integration of this design to the systems are issues to be considered. In the digital learning environments, there are different types of interactions such as learner-learner, learner-instructor, learner-content, and learner-assessment. Besides, recently learner-dashboard interaction has also started to be considered as a type of interaction in the digital learning environments (Khan & Pardo, 2016; Rei et al., 2017). Learners' time spent in the dashboard, interaction behavior after interaction with the dashboard, charts and graphics that were seen by the learners, etc. can provide important information about the learning and teaching process.

4 Design Principles

There is no clear evidence about which features should be included in the design of visualizations (Zhu, 2007). It will be very useful to prepare some guidelines in order to design effective and goal-oriented visualizations (Duval, 2011). Guidelines and design principles can be contributed to the field such as (a) guiding the designers and researchers, (b) determining the issues to be considered in the design, (c) contributing to the evaluation of the developed environments, (d) developing effective and appropriate designs for the stakeholders, etc. Few (2013) suggest three design principles: (a) the most important information should stand out from others in a dashboard that usually fits limited space on a single screen, (b) the information on the dashboard should support the awareness of the students and aid prompt understanding using various visualization technologies, and (c) the information should be disseminated in a meaningful way, and the information elements should support the students' decision-making goal and ultimate goal. Some design and evaluation principles of the dashboard were defined by Yoo et al. (2015):

- Goal orientation
- Information usefulness
- Visual effectiveness
- Appropriation of visual representation
- User-friendliness
- Understanding
- Reflection
- Learning motivation
- Behavioral change
- Performance improvement
- Competency development

In this context, design principles have been put forth in order to guide researchers and designers as shown in Table 27.3.

Table 27.3 Design principles for visualization and dashboards

Design principle	Design inquiry
Stakeholders	For which stakeholder is the dashboard/visualization intended?
Responsive design	On which device will the dashboard be displayed?
Presenting of essential information	What is the purpose of the presented information?
Presenting data in the context with the interaction types	How does the visualization relate to specific data in a specific context?
Selecting the appropriate visuals for the context	What is an unbiased visualization of the underlying data?
Selection of color	Are color codes included and can they be interpreted?
Dynamic update	What is an appropriate time for updating the visualization?
Presenting of related information together	Which visualizations may benefit from combined representation?
Highlight of important information	Is there information which requires special highlights?
Easy to use	How can stakeholders access the visualization quickly and without barriers?
Inclusive design	Is the design inclusive for any stakeholder?

References

Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019). Designing in context: Reaching beyond usability in learning analytics dashboard design. *Journal of Learning Analytics, 6*(2), 70–85.

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education, 58*(1), 470–489.

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270).

Baker, R. S., & Siemens, G. (2014). Educational data mining and learning analytics. In K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (2nd ed.). Cambridge University Press. 253–274 p.

Bertino, E., & Ferrari, E. (2018). Big data security and privacy. In *A comprehensive guide through the Italian database research over the last 25 years* (pp. 425–439). Springer.

Bodily, R., Ikahihifo, T. K., Mackley, B., & Graham, C. R. (2018). The design, development, and implementation of student-facing learning analytics dashboards. *Journal of Computing in Higher Education, 30*(3), 572–598.

Brown, M., McCormack, M., Reeves, J., Brooks, D. C., Grajek, S., Alexander, B., Bali, M., Bulger, S., Dark, S., Engelbert, N., Gannon, K., Gauthier, A., Gibson, D., Gibson, R., Lundin, B., Veletsianos, G., & Weber, N. (2020). *2020 EDUCAUSE horizon report, teaching and learning edition*. EDUCAUSE.

Card, S. K., Mackinley, J. D., & Shneiderman, B. (1999). *Readings in information visualization: Using vision to think*. Morgan Kaufmann.

Chen, D., & Zhao, H. (2012). Data security and privacy protection issues in cloud computing. In *2012 international conference on computer science and electronics engineering* (Vol. 1, pp. 647–651). IEEE.

Dabbebi, I., Iksal, S., Gilliot, J. M., May, M., & Garlatti, S. (2017). Towards adaptive dashboards for learning analytic: An approach for conceptual design and implementation. In *9th international conference on computer supported education (CSEDU 2017)* (pp. 120–131). Porto, Portugal. https://doi.org/10.5220/0006325601200131

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*, 319–340.

