Advances in Analytics for Learning and Teaching

Dirk Ifenthaler · David Gibson
Editors

Adoption of Data Analytics in Higher Education Learning and Teaching

Springer

Advances in Analytics for Learning and Teaching

Series Editors

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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.

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Preface

The UNESCO Chair for Data Science in Higher Education Learning and Teaching (https://research.curtin.edu.au/projects-expertise/institutes-centres/unesco/) aims to advance global knowledge, practice and policy in applying data science to transform higher education learning and teaching to improve personalisation, access and effectiveness of education for all. Currently, higher education institutions and involved stakeholders can derive multiple benefits from educational data mining and learning analytics by using different data analytics strategies to produce summative, real-time and predictive insights and recommendations. Educational data mining refers to the process of extracting useful information out of a large collection of complex educational datasets while learning analytics emphasises insights and responses to real-time learning processes based on educational information from digital learning environments, administrative systems and social platforms.

Although the field of learning analytics is receiving a lot of attention for its capacity to provide lead indicators of student failure and supporting learning processes, it has primarily focused to date on individual courses in isolation, rather than the capabilities of higher education institutions as learning organisations. Accordingly, the implementation of learning analytics at higher education institutions may have broad implications for the organisation (e.g., technological infrastructure, policies and regulations) and its stakeholders (e.g., students, academic staff, administrators) including changes in learning culture and educational decision-making.

This edited volume *Adoption of Data Analytics in Higher Education Learning and Teaching* provides insights into the emerging paradigms, frameworks, methods and processes of managing change to better facilitate organisational transformation toward implementation of educational data mining and learning analytics. It features current research exploring the (a) theoretical foundation and empirical evidence of the adoption of learning analytics, (b) technological infrastructure and staff capabilities required, (c) institutional governance and policy implementation, as well as (d) case studies that describe current practices and experiences in the use of data analytics in higher education.

Part I focuses on the organisation-wide adoption process of learning analytics. The first chapter titled "Adoption of learning analytics", reflects on the characteristics of an innovation and presents ways how to improve higher education with the adoption of learning analytics (David Gibson, Dirk Ifenthaler, Chap. 1). In addition, different roles in the complex process of adoption of learning analytics in higher education institutions are described. The next chapter "The politics of learning analytics" reviews the principles of learning analytics in higher education to frame it as ethically charged towards a responsible and more nuanced learning analytics in being *measured* (Reem Al-Mahmood, Chap. 2). The following chapter "A framework to support interdisciplinary engagement with learning analytics" discusses the issue of learning analytics access and ways to leverage learning analytics data between instructors, and in some cases administrators, to create interdisciplinary opportunities for comprehensive student support (Stephanie J. Blackmon, Robert L. Moore, Chap. 3). Next, "The framework of learning analytics for prevention, intervention, and postvention in e-learning environments" first looks into theoretical information on the concepts of prevention, intervention, and postvention and goes through their applications in e-learning environments and the results. It, then, presents a learning analytics framework (Muhittin Şahin, Halil Yurdugül, Chap. 4). Then, "The LAVA Model: Learning analytics meets visual analytics" explores the benefits of incorporating visual analytics concepts into the learning analytics process by proposing the Learning Analytics and Visual Analytics (LAVA) model as enhancement of the learning analytics process with human in the loop and applying the LAVA model in the Open Learning Analytics Platform (OpenLAP) to support human-centred indicator design (Mohamed Amine Chatti, Arham Muslim, Manpriya Guliani, Mouadh Guesmi, Chap. 5). Another chapter, "See you at the intersection: bringing together different approaches to uncover deeper analytics insights", describes a "research sprint" approach that aims to extend learning analytics capabilities in ways that are meaningful for a range of different stakeholders (David Paul Fulcher, Margaret Wallace, Maarten de Laat, Chap. 6). The final chapter of the first part "'Trust the process!' – Implementing learning analytics in higher education institutions" explains how the implementation process of learning analytics can succeed in an evolutionary way and how a well-known LA adoption model can be adapted to guide a bottom-up adoption (Armin Egetenmeier, Miriam Hommel, Chap. 7).

Part II focuses on role of learners and teachers in the learning analytics adoption process. The opening chapter "Students' adoption of learner analytics" is concerned with extracted learner analytics, Connect Analytics and the factors influencing its adoption during a live research project at Northumbria University in the UK (Carly Palmer Foster, Chap. 8). The next chapter, "Learning analytics and the measurement of learning engagement", aims to provide a "multi-modal data" based contribution to the research of student engagement in learning (Dirk Tempelaar, Quan Nguyen, Bart Rienties, Chap. 9). The following chapter "Stakeholder perspectives (staff and students) on institution-wide use of learning analytics to improve learning and teaching outcomes" draws on three separate but related studies regarding the use of learning analytics to support and improve learning and teaching (Ann Luzeckyj, Deborah S. West, Bill K. Searle, Daniel P. Toohey, Jessica J. Vanderlelie, Kevin R. Bell, Chap. 10). Next, “How and why faculty adopt learning analytics” examines a bottom-up and widespread diffusion of a learning analytics platform, the Student Relationship Engagement System (SRES), through an Australian university (Natasha Arthars, Danny Y.-T. Liu, Chap. 11). “Supporting faculty adoption of learning analytics within the complex world of higher education” encompasses both theory and practice. This multiple-case study discusses the efforts of a Learning Analytics Research Collaborative at research intensive schools in the Bay View Alliance, a networked improvement community designed to address teaching cultures in higher education (George Rehrey, Marco Molinaro, Dennis Groth, Linda Shepard, Caroline Bennett, Warren Code, Amberly Reynolds, Vicki Squires, Doug Ward, Chap. 12). Another chapter “It’s all about the intervention: Reflections on building staff capacity for using learning analytics to support student success” centres on the challenges associated with building staff capabilities needed to act on data provided from learning analytics, assuming a model where staff provide remedial support to individual students (Ed Foster, Rebecca Siddle, Pete Crowson, Pieterjan Bonne, Chap. 13). The final chapter of this part, “Experiences in scaling up learning analytics in blended learning scenarios”, focuses on the practical problem of scaling up learning analytics services in blended learning as a set of key principles for scaling up learning analytics in blended learning scenarios in a higher education institution in Germany (Vlatko Lukarov, Ulrik Schroeder, Chap. 14).

Part III features cases of learning analytics adoption including small- and large-scale implementations. The first chapter “Building confidence in learning analytics solutions: two complementary pilot studies” presents two preliminary studies conducted in two higher education institutions respectively in Germany and France, designed to gain insights about students who drop out and with the purpose of supporting students’ achievement (Armelle Brun, Benjamin Gras, Agathe Merceron, Chap. 15). Next, “Leadership and maturity: how do they affect learning analytics adoption in Latin America?” provides new evidence on the process of adopting learning analytics in the Latin American context, aiming to contribute to it with useful insights about what it takes to move learning analytics adoption forward in the region (Isabel Hilliger, Mar Pérez-Sanagustín, Ronald Pérez-Álvarez, Valeria Henríquez, Julio Guerra, Miguel Ángel Zuñiga, Margarita Ortiz-Rojas, Yi-Shan Tsai, Dragan Gasevic, Pedro J. Muñoz-Merino, Tom Broos, and Tinne De Laet, Chap. 16). “Adoption of bring your own device examinations and data analytics” considers how digital examinations can open up the black box of student work by enabling data analysis not just at the end of an assessment, but also during the process of producing it (Robyn Fitzharris, Simon Kent, Chap. 17). The following chapter “Experiential learning in labs and Multimodal Learning Analytics” demonstrates the potentials and prospects of providing multimodal learning analytics tools and services in laboratory-based learning scenarios (Anke Pfeiffer, Vlatko Lukarov, Giovanni Romagnoli, Dieter Uckelmann, Ulrik Schroeder, Chap. 18). “Web analytics as extention for a learning analytics dashboard of a massive open online platform” follows the goal of how learning analytics dashboards have to look like to assist especially teachers or any educators to understand the learning process of his/

her learners in order to improve their teaching and learning behaviour within a MOOC platform (Philipp Leitner, Karin Maier, Martin Ebner, Chap. 19). Another chapter focusing on MOOCs, “A dimensionality reduction method for time-series analysis of student behavior to predict dropout in Massive Open Online Courses”, examines the use of several data preprocessing techniques to model attrition on the basis of students’ interactions with course materials and resources (Eric G. Poitras, Reza Feyzi Behnagh, François Bouchet, Chap. 20). The concluding chapter “Evidence-based learning design through learning analytics” aims to investigate the degree of agreement between instructors’ opinion on their course design archetype and the archetype provided by Blackboard Analytics, and to identify any similarities in tool use between the local institution data and previous findings (Esin Caglayan, O. Osman Demirbas, Ali Burak Ozkaya, Mehmet Sahin, Chap. 21).

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.

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About the Editors

Dirk Ifenthaler (dirk@ifenthaler.info; http://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, the University of Oklahoma, USA. Dirk's research focuses on the intersection of cognitive psychology, educational technology, data analytics and organisational learning. His research outcomes include numerous co-authored books, book series, book chapters, journal articles and international conference papers as well as successful grant funding in Australia, Germany and the USA. He is the Editor-in-Chief of *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*.

David Gibson (david.c.gibson@curtin.edu.au) is Director of Learning Futures at Curtin University in Australia and UNESCO Chair of Data Science in Higher Education Learning and Teaching. Dr. Gibson received his doctorate (EdD Leadership and Policy Studies) from the University of Vermont in 1999 based on a study of complex systems modelling of educational change. His foundational research demonstrated the feasibility of bridging from qualitative information to quantifiable dynamic relationships in complex models that verify trajectories of organisational change. Dr. Gibson provides thought leadership as a researcher, professor, learning scientist and innovator. He is creator of simSchool, a classroom flight simulator for preparing educators, and eFolio, an online performance-based assessment system, and provides vision and sponsorship for Curtin University's Challenge, a mobile, game-based team learning platform, as well as the university's learning and analytics team. Dr. Gibson consults with project and system leaders, formulates strategies, and helps people articulate their vision for innovation, and then helps connect people with the resources needed to fulfil their aspirations. His research has extended from learning analytics, complex systems analysis and modelling of education to application of complexity via games and simulations in teacher education, web applications and the future of learning. Dr. Gibson has also advanced the use of technology to personalise education via cognitive modelling, design and implementation.

About the Contributors

Reem Al-Mahmood (r.almahmood@latrobe.edu.au) has multidisciplinary teaching, research and learning expertise in Higher Education at five Australian universities across Digital Education, Academic Development and Student Learning. She has a PhD in digital learning and teaching in higher education from the University of Melbourne. Dr. Al-Mahmood is passionate about higher education and the idea of the university, innovative research methodologies, digital technologies and culture, digital literacies, digital equity, adaptive personalised e-learning, digital ethics, and knowledge and research practices. She is currently a higher education research and academic consultant, and her previous recent role has been as a Digital Education Lecturer at La Trobe University, Australia.

Miguel Ángel Zuñiga-Prieto (miguel.zunigap@ucuenca.edu.ec) received a PhD in Computer Science from the Polytechnic University of Valencia, Spain. He received his Master's degree in Technology Administration from the San Francisco University of Quito, Quito, Ecuador (2005). Dr. Ángel has a diploma in Innovative Pedagogy from the Technical University of Loja, Cuenca, Ecuador (2008). He is an Associate Professor in the Faculty of Engineering and Director of the Department of Computer Science at the University of Cuenca. His skills and experience include the management of research projects and software development projects, both national and international. Dr. Ángel currently directs research projects at the University of Cuenca, among them, the team of the University of Cuenca is coordinating the project "Capacity Building for the use of Learning Analytics to improve Higher Education in Latin America (LALA)" co-funded by the Erasmus + Program of the European Union. The LALA Project seeks to develop the local capacity to create, adapt and use Learning Analytics tools in Higher Education Institutions in Latin America. He has also participated in the project "Incremental Development of Cloud Services Directed by Models and Customer Value Orientation" funded by the Ministry of Economy and Competitiveness, Spain.

Natasha Arthars (natasha.arthars@sydney.edu.au) is a current PhD candidate at the Centre for Research on Learning and Innovation (CRLI) where she studies epistemic environments and learning spaces in higher education.

Kevin R. Bell (kevin.bell@westernsydney.edu.au), from Newcastle, UK, received his BSc in Analysis of Science and Technology from Manchester University before spending two significant periods of his professional career overseas. After 9 years in Japan where he taught English, he moved to the USA in 1999, initially to take up the Master's degree course in Teaching at Marlboro College in Vermont. After graduation, Professor Bell's dot.com work segued into academic leadership roles, most recently at Northeastern University in Boston where he headed the Online Experiential Learning group and served 4 years as Executive Director and Senior Fellow for the Lowell Institute Innovation Incubator. The Institute was funded with a $4M "First in the World" federal grant with his research on intrinsic motivation of under-represented minority groups in STEM programs central to the application. Prior to Northeastern University, Professor Bell was at Southern New Hampshire University (SNHU) where he served as Chief Academic Officer for the College of Online and Continuing Education and was the academic lead on the first federally approved Competency-based, Direct Assessment degree: College for America. He received his doctorate from the University of Pennsylvania in 2014 for research into gameful design and student engagement in online courses.

Caroline Bennett (crb@ku.edu) is the John E. Sharp & Winifred E. Sharp Professor in Civil, Environmental, and Architectural Engineering at the University of Kansas (KU). She serves at the Lead for the KU School of Engineering Engaged Learning Initiative, and also served as a Faculty Fellow with the KU Center for Teaching Excellence from 2012 to 2016. Caroline works in multiple leadership roles at KU focused on bringing about change in higher educational practices, including serving on the university's Executive Data Governance Council, chairing the Academic Systems Steering Committee, co-leading an AAU mini-grant that is piloting STEM faculty interactions with LA, and co-leading the NSF-funded TRESTLE network. She has a long history of deep engagement with educational change initiatives at the University of Kansas. Caroline joined the KU faculty in 2006 after earning her doctorate from the University of Cincinnati. She is a licensed Professional Engineer in the State of Kansas.

Stephanie J. Blackmon's (sjblackmon@wm.edu) research area is teaching and learning, with a current emphasis on technology integration in various higher education and professional development contexts. She has conducted studies on college/university instructors' and students' experiences with three dimensional virtual worlds, massive open online courses (MOOCs) and various learning management systems (traditional and non-traditional); technology use in adult learning and professional development courses; MOOCs for professional development; and general teaching and learning topics for face-to-face, hybrid and fully online higher education and professional development settings.

Pieterjan Bonne (pieterjan.bonne@arteveldehs.be) is active as a lecturer, support staff and a researcher. As a member of the Office of Study and Career Guidance, part of his work focuses on students transitioning into and adapting to higher education. Although he has worked on many different aspects, like criteria for effective welcome weeks, he mostly focuses on academic language use. His expertise lies in listening skills, especially in a whole-class lecture context. In this research he has focused on both staff (didactics) as students (meta-cognitive skills). Recently, Pieterjan's interests shifted to learning analytics. He is involved in the OfLA project as the institution's coordinator and a member of the research team.

François Bouchet (francois.bouchet@lip6.fr) is an associate professor at Université Pierre et Marie Curie (UPMC) and a researcher at the Laboratoire d'Informatique de Paris 6 (LIP6) in the MOCAH team. He received his MEng from ESIEA in 2005 and both his MSc (2006) and PhD (2010) in Computer Science from Université Paris-Sud 11, with a thesis supervised by Dr. Jean-Paul Sansonnet at LIMSI, centred on the use of conversational agents for assistance, which resulted in the design of (1) a custom natural language processing chain for assistance requests and (2) a novel agent cognitive architecture taking into account personality and emotions. During his postdoc (2010–2013) at McGill University under Dr. Roger Azevedo's supervision, he has been the main architect of the Intelligent Tutoring System (ITS) MetaTutor and focused on applying data mining techniques (e.g., HMM, clustering, sequence mining) across multiple data channels (e.g., logfiles, facial expressions, eyetracking, electrodermal activity) to identify learners' profiles, in order to conceive a new generation of more adaptive ITSs. His latest research interests revolve around serious games and long-term interactions with pedagogical agents.

Tom Broos (tom.broos@kuleuven.be) is a doctoral researcher at the Leuven Engineering and Science Education Centre (LESEC) and Augment HCI research group in the Department of Computer Science at KU Leuven, Belgium. He participates in Learning Analytics related research projects including LALA (Learning Analytics in Latin America) and studies how data can be made actionable using (student-facing) dashboards. Tom has a background in Information Management (MSc) and Economics (BSc) and he worked for 8 years as a Business Intelligence Consultant for several high-profile customers in diverse industries.

Armelle Brun (armelle.brun@loria.fr) is an associate professor in computer science at the Université de Lorraine. She works on artificial intelligence, machine learning and data mining, including recommender systems, modelling atypical users' preferences, explainable algorithms, user privacy and ethics. For several years, her work is mainly conducted in the frame of education, specifically Learning Analytics, where she is interested in prediction and prescription tasks. She is involved in several European, national, regional and industrial projects, where she is in charge of work packages. Armelle has published over 90 articles and is regularly involved in conference organisation (including chairing).

Esin Caglayan (esin.caglayan@ieu.edu.tr) holds a BA in English Language Teaching and an MA as well as PhD in Educational Administration. As Director of the Teaching and Learning Application and Research Center, she leads the Center in providing and supporting the education technologies and faculty professional development programs regarding high quality instruction, distance education and the use of academic technologies. She received training on data mining and learning analytics and was appointed as the project manager for Blackboard Analytics implementation at IUE, which was completed in 2017. She has presented at various conferences in Turkey, Italy and the UK and is currently conducting research on the adoption and use of educational technologies. Dr. Caglayan also provides consultancy to assessment teams of some other universities in Turkey. Her research interests are education technologies, organisational behaviour, and testing and assessment.

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Pete Crowson (peter.crowson@ntu.ac.uk) is a social sciences researcher, with two distinct roles at Nottingham Trent University. The first is as a researcher for the OfLA project, specifically conducting qualitative research to support to the project. The second is in supporting planning and evaluation of outreach programs delivered by the Centre for Student and Community Engagement. With a background in Students' Union research, Pete has developed his skills in conducting research and listening to the experience of others. Pete's current focus is in understanding the experience of students and young people, the issues that this group faces, and how they can be supported into Higher Education and throughout their time at University.

Maarten de Laat (mdelaat@uow.edu.au) is professor in the School of Education at the University of Wollongong. His work focuses on informal learning and social capital development in networks and organisations. His research addresses learning and development, with a specific interest in the impact technology, AI, learning analytics and social design have on the way social networks and communities work, learn and innovate. He is the co-chair of the Networked Learning Conference and the Learning in Digital and Social Media minitrack at Hawaiian International Conference on System Sciences (HICSS). This year he coordinates the Australian Learning Analytics Summer Institute (ALASI) at Wollongong.

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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 is an Adjunct Professor on media informatics (research area: educational technology) and works also at the Institute for Interactive Systems and Data Science as senior researcher. His research focuses strongly on seamless learning, learning analytics, open educational resources, making and computer science for children. Martin 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

Armin Egetenmeier (armin.egetenmeier@hs-aalen.de) studied business mathematics at the University of Ulm. He graduated in 2013 with the Master of Science degree. Since 2013 he is an academic assistant at the Study Support Centre of Aalen University of Applied Sciences. At the SSC he is responsible for the professional supervision of students in the study entry phase, primarily in (business) mathematics. Another focus of his work is scientific accompanying research. In particular, he is responsible for developments of algorithms and visualisations. His research interests lie in the areas of transition from school to university, learning analytics, modelling of teaching and learning processes as well as educational data mining and data analysis.

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Robyn Fitzharris (robyn.fitzharris@brunel.ac.uk) is Executive Officer to the Vice-Provost (Education) at Brunel University London. She works on projects, policy and strategy related to education, collaborating with staff and students across the University as well as external groups and networks. Currently her main areas of work are Access and Participation and ensuring compliance with the UK Governments' Office for Students regulatory framework. Robyn holds a Master's degree in Data Science and Analytics and has research interests in education data mining, predictive analytics and the impact of digital assessment.

Carly Palmer Foster (carly.foster@northumbria.ac.uk) has worked in data and analytics for over a decade. Roles span the design and evaluation of passenger-facing transport systems and, more recently, embedding analytical practice in higher education institutions. Carly's research interests are focused on consumer interaction with data and technology and the impact that algorithms have on our engagement with the world.

Ed Foster (ed.foster@ntu.ac.uk) has worked in higher education for over 25 years in a variety of roles supporting students to engage better with their studies or reducing barriers to their participation. He has worked in learning development and quality enhancement, and from 2013 onwards, Ed has been responsible for the development of learning analytics at Nottingham Trent University, working with technology partner Solutionpath to build the NTU Student Dashboard using their StREAM technology. The Dashboard is designed to be used by both students and staff and has been developed to support student success. Ed has conducted educational research for a range of national and European projects including the UK wide "What Works? Student Retention and Success" and Erasmus+ projects investigating how learning analytics can be used to support student transition into higher education and student success (ABLE & STELA). He currently leads an Erasmus+ project (OfLA) investigating the challenges faced by tutors and advisers supporting students using learning analytics data. Ed's research interests include transition into higher education, student engagement, retention and success, disparities of attainment and strategies for supporting students. Ed blogs about the challenges of implementing learning analytics at www.livinglearninganalytics.blog

David Paul Fulcher (dfulcher@uow.edu.au) holds the role of Manager, Learning Analytics, at the University of Wollongong, Australia. He leads a team developing tools for teachers and others to identify students in need of support. David has over 15 years' experience working with analytics in complex organisations to support decisions and actions. This includes extensive involvement in the design, development and implementation of analytics tools across a variety of domains. David is also a PhD candidate investigating Australian university teachers' interpretation of learning analytics and its impact on practice.

Dragan Gasevic (dragan.gasevic@monash.edu.au) is Professor of Learning Analytics in the Faculty of Information Technology at Monash University. Before the current post, he was Professor and Chair in Learning Analytics and Informatics in the Moray House School of Education and the School of Informatics and Co-Director of Centre for Research in Digital Education at the University of Edinburgh. He was the Canada Research Chair in Semantic and Learning Technologies (Feb 2015–Feb 2018) and Professor in the School of Computing and Information Systems at Athabasca University (Jan 2007–Jan 2015). He served as the immediate past President (2015–2017) of the Society for Learning Analytics Research and holds several honorary appointments in Australia, Canada, Hong Kong, UK and USA. Funded by granting agencies and industry in Canada and Europe, Dragan is a recipient of several best paper awards at major international conferences in learning and software technology. The award-winning work of his team on the LOCO-Analytics software is considered one of the pioneering contributions in the growing area of learning analytics. Recently, he founded ProSolo Technologies Inc. that develops a software solution for tracking, evaluating and recognising competences gained through self-directed learning and social interactions.

Benjamin Gras (benjamin.gras@loria.fr) is a Postdoc in computer science at the University of Lorraine in France. Fond of computer science, he is interested in machine learning, data mining and natural language processing. His work focuses on user modelling in various contexts. First, in the area of recommender systems, he proposed an approach to modelling users with atypical preferences: grey sheep users. Since his PhD defence, he has been working on the modelling of learners in the context of learning analytics to prevent dropouts. He is now in charge of experimentation to evaluate the impact of learning analytics on students' results at the University of Lorraine.

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Part I
Focussing the Organisation in the Adoption Process

Chapter 1
Adoption of Learning Analytics

David Gibson and Dirk Ifenthaler

1.1 Introduction

This book's theme – *Adoption of Learning Analytics in Higher Education Learning and Teaching* – brought to mind the seminal *Diffusion of Innovations* (Rogers, 1962), which for decades has shaped research on adoption of innovations. The reader may be familiar with his notion that there are five kinds of people involved in the diffusion of an innovation, innovators, early adopters, early majority, late majority, and laggards, and that a 'critical mass' is needed for full, sustainable implementation of innovation. But Rogers went beyond the *actors* of adoption and also set a larger *context* in which the innovation itself, communication channels, time and the encompassing social system were also key determinants of whether and how an innovation such as learning analytics would be adopted. Learning analytics is considered a creative innovation in learning and teaching for three reasons: novelty, effectiveness and wholistic impacts. Learning analytics can produce novel near real-time information to improve teaching decisions; it is proving to be an effective method of abstracting and modelling meaning from information, and it contributes to a more wholistic interpretation of data by expanding the number and types of measures.

The still emerging field of learning analytics has introduced new frameworks, methodological approaches and empirical investigations into educational research; for example, novel methods in educational research include machine learning,

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network analyses and empirical approaches based on computational modelling experiments. Learning analytics have been 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, 2015). The new frameworks and adoption models focusing on learning analytics are required for successful integration of learning analytics systems into higher education institutions (Buckingham Shum & McKay, 2018; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). However, these models of practice and adoption vary across different institutions due to situational and historical conditions, within any individual organization due to disciplinary and contextual idiosyncrasies and across different countries due to these as well as cultural differences (Klasen & Ifenthaler, 2019; Schumacher, Klasen, & Ifenthaler, 2019).

In the next sections, we briefly review Rogers' model; those who are familiar with it may wish to skip to the discussion of examples, which will draw from our recent research and development activities. We also outline specific tactical applications where the adoption of learning analytics can add value to higher education, and we illustrate the cross-over between diffusion of learning analytics as an innovation and tactics developing within five major domains of higher education practice (marketing and recruitment, learner characteristics, curriculum, teaching and post-graduate community and communications) with examples from our and others' research.

1.2 Innovation Diffusion

1.2.1 Six Characteristics of an Innovation

Six characteristics of an innovation, according to Rogers (1962), include the (1) relative advantage compared to current tools and procedures, (2) compatibility with the pre-existing system, (3) complexity or difficulty to learn, (4) trialability or testability, (5) potential for reinvention and use for unintended purposes and (6) observed effects (see Table 1.1). If we establish an indicator scale from low to high (or little to ample) for each of these characteristics, we can imagine a minimum of 2^6 or 64 innovation configurations, as outlined in Table 1.1. This is surely a fraction of the myriad ways that learning analytics is actually evolving in higher education today, but perhaps offers a set of sufficiently unique categories to describe a range from 'little adoption' to 'full implementation' of the benefits of learning analytics.

Researchers might use these six characteristics of an innovation to reflect on the degree and extent of adoption of learning analytics in a higher education setting. For example, if the relative advantage of some innovation is high and the remaining five characteristics are all low, the innovation might still be deemed worth piloting for

Table 1.1 Six characteristics of an innovation

Characteristics	Low	High
Relative advantage compared to current tools or procedures	Little to no advantages	Large and evident advantages
Compatibility with the pre-existing system	Incompatible, does not integrate or requires significant reworking of the existing system	Highly compatible, works within or alongside the existing system, does not require significant reworking
Complexity or difficulty to learn	Simple to understand, easy to learn and apply	Complex or complicated, hard to learn and apply
Trialability or testability	Is difficult or costly to test or trial, trials do not result in definitive added value	Is easy or not costly to trial. Results from trials show definitive added value
Potential for reinvention and use for unintended purposes	Innovation is limited in scope of application	Innovation is flexible and can be applied to many varying cases.
Observed effects	Insignificant or limited effects	Significant and meaningful effects

adoption. The difficulties of overcoming the shortcomings of incompatibility with current systems, complexity, costliness and limited effects might be worth the effort, if the relative advantage is a matter of survival of the institution. In general, if the innovation has more high than low indicators, then it is easier and more worthwhile to adopt. The one indicator that seems to buck the trend is complexity, where at the low end, if easy to learn and simple to understand, it might be too simplistic and broad to be deeply helpful, as pointed out by researchers who have noted the issue of complexity as a challenge for leaders of analytics adoption (Dawson, Poquet, Colvin, Rogers, & Gašević, 2018; Gibson, 2012; Tsai, Poquet, Gašević, Dawson, & Pardo, 2019). In the context of Rogers' (1962) six characteristics, the degree and details of engagement by key actors can measure or characterize the diffusion of the innovation in some higher education context.

Other authors in this book point to the potential benefits of adopting learning analytics; to these we add that learning analytics has potential to disrupt and transform higher education learning and teaching across five major domains of higher educational practice: (1) acquiring students, (2) promoting learning, (3) offering timely relevant content, (4) using up-to-date delivery methods and (5) supporting learners as part of a network of successful alumni who continue to positively impact the world (Henry, Gibson, Flodin, & Ifenthaler, 2018; Mah, Yau, & Ifenthaler, 2019). Considering these domains of higher education practice in the sections to follow, we will outline 15 tactics that can influence the 5 domains, followed by case examples.

While requiring significant effort, bringing more people into better understanding of the complexities of the diffusion of learning analytics in higher education helps create conditions for a wider and deeper array of insights and more effective group and institutional responses, as noted by Rogers (1962). We will illustrate the innovation characteristics and specific tactics using some recent studies we have conducted or encountered.

1.2.2 Communication Channels

The degree of adoption of an innovation within an organization is a measure of the number of actors using the innovation or who have altered their practice because of the innovation. The process of the diffusion requires communication channels between potential actors, who then follow a well-known decision-making process (i.e. moving from unawareness to knowledge, then being persuaded that learning more will be beneficial, then trying out the change, then moving into routine implementation and finally creating confirmatory data and helping others) as the actors individually adopt or ignore the innovation. Influencers who wish to promote the adoption of the innovation must ensure and secure open communication channels and encourage people to start and stay on the journey of decision-making from awareness to action.

The ‘Concerns-Based Adoption Model’ (CBAM) emerged in the 1970s with survey metrics to help an educational organization self-assess its status on an innovation journey (Hall, 1974; Hall, Loucks, Rutherford, & Newlove, 1975). The tools track the percentage of staff who are sitting at each stage of the journey and offer a structured way to address the ‘next need’ of each group by focusing on moving people from their current state to the next decision-making focus. For example, if a large number of people do not know the benefits of learning analytics, the task is to first make them aware and have them develop knowledge, before they can become persuaded that adoption has any potential to make their life better. If a few early adopters are already implementing and providing confirmatory data, their ability to effectively model for others will be limited to the people who are already ready to decide to adopt. Communication channels are the riverbeds for the flow of energies from unawareness to action (Kotter, 2007). It goes without saying that the process takes time, so leaders who wish to influence and track adoption of learning analytics have to be ready to understand the processes and have patience – take the time needed – to allow the communication channels to work (Roll & Ifenthaler, 2017).