Drachsler, H., Dietze, S., Herder, E., d'Aquin, M., & Taibi, D. (2014). The learning analytics & knowledge (LAK) data challenge 2014. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 289–290).

Duval, E. (2011). Attention please! Learning analytics for visualization and recommendation. In *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 9–17).

Duval, E., Klerkx, J., Verbert, K., Nagel, T., Govaerts, S., Parra Chico, G. A., Alberto, G., Odriozola, S., Luis, J., & Vandeputte, B. (2012). Learning dashboards & learnscapes. In *Educational interfaces, software, and technology* (pp. 1–5).

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society, 15*(3), 58–76.

Ertmer, P. A., & Newby, T. J. (1993). Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. *Performance Improvement Quarterly, 6*(4), 50–72.

Few, S. (2006). *Information dashboard design: The effective visual communication of data*. O'Reilly Media, Inc.

Few, S. (2013). *Information dashboard design: Displaying data for at-a-glance monitoring* (Vol. 81). Analytics Press.

Fulantelli, G., Taibi, D., Ammirata, F., & La Mattina, C. (2019). A mobile learning analytics tool to foster students' self reflection. In *EdMedia+ innovate learning* (pp. 721–726). Association for the Advancement of Computing in Education (AACE).

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71.

Govaerts, S., Verbert, K., Duval, E., & Pardo, A. (2012). The student activity meter for awareness and self-reflection. In *CHI'12 extended abstracts on human factors in computing systems* (pp. 869–884).

Herman, I., Melançon, G., & Marshall, M. S. (2000). Graph visualization and navigation in information visualization: A survey. *IEEE Transactions on Visualization and Computer Graphics, 6*(1), 24–43.

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 447–451). Sage.

Ifenthaler, D. (2020). Change management for learning analytics. In N. Pinkwart & S. Liu (Eds.), *Artificial intelligence supported educational technologies* (pp. 261–272). Springer.

Ifenthaler, D., & Schumacher, C. (2019). Releasing personal information within learning analytics systems. In D. G. Sampson, J. M. Spector, D. Ifenthaler, P. Isaias, & S. Sergis (Eds.), *Learning technologies for transforming teaching, learning and assessment at large scale* (pp. 3–18). Springer.

Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning, 19*(1-2), 221–240.

Ifenthaler, D., Gibson, D. C., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology, 34*(2), 117–132. https://doi.org/10.14742/ajet.3767

Jin, S. H. (2017). Using visualization to motivate student participation in collaborative online learning environments. *Journal of Educational Technology & Society, 20*(2), 51–62.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In *European conference on technology enhanced learning* (pp. 82–96). Springer.

Johnson, L., Smith, R., Willis, H., Levine, A., & Haywood, K. (2011). *The 2011 horizon report*. The New Media Consortium.

Khan, I., & Pardo, A. (2016). Data 2U: Scalable real time student feedback in active learning environments. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 249–253).

Kuhnel, M., Seiler, L., Honal, A., & Ifenthaler, D. (2018). Mobile learning analytics in higher education: Usability testing and evaluation of an app prototype. *Interactive Technology and Smart Education, 15*(4), 332–347.

Kuosa, K., Distante, D., Tervakari, A., Cerulo, L., Fernández, A., Koro, J., & Kailanto, M. (2016). Interactive visualization tools to improve learning and teaching in online learning environments. *International Journal of Distance Education Technologies (IJDET), 14*(1), 1–21.

Lempinen, H. (2012). Constructing a design framework for performance dashboards. In *Scandinavian conference on information systems* (pp. 109–130). Springer.

Leony, D., Pardo, A., de la Fuente Valentín, L., de Castro, D. S., & Kloos, C. D. (2012, April). GLASS: A learning analytics visualization tool. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 162–163).

Mah, D. K., Yau, J. Y. K., & Ifenthaler, D. (2019). Epilogue: Future directions on learning analytics to enhance study success. In *Utilizing learning analytics to support study success* (pp. 313–321). Springer.

Malik, S. (2005). *Enterprise dashboards: Design and best practices for IT*. Wiley.

Mazza, R. (2010). Visualization in educational environments. C. Romero, S. Ventura, M. Pechenizkiy, & RSJ de Baker (Eds.), Handbook of educational data mining, 9-26. CRC Press

Mottus, A., Graf, S., & Chen, N. S. (2015). Use of dashboards and visualization techniques to support teacher decision making. In *Ubiquitous learning environments and technologies* (pp. 181–199). Springer.

Papanikolaou, K. A. (2014). Constructing interpretative views of learners' interaction behavior in an open learner model. *IEEE Transactions on Learning Technologies, 8*(2), 201–214.

Pardo, A., & Dawson, S. (2016). Measuring and visualizing learning in the information-rich classroom. In P. Reimann (Ed.), *Learning analytics*. (41–55p). Routledge.

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110.

Podgorelec, V., & Kuhar, S. (2011). Taking advantage of education data: Advanced data analysis and reporting in virtual learning environments. *Elektronika ir Elektrotechnika, 114*(8), 111–116.

Rei, A., Figueira, Á., & Oliveira, L. (2017, September). A system for visualization and analysis of online pedagogical interactions. In *Proceedings of the 2017 international conference on E-education, E-business and E-technology* (pp. 42–46).

Rieber, L. P. (1995). A historical review of visualization in human cognition. *Educational Technology Research and Development, 43*(1), 45–56.

Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action evaluation framework: A review of evidence-based learning analytics interventions at the Open University UK. *Journal of Interactive Media in Education, 2016*(1), 1–11.

Romero, C., & Ventura, S. (2010). Educational data mining: A review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40*(6), 601–618.

Şahin, M., & Yurdugül, H. (2019). An intervention engine design and development based on learning analytics: The intelligent intervention system (In^{2}S). *Smart Learning Environments, 6*(1), 18.

Şahin, M., Keskin, S., & Yurdugül, H. (2017). Determination of learner characteristics and ınteraction variables for e-learning design by feature selection algorithms. In *11th international computer and instructional technologies symposium (ICITS 2017)*. Malatya, Turkey.

Sarikaya, A., Correll, M., Bartram, L., Tory, M., & Fisher, D. (2018). What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics, 25*(1), 682–692.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78*, 397–407.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41.

Sedrakyan, G., Järvelä, S., & Kirschner, P. (2016). Conceptual framework for feedback automation and personalization for designing learning analytics dashboards. In *EARLI SIG 2016*, Date: 2016/11/30-2016/12/01, Location: Oulu, Finland.

Sedrakyan, G., Leony, D., Muñoz-Merino, P. J., Kloos, C. D., & Verbert, K. (2017). Evaluating student-facing learning dashboards of affective states. In *European conference on technology enhanced learning* (pp. 224–237). Springer.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2018). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*, 105512.

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages, 50*, 19–38.

Seiler, L., Kuhnel, M., Ifenthaler, D., & Honal, A. (2019). Digital applications as smart solutions for learning and teaching at higher education institutions. In *Utilizing learning analytics to support study success* (pp. 157–174). Springer.

Sin, K., & Muthu, L. (2015). Application of big data in education data mining and learning analytics--a literature review. *ICTACT Journal on Soft Computing, 5*(4), 1035–1049.

Song, D., Shi, E., Fischer, I., & Shankar, U. (2012). Cloud data protection for the masses. *Computer, 45*(1), 39–45.

Van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effects of learning analytics. *Computers & Education, 90*, 80–94.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*, 425–478.

Wong, J., Baars, M., de Koning, B. B., van der Zee, T., Davis, D., Khalil, M., … Paas, F. (2019). Educational theories and learning analytics: From data to knowledge. In *Utilizing learning analytics to support study success* (pp. 3–25). Springer.

Wu, F., Huang, L., & Zou, R. (2015). The design of intervention model and strategy based on the behavior data of learners: A learning analytics perspective. *Hybrid Learning: Innovation in Educational Practices, 9167*, 294–301p.

Yoo, Y., Lee, H., Jo, I. H., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In *Emerging issues in smart learning* (pp. 145–155). Springer.

Zhang, J.-H., Zhang, Y.-X., Zou, Q., & Huang, S. (2018). What learning analytics tells us: Group behavior analysis and individual learning diagnosis based on long-term and large-scale data. *Educational Technology & Society, 21*(2), 245–258.

Zhu, Y. (2007). Measuring effective data visualization. In *International symposium on visual computing* (pp. 652–661). Springer.

Index

M. Sahin, D. Ifenthaler (eds.), *Visualizations and Dashboards for Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-81222-5