1.2.3 Encompassing Social Systems

The dynamics of communications that support the flow of adoption processes are part of the complex social networks in the encompassing social system contexts involved in higher education (Kozleski, Gibson, & Hynds, 2012). Learning analytics researchers are beginning to take note. As recently pointed out (Dawson et al., 2018), the existing conceptual models of the adoption of learning analytics in higher education fail to operationalize how key dimensions interact to inform the realities of the implementation process, leading to a need to rethink learning analytics adoption through complexity leadership theory and to develop systems understanding at leadership levels to enable the movement of boutique analytics projects into the enterprise. Among the issues in the encompassing social systems of higher education, learning analytics adoption often faces a shortage of resources, barriers involving multiple stakeholder buy-in and the fears and paranoia of big data ethics as well as privacy concerns (Ifenthaler, 2017; Ifenthaler & Schumacher, 2016). Addressing these challenges requires agile leaders who are responsive to pressures in the environment, capable of managing conflicts and are capable of leveraging complex social systems for change (Gibson, 2000; Tsai et al., 2019).

Network analysis has emerged as one of the most promising methods for studying the complexities of social influence, layered hierarchies and the evolution of relationships. Network methods can be used (1) to define the spread and variety of behaviours, (2) to predict the pattern of diffusion of innovations, (3) for analysis of educational phenomena (Clariana, 2010; Ifenthaler, 2010; Ifenthaler, Gibson, & Dobozy, 2018), and (4) to identify opinion leaders and followers in order to better understand flows of information (Lazega, 2003). In the context of learning analytics, epistemic network analysis is of particular note (Gašević, Joksimović, Eagan, & Shaffer, 2019).

1.2.4 *Summary of Innovation Diffusion*

In summary, the diffusion of learning analytics in higher education is expected to involve:

- *Actors*. Levels of readiness of individuals and the emergent property that is the combined readiness of the social group of which those individuals are members
- *Innovation Configuration.* Six characteristics of learning analytics adoption as perceived by the individuals responsible for the innovation ((1) relative advantage compared to current tools and procedures, (2) compatibility with the pre-existing system, (3) complexity or difficulty to learn, (4) trialability or testability, (5) potential for reinvention and use for unintended purposes and (6) observed effects)
- *Communications.* Channel characteristics among the individuals and their social groups
- *Complexity Leadership.* Flexibility in the face of dynamic overlapping networks

1.3 Improving Higher Education with the Adoption of Learning Analytics

The five major domains of higher education practice, where adoption of learning analytics can improve both learning and educational organization, are as follows: (1) acquiring students, (2) promoting learning, (3) offering timely relevant content,

(4) using up-to-date delivery methods and (5) supporting learners as part of a network of successful alumni who continue to positively impact the world (Henry et al., 2018). In the sections below, we suggest 3 tactical areas for each domain – 15 tactical areas to consider when planning, undertaking or gauging the extent of adoption and influence of learning analytics in a higher education institution.

1.3.1 Acquiring Students

Market Understanding An analytics capability can generate profiles of in-demand skills in the market, track education trends and help the curriculum react accordingly by offering learning experiences and certifications that are sought by employers and entrepreneurs. For example, an analytics team can monitor and report on skills needs straight from a primary source such as highly dynamic job advertisements, using open source tools such as RapidMiner and R to gain insights from accessible online vacancy data (Berg, Branka, & Kismihók, 2018; Wowczko, 2015).

Personalized Recommendations Student and market information can be used to aid course selection and align student expectations. A recent innovation at one university found that some students mistakenly sign up for classes that informally require prior knowledge from earlier in the curriculum. With better automated guidance, the university could save time and frustration and improve retention with analytics-driven recommendations (Parkin, Huband, Gibson, & Ifenthaler, 2018). Students could also find out the likelihood of employability for their current skill set and explore prospects for the future in their selected areas of study by an analytics-driven approach that combines market understanding with personalized recommendations (Berg et al., 2018).

Community Engagement Analytics-driven market knowledge can be reflected in the outward-facing marketing and community engagement of the university, but perhaps more important may be the engagement of the public in developing policy that impacts higher education. 'Policy analytics' has been suggested as an emergent use of computational approaches to understanding and dealing with five major complexities inherent to public decision-making: use of public resources, multiple stakeholders, long time horizon, legitimacy and accountability and public deliberation (Tsoukias, Montibeller, Lucertini, & Belton, 2013).

1.3.2 Promoting Learning

Adaptive Support With full implementation of learning analytics, learning services can use interaction history to learn and become tailored to individual learning differences and preferences. This adaptive capacity, automated and available at scale, is a key mechanism of one of the primary benefits (and part of the puzzle of the emerging field) of the adoption of learning analytics – personalization of delivery (Gašević, Kovanović, & Joksimović, 2017; Ifenthaler & Widanapathirana, 2014; Schumacher & Ifenthaler, 2018). Model-based feedback that focuses on novice-to-expert differences can guide the adaptation of support (Ifenthaler, 2009, 2011).

Proactive Retention Management As many researchers are finding, students with high attrition risk can be identified early and receive targeted preventative interventions (de Freitas et al., 2015; Gibson, Huband, Ifenthaler, & Parkin, 2018; Glick et al., 2019; Ifenthaler, Mah, & Yau, 2019). Proactive retention is a prominent theme in the literature because it balances benefits to both learners and the educational system; for learners, it highlights that analytics can support decisions and develop human capabilities and at the same time can underpin organizational and educational efficiencies by saving time and money.

Personalized Communication With appropriate adoption of learning analytics, learning materials can be targeted to communicate with students based on learning characteristics, level of attainment and aspirations for achievement. Recent advances in analytics-driven applications include using network analysis to understand social and cognitive relationships in learning (Gašević et al., 2019) and creating conversational agents to enhance learning and the educational journey through higher education (Arthars et al., 2019).

1.3.3 Offering Timely Relevant Content

Adaptive Curriculum When the adoption level for learning analytics is high, curricula can be made dynamic, adapting in real time to employability needs, changes in global knowledge stores and student cognitive needs that are complementary to the personal learning process needs targeted by adaptive learning support, as well as to changing circumstances in the external environment. Systems can be designed around the semantic relationships of topic and subtopics (Li & Huang, 2006) as well as by using similarity measures among learning objects in relationship to decision modelling based on learner characteristics (Ifenthaler, Gibson, & Dobozy, 2018; Lockyer, Heathcote, & Dawson, 2013).

Scalable Delivery At advanced stages of adoption of learning analytics, which includes using machine learning methods to continuously discover, infer and feed information to adaptive curriculum and learning support systems, technologies using learning analytics can deliver content to all students and staff in a more participatory mode that allow 'scalable pedagogies' such as near-real time feedback and decision supports (Hickey, Kelley, & Shen, 2014).

Industry Integration Curricula in an analytics-driven system are designed to deliver in-demand competencies and support relevant work place learning, for example, via 'challenge-based collaborative problem-solving' (Gibson & Ifenthaler, 2018; Gibson, Irving, & Scott, 2018; Ifenthaler & Gibson, 2019).

1.3.4 Delivery Methods

World-Leading Pedagogy Analytical research into student cognition and teaching methods is used to define the higher education institution's practices and drive student self-awareness, in institutions with a high level of adoption. Signposts of the integration of analytics into teaching and the growth of the field can be found in the rapidly accumulating literature engendered by the Society for Learning Analytics Research (Gašević et al., 2017).

Adaptive Assessment In analytics-driven higher education environments, evidence of learning is measured continuously, allowing targeted, dynamic assessment that adapts to changing conditions and needs (Gibson & Webb, 2015; Gibson, Webb, & Ifenthaler, 2019; Ifenthaler, Greiff, & Gibson, 2018; Webb & Ifenthaler, 2018).

Managed Outcomes Framework With widespread adoption of learning analytics, students can be assessed against a granular framework, allowing for and supporting an iterative and formative approach to learning and recognition of micro-credentials (Mah, 2016; Mah, Bellin-Mularski, & Ifenthaler, 2016; Mah & Ifenthaler, 2019; West & Lockley, 2016).

1.3.5 Supporting Alumni Networks

Strategic Employment Similar to acquiring students with intensified and dynamic market analysis, an analytics-driven strategic employment strategy can utilize a unique assessment framework that assists students to find, prepare for and secure positions with high prestige employers. In one successful massively open online course at Curtin University, an Indian technology company guarantees a job interview for anyone who obtains a certificate from the experience.

Alumni and Lifelong Learning Communication Alumni and recurring learners can be engaged through better information on market and industry trends and via targeted and flexible opportunities for further study (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008).

Targeted Recruitment into Research Engagement in needed research areas can be developed from better analysis of history, current status and more finely detailed student competency profiles that fit with and extend the skills of researchers. Finding and developing talent, driving fact-based planning, making decisions, executing on strategy, managing tactics, measuring and both eliciting and validating learning are all within the boundary of adoption of learning analytics and related disciplines (Berg et al., 2018; Kiron & Shockley, 2011).

1.3.6 Cases

In the following two *Cases*, we illustrate the six features and five domains with examples and findings from our research and development efforts. The examples provided here give a taste for the application of the six features of innovation across the five major domains of higher education practice.

1.3.6.1 Analytics Teams in Business Units of a University

The first case is from a large university in Australia where executive interest and awareness of learning analytics has been growing since a pilot study in 2010. A senior executive briefing paper was then produced in 2013 by the strategy and planning group and brought to the senior executives, outlining some of the issues and opportunities of learning analytics, leading to increased awareness of applying learning analytics and resulting in the 15 tactics outlined in Sects. 1.3.1, 1.3.2, 1.3.3, 1.3.4 and 1.3.5. Since then, analytics teams have been springing up across the campus and now reside in operations areas such as recruitment, marketing and finance; in service delivery areas such as teaching; and in research areas devoted to increasing the university's computational capabilities.

Beginning in 2010, the pilot study showed that behaviours of students in a school of business could be grouped together to better understand the drivers of retention (Deloitte, 2010). The resulting model, termed the *Student Discovery Model* (SDM), utilized a self-organizing map methodology (Kohonen, 1990) to create clusters of behaviours that helped analysts discover new relationships, raise additional research questions and test assumptions and hypotheses. The effort was extended in 2013 to the largest domestic campus of the university. This involved creating clusters among 52,000 students over a 5-year period (Gibson & de Freitas, 2016) drawing at the time from 15 data systems (e.g. finance, student records, learning management system) and was used to conduct initial exploration of hypotheses as well as to identify correlations that warranted deeper analysis.

In 2015, a project in predictive analytics used machine learning (Chai & Gibson, 2015) to help make the case for the return on investment of building the university's capability in student retention. An investment in data architecture simultaneously established how the new exploratory analytics would interact with managed data systems of the university. A data scientist was hired in 2016 to lead the analytics group in learning and teaching, and that team has grown to three people. The theme of return on investment led to a second paper (Gibson, Huband, et al., 2018) that focused on the capability developed and methods underpinning continuous on-demand production of analyses and insights aimed to stimulate inquiry and action to improve retention. Data analysts have also been added in student services, recruitment, finance and elsewhere. These groups have not yet been brought together into an ongoing community of practice and typically pursue their own agendas with

Table 1.2 Adoption profile of analytics teams in business units of a university in Case 1

Actors	1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards	1. Data scientists, data analysts 2. Faculty level leaders, central learning and teaching staff, senior executives
Innovation configuration	1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects	1. High (new BI insights) 2. High (skilled people) 3. High (knowledge gap high) 4. Low (no way to compare) 5. Low (isolated teams) 6. High (significant effects)
Communications	Teams communicate primarily *within* rather than *across* the university. Informal communications are used as needed to solve local problems. There is as of yet no formal structure of communications *among* or *integrating* any of the teams	
Complexity leadership	University leadership has recently signalled that the central learning and teaching area is the entity now charged with learning and academic analytics. Leadership of all analytics is distributed, and separate teams work independently from each other without coordination to impact on other aspects of the student experience (e.g. recruitment, admissions, student life, finance, academic records, alumni networks)	

different toolsets, varied levels of accessibility to university data, supported by informal working relationships among the groups.

Analysing the case story briefly with Rogers' (1962) framework, in Table 1.2, one can see that the stage of adoption at the university is prior to 'early majority' – meaning that adoption is limited to a few innovators and early adopters. A dashboard capability for instructors is being introduced now and may help lead to an early majority of people using some form of learning and academic analytics to make decisions.

1.3.6.2 Adoption of Learning Analytics in Challenge-Based Learning Design

The second case illustrates how designers of challenge-based learning experiences have been building capability for adopting a data-driven approach to the design of scalable learning experiences. Challenge-based learning is a teaching model that incorporates aspects of collaborative problem-based learning, project-based learning and contextual teaching and learning while focusing on current real-world problems (Ifenthaler & Gibson, 2019; Johnson, Smith, Smythe, & Varon, 2009). The approach is particularly well-suited to industry integration and to extending formal learning into the community and world.

A digital learning experience platform – Challenge platform – has been developed to study the detailed time-sensitive user trails of interactions between a learner and content and among groups of learners collaborating to solve problems (Gibson, Irving, & Scott, 2018). The platform supports self-directed learning at scale with automated feedback and assessment in real time, at the point of learning. It promotes active engagement to enable deeper learning, evidence of which is captured via fine-grained data collection by a learning analytics engine. Challenge has the capability, for example, to identify and track who does what during team work to promote individual responsibility among participants. It can also engage students in peer feedback, supporting development of critical thinking and reflection skills, as team members work toward solving a wide variety of challenges.

Studies of the platform have focused on the dynamics and impacts of learning engagement as a multidimensional concept. This includes an individual's ability to behaviourally, cognitively, emotionally and motivationally engage in an ongoing learning process. Results indicate that engagement is positively related to learning performance (Ifenthaler, Gibson, & Zheng, 2018) and that team learning processes can be studied and related to performance using network analyses (Kerrigan, Feng, Vuthaluru, Ifenthaler, & Gibson, 2019; Vuthaluru, Feng, Kerrigan, Ifenthaler, & Gibson, 2019).

The innovating actors in this second case are application developers who are also researching the impacts of the innovation and advocating for others in the university to use the application to promote collaborative problem-solving and group projects in classes. Early adopters of the innovation have been a handful of individual instructors (e.g. one instructor in architecture, another in business and law) and student services units (e.g. the career counselling service centre). Currently, one faculty area has committed to widespread adoption the application in 2020, so the number of early adopters is expected to increase (Table 1.3).

Table 1.3 Adoption profile of analytics in challenge-based learning in Case 2

Actors	1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards	1. Application developers, data analysts 2. Individual instructors; business and law faculty 3. Student services content delivery
Innovation configuration	1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects	1. High (collaborative learning improved) 2. High (capstone projects supported) 3. High (easy authoring) 4. High (research on learning and teaching) 5. High (team learning innovations) 6. High (significant effects)
Communications	The current challenge is how to share the opportunity and help people to use the platform, including how to interpret and utilize the learning analytics information	
Complexity leadership	A group with the central learning and teaching unit is managing the infrastructure, budget, staffing and software development	

The innovation configuration profile in the second case is assessed to be primarily high. New collaborative learning knowledge is being published and is leading to new embeddings of automated analyses such as the cognitive and educational benefits of the challenge-based approach.

1.4 Discussion and Outlook

There are many different ways to improve higher education through learning analytics, and institutions are most likely to develop unique innovation configuration profiles based on their current circumstances, histories and priorities. Importantly, understanding an institution's learning analytics adoption profile needs to be framed with specific knowledge of the particular aspects of learning analytics applied to tactics such as those outlined in Sects. 1.3.1, 1.3.2, 1.3.3, 1.3.4 and 1.3.5. For example, an institution might be in an early stage in alumni relations while highly advanced in recruitment or adapting the curriculum. In addition, for an institution to be adopting learning analytics at scale does not necessarily mean covering all the aspects mentioned in the previous sections. Institutions will set priorities and may decide to make progress on only a subset of the possibilities.

The two cases discussed briefly above lead to observations about three user roles: (1) *informal* educators, those who provide student services and extension programs outside of the formal curriculum, who seek ways to go to scale; (2) *formal* educators who instruct classes and are interested in seeing the impacts of learning analytics on team-based classroom and curriculum projects; and (3) data and information science *experts* without a background in traditional instructional design who are helping people in roles 1 and 2 to create new digital learning experiences on the Challenge platform. Table 1.4 utilizes the Rogers (1962) framework to compare observations across these user role groups.

In one university, informal educators using analytics to drive design and deployment are about 2 years ahead of the formal educators and the experts. Formal instructors heard about the analytics and, as innovators, wanted to see if they could benefit. In one school setting, the success of the pilot innovator teacher has led to three other early adopters. Experts were added to the platform support team to continuously drive new innovations based on data analytics, so are considered innovators. Most striking in the comparison of informal with formal educators is that the former have built a team approach and have more of a strategic vision based in observed effects such as highly efficient scalability and the reinvention potential. This has led the team to significantly expand to impact nearly all students of the University. The formal educators, in contrast, work alone in their classrooms and have not had opportunities yet to write conference papers, conduct localized research or influence others in their fields of knowledge.

Table 1.4 Comparing user roles in higher education adoption of learning analytics

		Informal	Formal	Experts
Actors	1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards	1. Two 2. n/a 3. Four	1. Two 2. Two	1. Two
Innovation configuration	1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects	1. High 2. High 3. Low 4. High 5. High 6. High	1. Low 2. High 3. Low 4. High 5. Low 6. Low	1. High 2. High 3. High 4. High 5. High 6. High
Communications		Within team and bilateral with experts; small community of practice within the team	1:1 with experts; no community of practice has emerged	Small team communicates with all users, plus external researchers; community of practice is international
Complexity leadership		Relative advantages outweigh other considerations; commitment to innovation has led to team development	Time-poor and focused on pragmatic operations rather than theoretic advances; individual instructors are 'on their own'	Highly adaptable to other users, balancing time between helping others and creating insights from data

Use of analytics across these three groups varies in this instance. The informal team uses analytics to determine effectiveness of the *structure of their offerings* as well as the *extent of implementation*, for example, counting the number of 'compliance' experience expected to reach masses. In contrast, the formal educators are loners within their faculty areas, who are interested in innovation in their own teaching. They use the analytics to *understand team problem-solving* and especially *individual contribution to team products* in projects where in the past they had no visibility. Their observations about impacts on student learning are limited to one or two classes of their teaching load. The expert group utilizes data in these and several other ways, driven in part by the needs and foci of the informal and formal users, but also driven by *research questions and external feedback* from interested and collaborating international researchers.

At the level of small teams, even when a 'critical mass' is achieved in the actor network, such as in the informal team, adoption is shaped and limited by communications. In the formal instructors' experience, almost all communications are one-to-one with the supporting expert team, not with peers and not with any expectation from or knowledge shared by executive leadership in their faculty area. In contrast, the informal team has been empowered by the executive leadership to do as much as possible with the assets, experience and analytics.

The profile of the adoption of learning analytics that emerges from this brief cross-case analysis illustrates details that help explain the 'early-stage' status of adoption within the higher education institution. The two cases presented demonstrate the potential of Rogers' (1962) framework as a useful reflective tool in thinking about the processes and status of adoption of learning analytics.

The field of learning analytics is generating growing interest in data and computer science as well as educational science, hence becoming an important aspect of modern digital learning environments (Ifenthaler & Widanapathirana, 2014). Despite the high interest, the adoption of learning analytics in higher education institutions requires capabilities not yet fully developed (Ifenthaler, 2017). International perspectives on adoption models (Nouri et al., 2019) as well as on policy recommendations (Ifenthaler & Yau, 2019) may help to move the innovative efforts on learning analytics forward.

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Chapter 2
The Politics of Learning Analytics

On Being 'Measured'

Reem Al-Mahmood

2.1 Unfolding Scenarios

This chapter weaves theory and practice issues through unfolding scenarios.

> It's a sunny day and Paulo is a new lecturer in the Digital Education team and he's excited to be contributing to the development of new online subjects and reviewing completed subjects. He's at his desk tasked to conduct post-teaching reviews of blended/fully online subjects. He's a little apprehensive about all that he is privy to on the LMS (Learning Management System), and he's familiar enough with some of the built in LMS learning analytics (LA) reporting features. He can view all the content of discussion forums, the back end of the LMS activities and log-in times and dates, the IP addresses, log-in device types and the assessment grades; essentially he has access to everything about student and staff online activity! His son is a student at the university and is enrolled in the online subject he's about to review. Paulo is keen to view his son's performance as his son recently told him he was sure to have done well. So what stoty might the LMS data tell?
>
> Diana is a first year student at the same university, and her data analytics show that she's from a low socioeconomic group and first in her family to go to university. The LMS sends her an automated welcome message on her first day at university and alerts her to the fact that it will check in with her to see how she's going on a weekly basis and that she has a specially assigned university assistant called Sophia (unbeknownst to her, Sophia is a chatbot) to assist her with any questions 24×7. Diana is delighted to have received such a caring message and feels empowered and excited to be commencing her first year.

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2.2 The Promises and Challenges of Big Data and Learning Analytics for Higher Education

Learning analytics (LA) in education is a newly and rapidly growing field and emerging discipline (Long & Siemens, 2011) regaled at the 1st International Conference on Learning Analytics and Knowledge in 2011 (Lak'11, 2011). With the emergence of a 'dataistic paradigm' (Kitchin, 2014b; Ruckenstein & Pantzar, 2015), LA was predicted to reach 'maximum impact' in 3–5 years in 2015 (Johnson, Adams Becker, Estrada, & Freeman, 2015, p. 6). Indeed, the UK has been a significant leader (Sclater, 2014) in the field, and universities can learn from the innovations and challenges of early adopters and innovators. The 2017 *Handbook of Learning Analytics* (Lang, Siemens, Wise, & Gašević, 2017) is testimony of a rapidly emerging multidisciplinary field (Lang et al., 2017; Williamson, 2017).

Learning analytics promises improved student success and retention (Greller & Drachsler, 2012; Siemens, 2013) and uses Big Data (large digital data sets) (Dyche, 2012) to analyse learning and engagement. The allure of educational learning analytics has been appropriated from business by using learner profiling 'to build better pedagogies, empower students to take an active part in their learning, target at-risk student populations, and assess factors affecting completion and student success' (Johnson et al., 2015, p. 12). We have impactful developments in *personalised adaptive e-learning* (for examples, see Pardo et al., 2018; Pardo, Jovanović, Dawson, Gašević, & Mirriahi, 2019), quality learner experiences and greater collaboration given that students' digital interactions can be mined at increasingly affordable costs (Greller & Drachsler, 2012; Johnson, Adams, & Cummins, 2012; Johnson et al., 2013). Educational digital environments provide readily available dynamic and unobtrusive data tracking to provide learner feedback and comparisons with others, support and early warning systems, for example (Greller & Drachsler, 2012, p. 43). Digital profiling can be used for various purposes by various stakeholders from individual learners, educators, designers, administrators to external business organisations (such as the Pearson Education Group). Ultimately, our quantified and measured profiled digital selves are promoted – knowingly or unknowingly – to influence how we learn, consume and behave based on data-driven algorithms, algorithmic education *par excellence*.

There are indeed valuable benefits of LA that have been promoted to educational stakeholders as a way to improve and influence learning 'consumption' and 'behaviour' from the field of economic management using business intelligence and web analytics (Buckingham Shum & Ferguson, 2012). For example, the educational uses of learning analytics across academe can range from academic analytics (institutional analysis), action analytics (that require an action) to predictive analytics (that predict behaviours and outcomes, e.g. which students are likely to fail or succeed) (Greller & Drachsler, 2012; Long & Siemens, 2011). Gathering data and analysing data with the aim of optimising performances and improving outcomes is the basis of LA, and at first glance this is to be lauded. However, there are consequences also in that LA relies on tracking our digital imprints based on Big Data that is gathered, analysed, stored, interpreted and acted upon (Dyche, 2012; Spector, 2013) using algorithmic methods to detect patterns previously impossible (Romero & Ventura, 2013) – providing profiles of 'quantified selves' (Lupton, 2016). The promises for educational contexts is that to describe, diagnose and predict behaviour based on a 'quantified', 'measured', 'audited' and 'surveilled' self can improve and personalise learning. Proactively Prinsloo (2017) reminds us that 'once we have this Big Data, it behooves us morally to use it for improved educational purposes' that enhance students' academic study success (see, e.g. Ifenthaler, Yau, & Mah, 2019).

At its core LA is concerned with the question, 'Can we tell from your digital profile if you're learning?' (Buckingham Shum, 2014). This seems reasonable and innocent enough; however, it is vital for university researchers, educators, ethicists, lawyers and administrators to engage critically (Boyd & Crawford, 2012; Kitchin, 2014a; Selwyn, 2014, 2015) with the assumptions and consequences of LA that translate learning into numbers and visual patterns. Aptly, Lodge et al. (2017) provide a compelling discussion about how learning is inferred (and the limitations of LA) from big data sets across disciplines where there are 'different conceptualisations of learning' – echoing the importance of *being measured* in what LA can(not) achieve.

Taking on an ethics of care (Noddings, 2013) requires a criticality (hooks, 1994) in that our starting point has to be care for and care of *the being done to*, our learners and the consequences of their 'quantified selves', as well as care around LA processes. As Morris (2017) compellingly says, 'We don't get to stop asking questions about why and whether of our teaching simply because the digital provides algorithms that approximate answers'. Ultimately, in being measured by numbers, we are (con)figured by technology, algorithms and data through the constant scrutiny of algorithmic education and Big Data technology vendors.

This chapter shakes up the spaces around what, why and how we need to be *measured* in adopting LA given its performativity regimes (Ball, 2016) so that it can be 'transformative' and 'carefully thought through' (Long & Siemens, 2011). The argument is that we need LA policies and practices that are transparent, relational, co-designed and reflexive, which have at their heart social justice ethical and legal frameworks where power imbalances amongst stakeholders are confronted openly and critically.

Consequently, LA needs to be addressed in terms of its underlying performative politics (power) across ethical and legal aspects and knowledge production and across broader ecologies of learning (beyond the merely digital). This chapter provokes discussion around these issues by troubling what and how we measure (and what we don't), to open up LA as situated in contingent specific complexities and circumstances towards questions and implications for theory, methodology and practice towards a more nuanced and *measured* LA.

This chapter considers the politics and consequences of Big Data and LA as it (per)forms digital profiles to promote critical and rigorous considerations of adopting LA by university stakeholders across leaders, policy makers, educators, technologists, lawyers, ethicists, programmers and students. Firstly, the ethical and legal issues arising about data are considered – given that any use of LA should start from a robust ethical basis. Secondly, the knowledge that LA produces (automated, recursive, productive) and its uses are discussed, to thirdly suggesting richer learning ecologies. The chapter concludes with a brief discussion of developing a culture of LA and implications and considerations for universities.

2.3 Ethical and Legal Frameworks of Big Data and Learning Analytics

There are many 'disciplinary and ethical critiques' surrounding data *about*, data *for*, data *from* and data *by*, which are about power imbalances amongst LA's stakeholders (Buckingham Shum & Ferguson, 2012, p. 18, original italics). Consequently, ethical frameworks and legal frameworks around *data* and what *constitutes* data are paramount, for data is never neutral; it never *speaks* all on its own (Kitchin, 2014a); data is always part of larger performative assemblages that enact worlds and meaning into being. Data carries agendas that too often are not examined (Perrotta & Williamson, 2016). So issues around learning analytics' data need to address the nature of the data, their selection, analysis and use; the data's viewers and custodians; the data's longevity and storage; and data betrayal (Lupton, 2016), its privacy and concerns of commodification beyond a learning institution, for example, to potential employers or LMS and Big Data vendors. Vitally, transparent legal and ethical frameworks need to underpin the data protection and privacy of every individual's profile.

The data collected may already exist within automated systems such as the LMS or have specialised data mining programs and databases used to extract information from the LMS of an educational institution (Nelson & Creagh, 2013). Data sets may be analysed internally within an institution with a data/learning analytics unit or by external companies. Either way, data collected include an individual's institutional engagement and profile (Sclater, 2014). Whilst this type of surveillance may be considered for the better good of the student and the institution, Orwellian fears may well be cause for concern when an individual is unaware of the data collection – ultimately it is 'stealth data' (Spector, 2013). Campbell, DeBlois, and Oblinger (2007) also raised issues in using data analytics around privacy, profiling, data sharing and data stewardship. Long and Siemens (2011, p. 38) also highlight the need to leverage data 'associated with tracking students' and 'learning options based on deterministic modelling'. These are critical issues that need addressing across complex ethical and legal domains, and require institution-wide discussions.

There are also legal violations in using 'stealth data' without a person's consent. Beattie, Woodley, and Souter (2014) in a critically titled paper *Creepy Analytics* warn of the legal and ethical dangers inherent in *undisclosed* data collection that constitute a 'violation of trust' and 'academic freedom' – here we have 'data as a commodity'. There are power imbalances between data 'seers'/'viewers'/'controllers'/'interpreters' and 'receivers'. The power relationships are uneven. Indeed, online university students were significantly aware of being visible, traced, and tracked online where 'the LMS space and its permanence, visibility, and longevity raise significant complex traceability and surveillance issues for students and lecturers' (Al-Mahmood, 2012, pp. 24–25). Greller and Drachsler (2012) remind us of 'the double-edged sword' that learner data may not necessarily benefit learners, but rather the dynamic data availability adds to the *power* of educational institutions, governments and commercial organisations 'to increase manipulative control over students, employees, and citizens, thereby abusing LA as a means to reinforce segregation, peer pressure, and conformism rather than to help construct a needs-driven learning society' (p. 54). Clearly, there are significant ethical and legal implications around data for all stakeholders to consider, but significantly the voices of our students (Sclater, 2015) need to be at the heart of an ethics of *care*fulness in being *measured*.

Encouragingly, a few universities have adopted *codes of practices* to proposals for *Student Charters* (e.g. Beattie et al., 2014; Drachsler & Greller, 2016; Ferguson, Hoel, Scheffel, & Drachsler, 2016; Greller & Drachsler, 2012; Nelson & Creagh, 2013; Pardo & Siemens, 2014; Prinsloo & Slade, 2016; Sclater, 2014; Sclater & Bailey, 2015; Slade, 2016; Slade & Prinsloo, 2013). Vitally, we need 'the highest ethical standards' 'based on open, transparent, participatory, accountable, shared, and ethical principles of inquiry' (Stevens & Silbey, 2014, online). The Asilomar document outlines the six pivotal principles about data use: 'Respect for the rights and dignity of learners; beneficence; justice; openness; the humanity of learning; and continuous consideration of the ethical dimensions of learning research' (Asilomar Conference, 2014). Inevitably, there are challenging ethical, ideological and epistemological assumptions about data (Slade & Prinsloo, 2013, p. 1510).

Paulo discovers that his son, Dimitri, had only logged in once a week into the subject's LMS and had only made a handful of contributions to the discussion forum.

2.4 Knowledge Production: Algorithmic and Datafied Education and Its Consequences

How might we produce new or novel approaches to interpret and understand data patterns and produce new knowledge? The challenges of LA are in how we model learning interactions based on Big Data with a 'transformative potential' to inform learning and decision-making at an individual and institutional level (Long & Siemens, 2011). Currently, 'algorithmic' paradigms underpin many analyses (Perrotta & Williamson, 2016; Williamson, 2017) to lead to 'actionable intelligence' (Campbell et al., 2007). For example, in the case of the Signals system at Purdue University, the 'actionable intelligence' is about 'guiding students to appropriate help resources and explaining how to use them' (Arnold, 2010). The Purdue

Signals analytics are based on a student success algorithm to provide a student facing dashboard of red, yellow and green lights to indicate where the student is at and suggest actions. (And even in this visualisation, there are cultural biases and accessibility issues). There are various levels of analytics for various 'actionable intelligence' outcomes ranging from academic analytics to learning analytics. For example, Buckingham Shum and Ferguson (2012) have developed a sophisticated and rich range of LA from social learning network analytics, social learning discourse analytics, social learning disposition analytics, social learning content analytics to social learning context analytics to offer visualisations and recommendations to support learning. LA's promises are in their power for prediction based on large-scale data sets and various statistical and mathematical algorithms where Big Data is translated into reflective and predictive discourses to assist decision-making through the 'the quantified self" (Lee, 2013; Lupton, 2016) or 'the quantified institution'.

Further, Lodge et al. (2017) highlight the fraught dangers and reductionisms in LA as it stands in privileging quantification data and not capturing the multiplicity and complexity of learning, with a 'bias towards quantification, and that implies that anything that cannot be measured is not worthwhile' (Lodge et al. 2017, p. 389). The question is: What can('t) numbers do? And what can digitisation never capture? How do we capture engagement beyond digital clicks and algorithmic overtaking? So the caution here is that we need to be *measured* in understanding the limitations of the specific LA developed and in use and what underpins the learning pedagogy of the algorithmic weightings and data captures.

> Dimitri has received weekly emails from the university alerting him to the paucity of his online subject contributions, which have increased his anxiety greatly.

> Diana has been actively participating in the LMS weekly discussions and has received weekly encouragement reminders by Sophia, based on her LA data.

2.4.1 On Algorithms and Data

Learning analytics' power is to predict and enable student success and retention (Colvin et al., 2015) through decision-making algorithms, but therein lie their potential dangers when relying on merely quantitative data without qualitative information for 'aligning and regulating performance and behaviour of individual teachers or learners against a statistical norm' (Greller & Drachsler, 2012, p. 47). Phillips et al. (2011) have shown the limitations of using quantitative web analytics and the need to include rich qualitative data to extend understanding of how participants learn and use LMS environments. Despite the predictive promises of LA, there are ethical problems in judgments made about an individual learner based on machine or human interpretation of machine-generated algorithmic data. This could 'potentially limit a learner' (Greller & Drachsler, 2012, p. 48; Lodge et al. 2017) in terms of 'confirming old-established prejudices of race, social class, gender, or other with statistical data, leading to restrictions being placed upon individual learners'. Some studies show the greater the engagement with peers in a learning community is what produces the strongest positive effect on learning and can better predict more successful student outcomes (Macfadyen & Dawson, 2010), but learning can never be captured from solely digital environments. By monitoring clicks and digital spaces, we miss the richness of other learning that happens beyond formalised digital learning environments to the infinite array of formal and informal physical environments.

The diversity and complexity of learning, judgments made about learning impact and what data is used will always mean that 'the reliability of a LA-supported learner profile and its usefulness to the learners will remain questionable' (Greller & Drachsler, 2012, p. 48). Basing judgments merely on numbers alone limits the possibilities of interpreting learning in its distributed nature beyond just the digital space alone (Long & Siemens, 2011). Further, as Buckingham Shum and Ferguson (2012, p. 19) advocate, we 'must engage fully with questions around the academic, pedagogical and ethical integrity of the principles for defining such patterns and recommender algorithms, and who is permitted to see them within the set of stakeholders'. Learning is complex and so much more than simple models can capture. And just as significantly, there are problems with assuming that a digital log in pertains to a single student, for students may work on group activities under one log in and so on; this is what Greller and Drachsler (2012, p. 49) refer to as 'enmeshed identities'.

Data itself is never generated free of theory, and no data can ever be objective – it 'is always framed' through a particular worldview (Kitchin, 2014a). The issue with analytics is it can 'present the illusion of automatically discovering insights' and removing human bias (Selwyn, 2015). Yet there are infinite algorithms that can be used which are 'imbued with particular values and contextualized within a particular scientific approach' (Kitchin, 2014a, p. 5). Different algorithms play different politics in that the methods used on the same data set will result in different outcomes and 'actionable intelligence', and with this come invisible biases and assumptions. Buckingham Shum and Ferguson (2012, pp. 18–19) alert us to the politics at stake here: 'who is defining the measures, to what ends, what is being measured, and who has access to what data?'. Further, who has the evaluation skills and competencies to interpret complex sets of data and patterns in our universities, and how can these be developed and sustained? So how will our universities evolve algorithmic educational expertise and training to build not only data analyses capacities but interpretative capacities towards open, reflexive and transparent, multidisciplinary understandings of learning (Lodge et al. 2017)? Some universities have progressed this significantly, such as the UK's Open Universities New Media Institute which started in 1995 to grow to 70 research staff in 2012, who are leading the discipline of analytics (Buckingham Shum & Ferguson, 2012). Newly established centres in Australia have drawn expert staff from there to establish the Connected Intelligence Centre at the University of Technology Sydney, in

Australia, which conducts transdisciplinary cutting-edge research on using data analytics to improve student learning, but other universities await such centres.

> Dimitri is troubled by the alert emails as he has contributed significantly in the f-2-f discussions and had even set up a subject debating session, as well as a weekly exam study group. Perplexed by the ongoing emails, he now finds the LMS space with its formulaic structure a burden.

> Meanwhile Diana has been telling her parents about how lucky she is to have her own personal university assistant, Sophia, and how it has motivated her to set up an online study group given that she doesn't have a lot of time to be on campus physically.

2.4.2 On Interpretation and Contextualisation

Interpretation of data analytics requires contextualisation and multidisciplinary framing (Lodge et al. 2017) as data needs to be presented to stakeholders with the capacity to be understandable with the view to 'surprise', 'compel' or 'motivate change' (Macfadyen & Dawson, 2012, p. 161). Hence the usefulness of learning analytics' data and its usability will depend on how it is presented to various stakeholders and definitions of success. Exploring meaningful patterns is one way through this, with explanations. However, patterns alone do not convey much without an integration of social theory and deep contextual knowledge (Selwyn, 2015). Data patterns can provide a starting point for additional analysis, along with other data sets. Another issue in data framing is the comparative aspects of comparing a person with others in a subject or course cohort by sheer algorithmic reduction – humans are 'way more complex, contingent and messy… to be reduced to formulae' (Kitchin, 2014a). Overall, there are limitations to quantitative analysis that 'need to be complemented by other approaches' (Kitchin, 2014a, p. 9). A LA health barometer might be well placed around 'the quality of debate around what technology renders visible and leaves invisible' (Buckingham Shum & Ferguson, 2012, p. 19). So assuming that we can get multiple and accessible LA data interpretations, how might these be communicated, and how might a LA culture be adopted, for better or for worse? Ultimately, any interpretations must be contextualised, but developing and communicating a LA culture becomes essential for LA to have any traction.

> Paulo wonders if his son or for that matter any of the other students have access to the data to which he is privy and if it would make any difference to their grades. He wonders if they have been consulted about what might be important for them to assist with their learning?

> Diana wonders about how Sophia seems to know so much about her and how she seems to provide just the right suggestion to her at the most opportune times. Diana likens it to 'the Goldilocks effect' – just right!

2.4.3 On Communicating and Adopting a Learning Analytics Culture

How LA analyses are presented should depend on the various stakeholders, and within a learning institution will typically involve strategic, administrative and academic staff, as well as tutors, laboratory demonstrators and students. The aim is to contrast perception versus actual behaviour (Greller & Drachsler, 2012) to provide 'actionable intelligence' towards desired actions on some level for some stakeholder. To what extent is this achievable? An example of actionable intelligence is the little-used large-scale LA intelligence in the strategic decision-making process around the LMS (Macfadyen & Dawson, 2012). Audiences matter and need to be engaged in how LA can be communicated effectively. Educators' voices have been considered in works by Corrin, Kennedy and Mulder (2013, p. 204) to explore lecturers' needs, perceptions and disciplinary differences of LA's potential to show that there was a 'considerable amount of skepticism and confusion over the utility of learning analytics' by lecturers and that the LA dashboard reports had a 'disconnect' aspect to them, and they also expressed 'concerns about the level of skill and time required to adequately engage with learning analytics in a useful way'. Whilst there are various ways that data can be presented to students and staff, with commonly used dashboard traffic light adoptions (Arnold, 2010), the assumption is that 'actionable intelligence' is achievable and decipherable by students and for that matter usable and understandable by lecturers. There is need for more promising work on what would constitute accessible and meaningful information such as that by Olmos and Corrin (2012) and the SNAPP visual developments by Dawson, Tan, and McWilliam (2011).

Further, there are concerns with how LA may 'disempower learners, making them increasingly reliant on institutions providing them with continuous feedback, rather than developing meta-cognitive and learning-to-learn skills and dispositions' (Buckingham Shum & Ferguson, 2012, p. 19). Learners can also stress over endless comparison with their peers (Long & Siemens, 2011, p. 36). In a study of learner LMS experiences (Al-Mahmood, 2012), perceptions about the LMS platform certainly meant that students were aware of performing the good student online, or at the other extreme loathed the online platform which curtailed the length of time spent in its spaces.

> Dimitri realizes that he could decide to post more often to the discussion forum and maybe the email alerts telling him he has only logged in once would cease.
>
> Diana has been wondering about other students and if they too have an individual digital mentor/assistant assigned to them. She is reluctant to ask but assumes they do (but only equity and at-risk students have had this feature assigned to them).

Hence we need to be *care*ful and *measured* then with what we communicate and how we communicate any LA. We need to be cognisant not to fall into using 'economically motivated data analyses' and a 'language of economics' with LA audiences (Baym, 2013, p. 14).

For LA to be adopted by a university, there needs to be strategic vision of the complex issues involved. The work by Lodge et al. (2017); Norris and Baer (2013); Davenport, Harris, and Shapiro (2010); and Davenport, Harris, and Morison (2010) all provide strategic organisational approaches and cycles for insightful consideration. Above all, whatever the platforms chosen, whatever data chosen and whatever the ways to interpret data and feedback cycles, there needs to be considerable investment by the organisation in creating, building, sustaining and evaluating a culture of analytics (Corrin et al., 2013; Norris & Baer, 2013; Davenport, Harris, & Morison, 2010, Davenport, Harris, & Shapiro, 2010). Whilst the culture of LA adoption may seem innocent enough, there are further matters of epistemological concerns to consider.

By the final weeks of his subject, Dimitri is becoming more anxious as he now has a strong sense of being under surveillance and is feeling harassed. He simply wants to plead, 'please let me be. I have enough study and work to do'.

Diana is progressing well and managing to stay up-to-date with everything given the reminders and actionable intelligence provided by Sophia. She's feeling confident about the final semester exam given that she has achieved 50% of her marks already in assignments and tests.

2.4.4 On Data Reduction and Knowledge Production

By deconstructing and simplifying learning into algorithms, and focusing on selective data, LA can easily fall into simplistic solutionism (Selwyn, 2015) and data 'seductions' (Kennedy, Corrin, & de Barbara, 2017) where learning becomes a 'spectacle' (Ball, 2016). Fanghanel (2012, p. 24) so pertinently asks, 'To what extent is this visualization (measuring and displaying of performance) informative? …. What is actually happening in practice is erased from these public computations'. We need to therefore be *measured* when using LA that are solely based on reductionist approaches as learning is far richer and messier and 'a contestable process' (Selwyn, 2015, p. 75). Greller and Drachsler (2012, p. 52) also highlight the limitations of merely considering LMS digital data given that 'learning' occurs 'in a lifelong and diverse ecosystem', where 'an exclusive data view on single elements may provide a stimulus for reflection but not a sound basis for assessment'. Big Data may provide some insights, but they are inevitably limited to specific types of knowledge that deal mainly with quantification rather than measuring quality. Hence LA will always need contextualisation relative to other information.

We will always still need to put theories and context back into numbers and patterns to make sense of the world. Learning will always be more complex, and knowledge production belies values and worldviews that will need to be made explicit – ultimately LA is multidisciplinary (Lodge et al. 2017). For better or for worse, perhaps a humbler claim of LA might be to be a 'blunt indicator' (Lodge & Lewis, 2012) to be used with other information and indicators of student success. As Booth (2012, Online) highlights, 'the adoption of learning analytics … must be informed not only by what can be measured but also by what cannot. There will be limits in what learning analytics can do. …. not every aspect of learning can be captured by the powerful tool that analytics promises to be. Sometimes learning is ineffable!'. The best that we might aim for is to use 'multiple methods for assessing learning' (Booth, 2012). Hence we need to consider broader ecologies of learning.

Dimitri has managed to submit all his subject assignments online and has worked very hard on them and is hoping for a good mark.

Diana discovers that her other friends don't have a Sophia mentor assigned to them, and she feels very special to have had Sophia's personalised guidance and direction.

2.5 Ecologies of Learning: Towards a Measured Learning Analytics

At the heart of LA, students' learning and engagement need to be considered in their ecological richness which extends learning beyond mere digitised Big Data. By focusing on only digital LA, we lose all the other connections and complexities of a student's learning assemblages nuanced in the physical and the immeasurable. This ecological view might provide for a reflexivity where we are open and transparent about how we come about analysing and understanding learning and the limits of LA. Armed with relational and reflexive stances that highlight our politics, ethics and values, we might then use an 'ensemble approach' to LA to 'build multiple solutions' (Kitchin, 2014a, p. 2). Reflexivity means that we shake up the 'uncritical faith in numbers' (Baym, 2013, online), adding 'qualitative sensibilities and methods to help us see what numbers cannot' (Baym, 2013, online). Only then might we be able to be *measured* about the degree of trust we place in LA and algorithmic education, for if we are not *care*ful, we risk reducing 'humanity to quantity' (Ball, 2016, p. 1054).

Paulo knows how much effort his son has put in to getting to university and studying. He's saddened to see that despite all the work his son has put in, the LMS analytics highlight Dimitri as an at-risk and borderline student.

2.6 Implications for Universities Adopting Learning Analytics

This chapter has explored the power and politics of Big Data and LA to move it beyond simple solutionism approaches so that universities can evolve rich and rigorous dialogues, policies and processes with all of their stakeholders. If LA is to have impact to do what it promises, then significant further research is required underpinned by robust ethical and legal frameworks that are based on codesign by all stakeholders. For example, the Open Universities in the UK (Johnson et al., 2015) have used participatory design and implementation of their LA with a university-wide engagement and awareness. Students are automatically opted in for analytics but with the possibility of opting out. Their eight principles 'ensure openness and transparency around the data being collected and what is being done with it.… Learning analytics is seen as an ethical process with the student at the heart of it. Learners are not wholly defined by the data the University has about them which can never reflect the totality of the individual's experience' (Sclater, 2014, p. 55). The timely work by Corrin et al. (2019) also provides an updated and important contribution by LA leaders. Whatever we evolve, student voices and participatory designs have to be at the heart of how LA might progress, beyond vendor-produced products. Students as active co-designers and engaged stakeholders (Ifenthaler & Schumacher, 2016) can provide vital insights and ways to deal with the power imbalances of being acted on. Figure 2.1 encapsulates some of the vital steps in the codesign and *mea-*

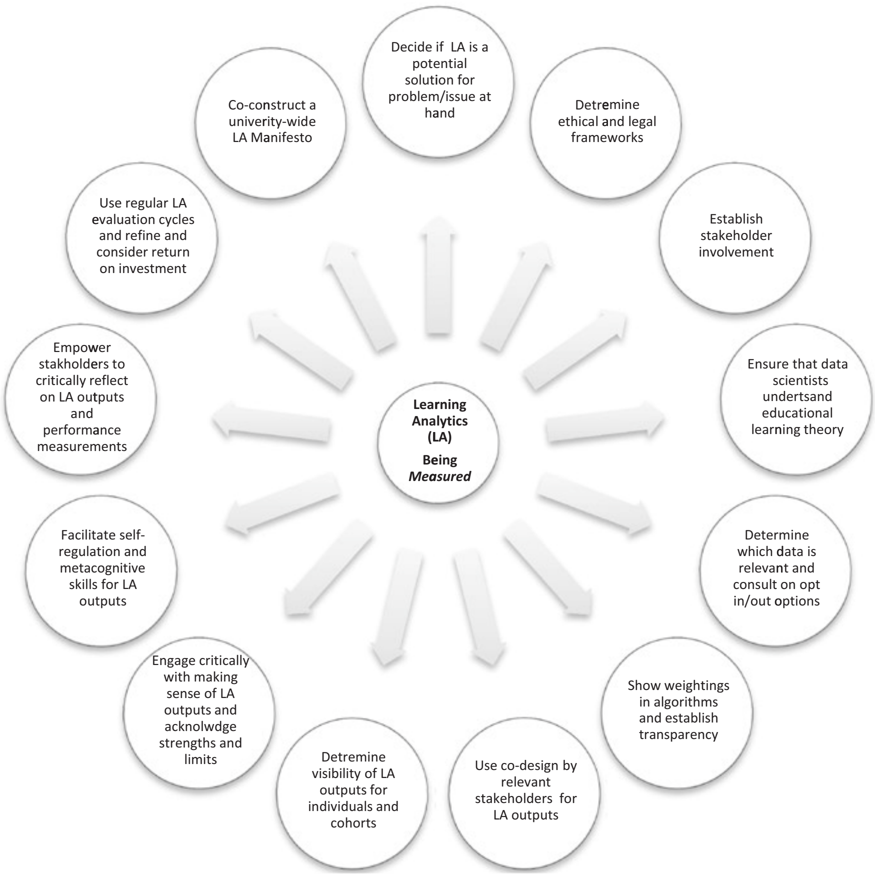

Fig. 2.1 Learning analytics model on being *measured*

sured possibilities of LA. Let us open up and extend a *measured* LA then that is more inclusive, transparent, negotiable and accountable for all stakeholders.

Dimitri has received 49% for his subject and is aghast. He had told his dad that he would be bound to pass everything. After all, he had worked night and day on this one subject in which he was enrolled and completed extensive reading research for the major assignment. Deeply troubled he decides to go and see the lecturer in person on campus. As he makes the trip across the other side of town, he rushes across amber lights and is hit by a speeding car, despite using his cane for his vision impairment.

Diana knows Dimitri as he was in her online study group that she established. She is terribly saddened to know this news. She wonders why he was not provided with a Sophia just like she was, but it turns out he did not alert the university to his vision issue, as he was a highly independent learner, and so was not picked up by the LMS system as an equity student.

What this chapter has sought to highlight is that there may well be value to a well-executed and considered LA that is *measured* in its claims, open, inclusive, transparent and reflexive, but that there are significant areas that need to be evolved. Any LA adoption requires engagement across all stakeholders in rigorous discussion to suit the requirements of each university. The considerations below raise important questions for universities to provoke robust and deep discussion amongst all stakeholders:

1. What is your university's vision and purpose of LA use? (This question should be revisited frequently and cyclically by any institution.)
2. How does your university envision a successful LA adoption?
3. At what cost is LA to your institution (e.g. platforms and programs, financial, digital storage, expertise, impact, benefit, dangers, contingencies, etc.)?
4. How will your university implement LA at the macro, meso and micro levels? Who will be responsible? How will you recruit for expertise?
5. What is your university's conceptualisation of learning to assist in how your LA could look and what it would capture and what would constitute data?
6. How will your university incorporate qualitative data to the quantitative LA analyses?
7. How will your university facilitate interpretive capacities and negotiated understandings of LA outputs for stakeholders to ensure meaningful analyses?
8. How will your university's LA promote self-regulation and metacognitive awareness for students and other stakeholders?
9. How will your university establish stakeholder buy-in?
10. How will your university include student voices, needs and permissions?
11. How will your university navigate guiding policies and ethical and legal frameworks, locally and globally?
12. How will your university address data ownership and privacy laws and permanency and longevity?
13. How will your university navigate educational LA data and analyses via outsourcing to commercial vendors versus internal to your educational custodians? Who will be your data custodians?
14. How will your university ensure that your data analysts/scientist/educators are also trained in and understand educational learning theories?

15. How will your university ensure that practitioners of LA have a code of conduct around data privacy?
16. How will your university establish opt-in or opt-out options for stakeholders?
17. How will your university build digital capacity around LA?
18. How will your university evolve digital literacies to include LA and its consequences for educators and students and beyond? Who will teach and promote this?
19. What stories and whose stories will be told via your LA and for whom and by whom?
20. How will your university select data visualisation and interpretations of LA dashboards?
21. How will your university ensure your duty of care for all?
22. How will your university critically evaluate your LA adoption, its value, benefit and sustainability?
23. How will your university ensure an ethics of carefulness in your institution, and what would that look like for your institution? What does your responsible and responsive LA look like?

In conclusion, whilst LA is a rapidly evolving field that more recently is showing more nuanced use in adaptive personalised e-learning development, for example (and this too could be argued is problematic in what it enforces upon learners and prevents them from exploring, e.g. serendipitous learning), we need humbler claims that incorporate the ethics of the data, and we need richer data to inform/transgress/challenge algorithmic reductions and their power in the age of algorithmic education. We need to consider whose narratives get told through LA and all the other learning narratives that don't get told (or seen) to move beyond singular, simplistic, reductionist accounts that LA falls into that we might empower learner agency to create agendas where our students use LA on their own terms and in their own ways – openly, knowingly and judiciously – to see LA as merely one glimpse of a quantified digital self, amongst much richer ecological selves. As Prinsloo (2017 online) captures it so potently, we need a 'responsible learning analytics' that 'is found in the nexus between their stories and ours. We cannot afford to ignore the fact that it is their data, their aspirations, their learning journeys and that our data collection, analysis and use may not tell the whole story' – so let's be *measured*.

A few months later, as Dimitri recovers, he receives an email from his lecturer, alerting him to an error in the LMS involving a typo by his tutor and that his grade is in fact 94% and not 49%. This was instigated as a follow-up by his dad Paulo who was puzzled by his son's mark as he knew how hard he had studied. Sometimes it really is useful to be privy to certain information!

At the end of the year, both Diana and Dimitri are delighted to be invited to be student representative voices on the Learning Analytics Evaluation Committee that meets monthly at their university.

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Chapter 3
A Framework to Support Interdisciplinary Engagement with Learning Analytics

Stephanie J. Blackmon and Robert L. Moore

3.1 Introduction

Learning analytics, first introduced circa 2011, has become an emerging field at institutions around the world (Ferguson, Clow, Griffiths, & Brasher, 2019). The emergence of learning analytics can be linked to the digitization of student records – from activity within the learning management system (LMS) to efforts to identify patterns for retention and enrollment management – and has only served to make digital data an invaluable commodity for higher education institutions (Daniel, 2015; de Freitas et al., 2015; Prinsloo & Slade, 2018). Thus, it is no surprise that the value of data has increased for higher education and has become an essential component in efforts to improve student recruitment and retention as well as identify students who need additional support in their educational pursuits (Asif, Merceron, Ali, & Haider, 2017; de Freitas et al., 2015). The role of data can be looked at from either the administrative or the instructional side (Picciano, 2012; Shum, 2012). A term frequently used, big data, has been defined by Picciano (2012) as encompassing both the information and systems used to store the digital data as well as the specific transactions found within this data. Yang (2013) further explains that while data may be in the term "big data," the term itself is referring more to how the data is being used and the technologies used to process these data points. While there is still debate about the most effective and ethical way to make use of this student data, there is no dispute that the role of data is an important conversation within institutions of higher education. The need to determine who has access to data, what the data should be used for, and what role students should have in the decision-making

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process around their data are all important considerations for higher education institutions. Thus, we focus our chapter on a discussion of the role this analytics data can play in fostering an interdisciplinary approach to student support.

3.1.1 What We Mean by Interdisciplinary

In Rhoten and Pfirman's (2007) article on women in interdisciplinary science, they combine several works to develop their working definition of interdisciplinary as "the integration or synthesis of two or more disparate disciplines, bodies of knowledge, or modes of thinking to produce a meaning, explanation, or product that is more extensive and powerful than its constituent parts" (p. 58). For the purposes of our chapter, we will employ Rhoten and Pfirman's (2007) definition of interdisciplinary. Not only can learning analytics be used across disparate disciplines, but also in disparate ways. It is our assertion that leveraging benefits and mitigating challenges of learning analytics can best be done when institutions adopt a collaborative approach to the implementation of analytics broadly: "integrate" the perspectives, "bodies of knowledge, or modes of thinking" of various disciplines and departments across the institution in order to achieve a more inclusive application of analytics for the overall benefit of students. Therefore, when we refer to interdisciplinarity throughout this chapter, we do so with the aforementioned assertion in mind.

3.1.2 Big Data and Learning Analytics

Big data is the driving force of learning. analytics. Learning analytics describes the process of not only collecting these data points but also analyzing and utilizing the data to inform decisions to improve and support student learning and success in educational contexts (Corrin et al., 2019; Ferguson et al., 2019). This type of distillation of the various data points into individualized student outcomes and impacts is one reason that learning analytics is an emerging field of study (de Freitas et al., 2015). Scheffel, Tsai, Gašević, and Drachsler (2019) point out that despite the increased conversations regarding the use of learning analytics in higher education, institutions are in the early stages of truly understanding how to make use of this student data. Learning analytics does not always need to be about remediation or rescuing students. One of the unique features, and attractions of, learning analytics is that there is tremendous flexibility in how it can be used. The challenge, however, is determining what should be used and how it should be used.

Shum (2012) identifies three levels – macro, meso, and micro – for understanding how learning analytics is used within higher education institutions. The overall view of learning analytics would be considered the macro-level. It is at this level that institutions would leverage the data to establish cross-institutional data points.

An example might be a university system looking at graduation rates in a specific major to ensure student success. Another example at the macro-level would be using data to identify patterns in student behaviors across their entire educational experience, which can be used to impart the insights necessary to provide remediation to students who are experiencing academic challenges (Daniel, 2015). The next level would be the meso-level. At this level, the data is looked at within the institution or a program. A common example here would be enrollment management plans (Voithofer & Ham, 2018). These are plans that look at past patterns of student enrollment in specific courses, and this data is used to develop predictive models that determine how resources are allocated at the program or department level. The third and final level is the micro-level. At this level, the data is being directly delivered to the students and instructors, often in the form of a dashboard, report, or tool (Shum, 2012). An example for teachers could be a log report from a learning management system (LMS) that tracks what specific course pages or resources are being used by the students. For students, they may have a dashboard that tracks their progress in a specific course or their overall program of study. These dashboards and reports allow students to get more real-time feedback and have more control over their own learning paths (Pardo & Siemens, 2014; Roberts, Howell, Seaman, & Gibson, 2016).

While learning analytics has applications across a number of areas, we focus our attention on higher education institutions. As technology has become more and more integrated into business operations at universities, we are seeing a marked increase in the amount of student data that is being collected (and potentially available for analysis) (Asif et al., 2017; Daniel, 2015; Picciano, 2012; Roberts et al., 2016). One of the primary ways that student data is being collected is using learning management systems, such as Blackboard, Sakai, and Moodle. These LMSs offer new ways to capture the activities and learning behaviors of students, such as tracking which resources were accessed and how long students stayed within certain content areas (Moore, 2019).

Just as the use of learning analytics varies between instructors, so too does the use of the LMS. For some instructors, the LMS is simply used to distribute the syllabus, and for other instructors, the LMS is used to manage student interactions in the course from the submission of assignments to discussion forum activities to the calculation of final grades (Moore, 2016). But even when a learning management system offers the potential of rich student data, access to the information may be on an opt-in basis at the university level, leaving lecturers/instructors who may want access to that information with little to no recourse if their institutions do not opt in for learning analytics data. For institutions that do opt in to access learning analytics data, the use of that data may be very individualized from course to course and miss important opportunities to connect data across courses for students' overall success.

This chapter will provide concrete areas as a framework to support the interdisciplinary application of learning analytics data, with considerations related to access and implications of learning analytics use.

3.2 Learning Analytics in Higher Education

The following section discusses the use of learning analytics in higher education administration and in higher education classrooms, and the subsequent section will combine these two areas in order to present an interdisciplinary approach to learning analytics.

3.2.1 Organizational Drivers

Analytics use in higher education administration is often discussed in terms of big data that encompasses classroom data as well as data from campus card access and students' usernames for other online services a campus may provide (Aguilar, 2018; Long & Siemens, 2011; Shorfuzzaman, Hossain, Nazir, Muhammad, & Alamri, 2019; Wintrup, 2017). The term "big data" has become one of the educational buzzwords that encapsulates many meanings. For the purposes of this chapter, we will use the definition of big data that looks at the technologies that are used to process and analyze the voluminous amount of data collected and stored by institutions of higher education (Daniel, 2015; Picciano, 2012; Yang, 2013). Using the level definitions from Shum (2012), the administrative level would be using macro- or meso-level types of data. Common examples of micro-level approaches include the development of predictive tools and models that allow for tracking students and imposing early interventions for students who are struggling (Daniel, 2015). Several researchers have pointed out that learning analytics is often used for information on students' progress and overall retention (Bronnimann, West, Huijser, & Heath, 2018; de Freitas et al., 2015; Gray & Perkins, 2019; Villano, Harrison, Lynch, & Chen, 2018). For example, Lonn, McKay, and Teasley (2017) discussed a university-wide analytics initiative at the University of Michigan. Several learning analytics projects were developed as a result of the initiative, and even though there are no specific details available about whether or not learning analytics played a role in overall administrative development, the initial vision of a campus-wide analytics approach was possible as a result of high-level administrative support. Wintrup (2017) used a macro-level approach to address various aspects of learning analytics integration in higher education, specifically in the United Kingdom. The United Kingdom has suggested a "new national framework that enables the assessment and comparison of teaching quality across higher education (HE) institutions," and one of the three measures they will use is "students' progression and retention" (Wintrup, 2017, p. 87). Administratively, Wintrup noted the importance of students having an overall understanding of what will be observed, and how it will be used, and options for participation (or non-participation) in these observations, as well as understanding how surveilling and labeling students can impact their experiences (p. 99).

Administrators' (technology staff, department directors, etc.) involvement can influence the way institutions use learning analytics across various areas of a university, but their lack of involvement can influence learning analytics as well. For example, in Klein, Lester, Rangwala, and Johri's (2019) study on learning analytics in higher education, they found that the absence of messaging from upper-level administration on the use of learning analytics around the university proved to be a barrier for instructors and advisors. Like the Lonn et al. (2017) work, the Klein et al. study focused on a decentralized higher education institution. However, the university Klein et al. discussed did not have centralized messaging or opportunities related to learning analytics. The frustration those study participants noted is consistent with Macfadyen and Dawson's (2012) findings related to learning analytics and learning management systems. Although the administrators for the institution they studied were involved in initiating the conversation about learning analytics and the university's LMS, the findings were not incorporated into the institution's strategic plan (Macfadyen & Dawson, 2012), which could also be viewed as a barrier for the use of learning analytics because others across the institution might get the impression that learning analytics is not a priority for the university.

3.2.2 Classroom-Level Use of Learning Analytics

Learning management systems (LMSs) sometimes provide myriad ways for instructors to access learning analytics for instructional purposes. This data can be used to both deliver and evaluate instruction. Learning analytics can be used for both modalities of instruction – whether asynchronous/synchronous online or face-to-face (Martin & Ndoye, 2016). For example, Juhaňák, Zounek, and Rohlíková (2019) conducted a study on the use of analytics for examining students' patterns when taking quizzes. Learning analytics, more specifically social network analysis, made it possible for Xie, Yu, and Bradshaw (2014) to explore students' participation patterns in an online course when they were assigned the role of moderator. Similarly, Kim, Yoon, Jo, and Branch (2018) investigated learning analytics as it related to self-regulated learning in asynchronous online courses. Learning analytics allowed instructors to explore elements such as the content that students accessed as well as the amount of time spent on content (Kim et al., 2018). Iglesias-Pradas, Ruiz-de-Azcárate, and Agudo-Peregrina (2015) used learning analytics to understand graduate students' competencies related to teamwork and commitment in an online program.

Learning analytics also makes it possible to support students' self-regulated learning by offering student dashboards (Roberts et al., 2016). A unique characteristic of a student dashboard is that it can potentially leverage data at all three levels – from providing information to students on how they compare to other students within a university system (macro), to how they are performing across their home institution (meso), to how they are performing within a specific course (micro) (Shum, 2012). At the meso level, like the micro level, the student data that is being used is typically captured through the learning management system interactions. The LMS has the ability to not only organize and deliver the course content, but also track and monitor student interaction and behavior patterns (Moore, 2019). There are thousands of different datapoints being collected within the LMS, and dashboards are a visually effective way to display that data. More importantly a dashboard allows for the data to be displayed in a way that can be informative and helpful, not only for students but also for instructors and administrators. As Pardo and Siemens (2014) discuss, these dashboards can give students a real-time analysis of their progress and allow them to take control over their own learning. Since the dashboard is working in real-time, it can also provide on-demand feedback and progress. For instance, a student can visually tell how much of a specific unit module they have completed, what is remaining to be completed and potentially receive automated feedback on assignments. An example of the use of student dashboards at the micro and meso levels can be found in the Course Signals study conducted at Purdue University (Arnold & Pistilli, 2012). The Course Signals tool was deployed as an early notification system that would allow an instructor to not only flag a student who might be experiencing academic challenges, but also contact them to offer assistance or remediation. Through the use of this tool, students reported that it was useful and helped them be successful at Purdue, while the instructors felt that it empowered students to improve their academic performance (Arnold & Pistilli, 2012). While this tool was being specifically delivered and used at the micro and meso level, it could feed up to the macro level and give Purdue useful information to employ for overall evaluation and allocation of resources.

In many studies, learning analytics created opportunities to explore components of courses that may not have been accessible previously. However, there are very few works that address the use of learning analytics across a student's overall experience at an institution.

3.3 An Interdisciplinary Approach

The focus on interdisciplinary connections of learning analytics data lends itself, primarily, to undergraduate students. However, using an interdisciplinary approach for learning analytics can also benefit graduate students enrolled in dual degree programs, professional development or continuing education students, and graduate students who take courses outside of their programs or can encourage more cooperation within various programs because, as we noted earlier in this chapter, incorporating various disciplines, departments, and perspectives can be beneficial in analytics application. We offer three key areas as a framework to foster this type of approach: awareness, access, and resources (Fig. 3.1). Each of these areas can assist institutions with developing an interdisciplinary approach to learning analytics for students' overall success.

Fig. 3.1 Awareness, access, & resources framework

3.3.1 Awareness – What Is Being Collected and Why

Awareness of the data collection process involved in analytics brings in the role of the subjects of the data collection efforts – students. One challenge is that the pace at which the area of learning analytics is evolving is faster than the pace at which ethical considerations are deployed to protect the collection and subsequent use of the data (Roberts et al., 2016; Slade & Prinsloo, 2013; Swenson, 2014). The first issue is that decisions are often being made about data collection without any input from students (Roberts et al., 2016). This is not to say that the institutions have ill intent; instead, they may not have considered how to incorporate student voices into the decision-making process. Not involving students may be a missed opportunity, as students can offer a unique perspective and address potential administrative "blind spots" (Moore, 2019). Also, students have their own ideas about what information they want to share and how it can be used (see, for example, Ifenthaler & Schumacher, 2016), so their input is crucial to the conversations regarding learning analytics and how or if they participate in these data collection processes. Perhaps one of the key components of the interdisciplinary application of learning analytics data is helping students understand how to access, use, and interpret the data. Students need to know what data is being collected, how administrators and instructors can use the data, and what safeguards exist for protecting their data (Cumbley & Church, 2013; Rubel & Jones, 2016). Including students in their own learning analytics conversations gives them the opportunity to view their progress across courses and disciplines. Furthermore, informing students about using learning analytics helps them become more prepared to use this type of data in their respective careers and is one integral step in helping curtail the concern about an overarching analytics narrative. For example, Scholes (2016) discusses the example of "at-risk" or "risky" students (p. 940–941). She points out that "interventions" for these students "could include restriction on the number of courses studied…extra phone calls to encourage engagement," and the like (Scholes, 2016, p. 940). Scholes goes on to say that these methods may work well for some students, but may not work well for others; the grouping of students in this way, through the use of analytics, can result in students' harm – perpetuating inequities, demeaning students, etc. These should be areas of alarm for institutions broadly. Including and informing students about analytics use and processes is a crucial component of an interdisciplinary approach. If students are concerned about the narrative the data perpetuates, then they have an opportunity to understand that this is happening and get guidance on how to address any issues they may have with what those analytics narratives present. Institutions must understand that students may have concerns about the sharing of data across units; however, a benefit to eliciting various perspectives through an interdisciplinary approach means that students can get support in areas that may not have been visible initially. Analytics collection processes should explicitly state who can access students' analytics profiles and who cannot. For example, students will need to know that these all-inclusive analytics profiles will not be available to just anyone, and institutions should reiterate the information protections in a number of areas of the university. Instructors, administrators, and other university staff will need this information as well in order to understand what they can and cannot do related to students' analytics data.

3.3.2 Access – Who Can Get to the Data

Once the university community is aware of the data being collected and the reasons for collecting it, the next area of focus is who gets access to the data. One of the major challenges related to an interdisciplinary approach to learning analytics, and sometimes learning analytics in general, is access. For example, Klein et al. (2019) noted that in certain contexts, even when learning analytics is used at a university, some areas of that university may have funding to pay for access to analytics data that other areas of the university cannot afford, as it is not uncommon for LMS providers to offer paid options for access to various tools and features. Furthermore, in contexts where funding for analytics access may not be an issue, there is still the challenge of who has permission to access data – an issue that Klein et al. (2019) bring up when discussing academic advisors' permission (or lack thereof) to access analytics data when advising, and one that Shum and Ferguson (2012) note when mentioning the possibility that "analytics could disempower learners" (p.19). Such disparities are not new, but if an institution believes that the overall use of data analytics is beneficial for students, despite various concerns, then applying the data in such different ways means that some students get more benefits than other students. The lines for access are drawn between students in areas on a campus that have robust analytics access and students in areas that do not have such access. By coordinating efforts with the university-level information technology office or an on-campus teaching and learning center, universities can keep track of the various learning analytics tools in use across the institution. This does not mean that units will have to forgo making decisions about analytics that are unique to their areas of the university. However, this practice does mean that there should be institutional messaging as well as an institutional understanding of what analytics data is being accessed and how it is being applied. Again, the interdisciplinary approach is designed to integrate the multiple perspectives and experiences of units in order to use that collective knowledge and input for the inclusive application of analytics. Since these enterprise-level offices are often the ones that make decisions about learning management systems, and LMSs are the key point of entry for access to learning analytics tools, it could prove more efficient to have those offices track how various departments and units use campus-wide learning analytics tools. Offices can begin by surveying each unit or department on the campus to get an idea of current learning analytics tools and continue conducting the survey periodically, as learning analytics tools change frequently. Different areas may see their access to analytics as proprietary (see Klein et al., 2019), so they may be reluctant to share information across areas. Therefore, a focus on interdisciplinarity coupled with centralized messaging and information gathering could remove some of the ambiguity around how the tools will be used and who has access to them; the information will become part of a university initiative to focus on improving all students' learning and experiences.

3.3.3 Resources – Where Is the Data Stored

Building on the access area, we next focus on the resources, specifically where the data is being stored. Once people are aware of the data being collected and know who has access to this data, they will need to know where this data is stored, not only for retrieval purposes but also to understand the ethical implications involved with data storage (on-site or off-site locations, possibly third-party terms related to privacy, length of time locations hold/have access to data, etc.). The aforementioned extant literature indicates that many analytics efforts are siloed – either in individual areas of a university or in individual classrooms. While this silo approach may be useful for developing security and access protocols, it limits potential information sharing and collaborative opportunities. The individualized approach to learning analytics can hamper interdisciplinary efforts, and that issue can be exacerbated by lack of analytics resources. One example occurs with undergraduates. A student may be taking courses across multiple instructors or departments within the university. If one department has one set of data resources and another has a different system in place, it can prove difficult for the institution (or even the instructors) to track that student's progress and make it difficult to identify students who may be in need of additional support. The colloquial term for this is a student who has "fallen between the cracks"; those cracks are the siloed resources. Some LMSs, for example, may not automatically provide learning analytics dashboards, and even when they do, some instructors may be unclear about how to best access and implement the analytics dashboard data. Once institutions develop a centralized analytics effort through IT or a teaching and learning center, as suggested in access area of this chapter, they can create an online space, internal or external, explaining what analytics features and resources are offered at their institution or through their current LMS. They could also discuss what third parties like LMS organizations and software providers can access and how long they have access to this data. The site itself would function as a resource for learning analytics support around the university.

This area of the framework is particularly important because it does not assume that all instructors will know how to access and apply learning analytics data. The site could also contain tutorials showing the steps for retrieving analytics data through the LMS, as well as information on how the data can be used by instructors. The site should also take an opportunity to address any privacy concerns instructors may have, and this section of the page should be developed in conjunction with the institution's legal team to ensure that the measures and information are in alignment with current higher education legal practices. Furthermore, the site should address how the university plans to use information on how instructors apply analytics data in courses. For example, some instructors, depending on their position with the university (tenure track, tenured, adjunct or casual instructors, etc.), may be concerned about the role their use of learning analytics will play in their overall evaluations. This step creates an opportunity for leveraging shared governance, as institutions with representation from various groups can include those groups in the development of the policies. Even when institutions do not have formalized groups, they can send surveys to instructors, as a needs assessment of sorts, in order to gain their input on how the use of learning analytics impacts them. These surveys could be delivered individually or from units around the university. For example, departments or units can gather information from the instructors in their areas and share that information with IT or the teaching and learning center. Universities should also be clear about who will use analytics data: these will be the people and units that require additional training and support related to the collection and use of learning analytics information. One major challenge to the implementation of this process, however, is time. The aforementioned tutorials take time to complete, which adds more work to schedules that, in most cases, are already full. However, if universities are going to use analytics, then that comes with the responsibility for the ethical, inclusive collection and use of that data. If institutions want to use analytics data, then they must provide designated time for instructors, students, and administrators who use the data to get the appropriate training, and these opportunities must be incorporated into existing structures, not add another item to an already lengthy list. There are a number of policies, laws, and codes that govern how universities can (and cannot) use information. The potential litigation involved in violating certain policies can result in much lengthier, more expensive processes than working with units to develop designated, incorporated times for data analytics training. In order to truly leverage learning analytics for interdisciplinary purposes, all levels of administrators, instructors, and students must feel included, respected, and protected in the process.

3.4 Future Directions

Each area listed provides a foundation for an interdisciplinary approach to applying learning analytics. Administrators, instructors, and students can work together to understand what information can be accessed, how it will be accessed, and how it will be connected to create an overall profile that administrators, instructors, and students can use to better understand students' learning and higher education experiences across courses and activities. With current and future uses of learning analytics data, it will be important for institutions to take any concerns about information sharing and privacy seriously because if users feel that their concerns are dismissed, then they may be reluctant to use learning analytics tools. Another key component to the overall implementation of an interdisciplinary approach, now and in the future, is having clear guidelines about who can access data. For example, in the Klein et al. (2019) text, advisors were concerned about their lack of access to learning analytics data. This is why the access area of the framework is so important. As the Lonn et al. (2017) text showed, there is a benefit to campuses taking a more centralized approach to learning analytics. Addressing issues related to who can access the data and for what purposes is integral to the successful application of an interdisciplinary approach to learning analytics. However, universities will have to be very clear about how they will use this centralized data so that instructors, administrators, and others can know what (if anything) the centralized data will mean for tenure, promotion, job security, and other areas.

Addressing analytics adoption with a framework that supports interdisciplinarity could also provide an overall benefit of helping students develop technologically. If there are students who still do not understand the power of a digital imprint, and the narratives analytics create are a form of digital imprint, then analytics discussions can bring these issues to the fore, along with larger discussions about the ethics of these panoptic practices. If universities want to create more technologically savvy and responsible students, then helping students understand their own on-campus digital imprints via learning analytics is one of the many ways to work toward that goal. Although the discussion of analytics is not a substitute for larger discussions about digital literacy, it is one of many entry points for that conversation. Institutions can include this information as a part of orientation for any online or face-to-face students who are new to the university. The information can also be reiterated in courses, particularly courses designed to teach students about study skills and other aspects of the university. Having an all-inclusive approach to data, and introducing this to students early on, can be crucial to their success at an institution and can help them explore areas where they think they need more support or where they would like to improve. Because the interdisciplinary information will be combined in a university profile, students can access this information across their various courses, as well as have a say in how this information is used.

3.5 Conclusion

In this chapter, we began with an overview of learning analytics and the use of big data in institutions of higher education. We next provided a discussion of the ways that data can be used both at the administrative level and in the classroom. Using this as the background, we offered three key areas as a framework that institutions should use to develop an interdisciplinary approach to learning analytics. Big data and learning analytics can be leveraged together to improve student outcomes within higher education institutions (Moore, 2019). This synergy can be found with the development of prediction models for retention (de Freitas et al., 2015) and with course-level data providing individualized student feedback and scaffolding (Arnold & Pistilli, 2012). Through the three areas of awareness, access, and resources, we hope to provide information that will be useful to higher education institutions as they consider how to build the infrastructure for their learning analytics apparatus. The potential impacts and benefits for students have been identified, but it is up to institutions to determine what their specific needs and goals are and how they can develop a sustainable and institution-specific system. At the heart of these discussions are more comprehensive connections between administrators, instructors, advisors, and students. Figuring out ways to incorporate students in the decision-making process can only help to make the system more responsive and effective toward the overall goal of improving student success within the institution.

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Chapter 4
The Framework of Learning Analytics for Prevention, Intervention, and Postvention in E-Learning Environments

Muhittin Şahin and Halil Yurdugül

4.1 Introduction

Learning and teaching processes are dynamic. The dynamism in these processes has recently become prominent, especially with instructional technologies. The most recent definition of instructional technologies by AECT highlights the following aspects: (a) facilitating learning, (b) improving learner performance, and (c) making scientific contribution in the field of learning and instructional technologies (Januszewski & Molenda, 2013). In this regard, learning analytics has emerged as a young field of study based on data-oriented approaches in e-learning environments to facilitate learning and to improve learning performance. Because learning analytics focuses on improving environments by addressing educational difficulties (Ferguson, 2012) and provides powerful tools to improve learner performance and to enhance learning efficiency (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). Learning analytics is defined as collecting, analyzing, measuring, and reporting the data regarding learners and learning processes to understand and improve processes in learning environments (Siemens & Gasevic, 2012). Tracing back to the history of learning analytics, they were first introduced to the literature through Course Signals by Purdue University (Arnold & Pistilli, 2012) and have been widely discussed in the recent years. Intervention studies based on learning analytics can be divided into report-based analytics and automated. The Course Signal study is also an example of report-based learning analytics. Automated intervention systems require machine learning. Intelligent tutoring systems (ITS), intervention engines, and adaptive engines are examples of automated intervention systems.

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Learning analytics (mentioned as analytics in the report) was presented in the time-to-adoption horizon of 1 year or less in the 2019 Horizon Report prepared by the New Media Consortium (Alexander et al., 2019). The initial studies on learning analytics were limited to the presentation of learner performance with the use of dashboards and did not benefit from psycho-educational theories. In the later years, learning analytics went beyond being merely dashboards and was considered as a system that can intervene with learners (Arnold & Pistilli, 2012; McKay, Miller, & Tritz, 2012; Şahin & Yurdugül, 2019; Tlili, Essalmi, Jemni, Chang, & Kinshuk, 2018). Notably, the studies on learning analytics have various purposes such as: (a) to predict learner performance, (b) to increase reflection and awareness, (c) to identify inappropriate learner behaviors/patterns, (d) to make an estimation, (e) to provide feedbacks, (f) to make an adaptation, g) to make an intervention, and (h) to conduct monitoring and analysis (Chatti, Dyckhoff, Schroeder, & Thüs, 2013; Verbert, Manouselis, Drachsler, & Duval, 2012). This study reviews the studies regarding intervention. Accordingly, it first presents the theoretical definition of the concept of intervention and its contribution to learning analytics.

Intervention is defined as a planned modification of the environment made for the purpose of altering behavior in a pre-specified way (Tilly III & Flugum, 1995). In this regard, *Feedback Intervention Theory (FIT)*, which was developed in the 1900s to provide information to improve learning performance, is notable in the relevant literature (Kluger & DeNisi, 1996). Narciss, Körndle, Reimann, and Müller (2004) report that feedback is an important factor to support learning in computer-based learning environments. Learners are presented with different feedbacks such as tips, analogies, and explanations, useful strategic information for the learning tasks they are assigned to (Narciss & Huth, 2002). Intervention is a broad concept that incorporates not only feedback, but also feed-forwards and feed-ups. In other words, it can be said that every feedback is an intervention, but not every intervention is feedback.

Educators and interventionists rely on learner outcomes as an empirical indicator for intervention (Riley-Tillman & Burns, 2011). In traditional approaches, learner outcomes are considered as the end-of-term success and attendance of students, etc. Thus, it was possible to determine whether the intervention made was useful or not. However, instructional technologies and online learning environments as a product of these technologies allow for recording interaction data (log data) and revealing significant patterns in these data through educational data mining. Analyzing the data gathered from learners in educational environments and their interaction with information technologies is a promising approach to understand learning process (Gašević, Dawson, & Siemens, 2015). The behavioral models of learners on progress, efforts made, and time management can be better understood and explored by analyzing their interactions in online learning environments (Li, Flanagan, Konomi, & Ogata, 2018). With a better understanding of learning processes based on the data, it is possible to make more appropriate interventions.

Despite various advantages offered by online learning environments, the big problem of e-learning in terms of time and cost spent is learner dropouts (Jun, 2005). Therefore, instructors in higher education are critically in need of new tools and strategies that will allow them to quickly identify at-risk students (Macfadyen & Dawson, 2010). Interventions with learning analytics aim to improve the undesirable situations in the learning process, such as high dropout rates of learners (Wong & Li, 2019). Yet, it is obvious that the concept of intervention alone does not correspond to all of these activities. In the relevant literature, the activities carried out before an incident are called prevention whereas the activities aimed at reducing the effects of an incident after it happens are called postvention. The studies on learning analytics also include the concepts of prevention, intervention, and postvention. Thus, this study designs and proposes the framework of learning analytics for prevention, intervention, and postvention. It, further, explains the differences between these three concepts and discusses them by transferring them from psychology to e-learning environments.

Accordingly, this study first looks into theoretical information on the concepts of prevention, intervention, and postvention and goes through their applications in e-learning environments and the results. It, then, presents the proposed framework. The proposed framework is developed based on the studies on learning analytics, early warning systems, dropout, intervention, prevention, and postvention. The framework also builds on the metrics and graphs, which are used as interaction data in these studies, and the results of these studies.

4.1.1 Prevention

Prevention is divided into three basic categorizations by Caplan (1964) as (i) primary prevention, (ii) secondary prevention, and (iii) tertiary prevention. However, these concepts are today named as prevention, intervention, and postvention (Leenaars & Wenckstern, 1998).

Romano and Hage (2000) argue that prevention seeks to (a) stop a problem behavior from ever occurring, (b) delay the onset of a problem behavior, (c) reduce the impact of problem behavior, and (d) strengthen knowledge, attitudes, and behaviors that promote emotional, physical, and social well-being. As the definition suggests, prevention refers to the activities performed or measures taken prior to an incident. Its target group is divided into three: (a) no-risk group, (b) at-risk group, and (c) group with early symptoms of the problem (Gordon Jr, 1983). Although prevention has been mostly studied in the fields of community health, psychology, medicine, child, and family development, studies on prevention have been recently available in the field of education (Merrell, 2010). Prevention enables individuals to make their own choice by granting them more control over themselves through informing them (Mittelmark, 2003).

In the literature, prevention is considered as a process that can be carried out with early intervention (Walker & Shinn, 2002). Early warning systems in the studies on online learning environments are an example of this. Studies on prevention are also significant in identifying the students at risk of dropout and in designing necessary activities to prevent them from dropping out (Heppen & Therriault, 2008). It is particularly noted that there is a risk of dropout in e-learning environments (Lara, Lizcano, Martínez, Pazos, & Riera, 2014; Park & Choi, 2009; Willging & Johnson, 2009). The proposed framework also provides insight into the components that can be integrated into online learning environments in the context of prevention to prevent students from dropping out.

Early warning systems (EWSs) use historical and formative educational data to identify students who might be at risk of academic failure, often doing so in near real time (Lonn, Aguilar, & Teasley, 2015). EWSs seek to predict at-risk students and to help teachers develop strategies to prevent it (Campbell, DeBlois, & Oblinger, 2007). In addition to the studies in online learning environments, numerous schools have studied EWSs to identify the students who will drop out and to take the necessary measures. Some of the examples of these studies are the studies by Heppen and Therriault (2008), and Beck and Davidson (2001), as well as the study performed with data mining methods by Dekker, Pechenizkiy, and Vleeshouwers (2009). This study considers systems developed for online learning environments. Prevention applications involve taking steps to eliminate sources of risk (MacNeil & Topping, 2007). Prevention can be described as measures/activities taken or performed for at-risk individuals. Therefore, it can be argued that prevention and early warning systems serve a similar purpose.

Studies aimed at identifying at-risk students in e-learning environments are available (Hu, Lo, & Shih, 2014; Levy, 2007; Lonn et al., 2015; Macfadyen & Dawson, 2010; Park & Choi, 2009; Tabaa & Medouri, 2013; Willging & Johnson, 2009). Variables have varying effects on learner engagement in e-learning environments. Among these variables, learner satisfaction is proved to be one of the most effective factors on engagement (Levy, 2007; Park & Choi, 2009). Further, successful learners have a high interaction with e-learning environments and engagement (Macfadyen & Dawson, 2010; Willging & Johnson, 2009). Willging and Johnson (2009) report that students leave the program for the following reasons: personal, job-related, program-related, and technology-related reasons. Besides, Nkhoma et al. (2019) reveal that (a) time-management, (b) problems in understanding learning materials, and (c) problems in evaluation have an impact on students' decisions to drop out. Thus, a clear understanding of the factors that contribute to dropout in e-learning courses can help course designers and instructors to improve and support courses in these initiatives (Levy, 2007). This is why this study looks into studies on dropout, and the framework developed in this study incorporates prevention components to overcome the difficulties faced by learners.

4.1.2 Intervention

Intervention is defined as the practice of preventing learners from failing academically by monitoring their improvement and offering additional instructions or support to meet their needs (Wong & Li, 2019). The intervention seeks to enhance student achievement and improve their learning experiences (Pardo & Dawson, 2016). With the support of learning analytics, interventions usually aim to improve undesirable situations, such as student dropout rates or failing scores, and to improve undesirable situations reported by data in the learning process (Wong & Li, 2019). Intervention studies based on learning analytics can be divided into two groups. The former encompasses interventions by the adaptive engine, which makes interventions to the system; the latter includes interventions by intervention engine, which involves interventions to the individual. The systems discussed in this study are intervention engine systems, which make interventions to the individual.

The signalization study conducted at Purdue University can be given as an example of the studies on intervention in the literature. In their study, Arnold and Pistilli (2012) sent students individual e-mails about their performance, employed learning analytics on the data collected on the learning management system and the demographic information of the students, and presented their performance through the visual indicator of the traffic signal. Their findings show that learners hold positive views on the proposed system. Learners also find the visual indicator of the traffic signal and e-mails to be positively effective in changing their behavior. Another study based on learning analytics is the study by Şahin (2018), who designs an intervention engine and includes different types of interventions. The developed engine system incorporates the components designed for instructional, supportive, and motivational interventions to the learning environment, as suggested by Geller (2005). The study concludes that students find the system useful and have a positive view.

Wong and Li (2019) examine the intervention studies carried out using learning analytics in the years 2011–2018 and list their purposes as follows: (a) to enhance learner success, (b) to offer individualized feedback to learners, (c) to increase learner engagement, (d) to help learners in academic decision-making, (e) to increase the levels of self-awareness/self-reflection/self-regulation among learners, (f) to enhance the effectiveness of the process where learners monitor their learning process, (g) to support academic advisors for immediate decision-making, and h) to promote cooperative learning. The intervention studies performed based on learning analytics indicate: (a) improved learner performance, (b) increased level of participation among learners, (c) increased effectiveness of learning and teaching, (d) positive views among learners, and (e) promoted learning performance (Arnold & Pistilli, 2012; Chen, 2011; Klein et al., 2019; Şahin, 2018; Wong & Li, 2019).

4.1.3 Postvention

Postvention is defined as appropriate and helpful acts that come after a dire event (Shneidman, 1972; As cited in Campbell, Cataldie, McIntosh, & Millet, 2004). Andriessen (2009) argues that postvention is those activities developed by, with, or for suicide survivors, in order to facilitate recovery after suicide and to prevent adverse outcomes including suicidal behavior. It also refers to acts intended to minimize the likelihood of a person who committed suicide or other persons committing suicide (King, 1999).

As can be seen from these definitions and the relevant studies in the literature, this concept is widely used in the field of psychology and for suicide cases; yet, there is no consensus regarding the concept. This study introduces the concept of postvention as the activities conducted for learners in online learning environments. Accordingly, postvention is defined as activities and regulations that can be made for learners with undesirable behaviors such as dropping out from e-learning environments and failing in courses, etc.

4.1.4 Differences Between Prevention, Intervention, and Postvention

This section seeks to point out the difference between prevention, intervention, and postvention, which are discussed in this study. First of all, the purpose of all these interventions (prevention, intervention, and postvention) is to produce a difference between the initial and post-intervention performance levels (Gresham, 2005). Prevention indicates the activities before an incident; intervention refers to those during the incident, and postvention includes those after the incident (Leenaars & Wenckstern, 1998). More precisely, prevention covers the activities aimed at preventing the onset of behavior before it happens. Intervention is the activities performed while the behavior is occurring, and postvention refers to the activities aimed at reducing the effects of the behavior after its onset or eliminating its negative effects. Figure 4.1 presents this process.

As seen in Fig. 4.1, prevention is practiced before an undesirable behavior or while the signs of an undesirable behavior manifest; intervention is implemented during the undesirable behavior and postvention in the activities after the undesirable behavior occurs. It is possible to further elaborate on this definition by using a situation that may happen in online learning environments as an example. One of the undesirable situations in online learning environments is dropouts. Dropout is

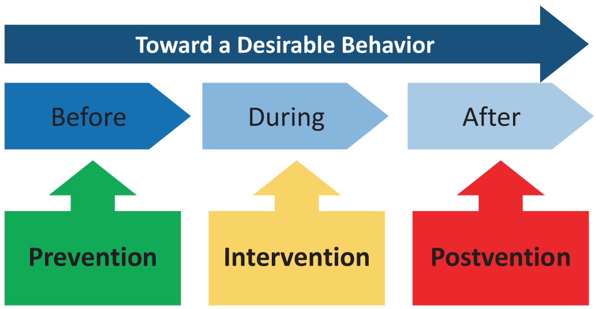

Fig. 4.1 Prevention, intervention, and postvention as a process

defined as students that voluntarily withdraw from e-learning courses (Levy, 2007). To avoid this, prevention strategies should be employed to allow for interaction between the system and the learner before the signs of dropping out manifest themselves. When the signs of dropping out become evident, intervention strategies should be used to prevent the learner from dropping out. If the learner drops out against all these measures, postvention strategies are required to reduce the negative effects of the situation or to prevent it from happening again in the next online course. This study adapts the concepts of prevention, intervention, and postvention, which are psycho-educational constructs, to online learning environments based on learning analytics. Learning analytics improves final learning and teaching efficiency (Elias, 2011). This adaptation will potentially help to increase the efficiency and effectiveness of learning environments and to reduce the frequency of undesirable behaviors in these environments.

4.2 Proposed Framework

To develop the proposed framework, this study first presents the risk factors that may arise in online learning environments, that is, undesirable behaviors in these environments. Then, it explains the potential reasons for these behaviors and discusses what can be done in the context of prevention, intervention, and postvention. Studies report certain undesirable behaviors in online learning environments, including dropout, avoidance of learning activities, locus of control, procrastination, lack of learning strategies (Elvers, Polzella, & Graetz, 2003; Levy, 2007; Li et al., 2018; Michinov, Brunot, Le Bohec, & Juhel, 2011; Nkhoma et al., 2019; Wolters, Pintrich, & Karabenick, 2005). The framework proposed by this study elaborates on these undesirable behaviors reported in the literature and describes the potential reasons for these behaviors as well as risky behaviors. Following the description of undesirable behaviors, the paper explores prevention, intervention, and postvention strategies. Table 4.1 shows the strategies that can be used in relation to these concepts.

Table 4.1 Prevention, intervention, and postvention strategies

Prevention strategies	Intervention strategies	Postvention strategies
Identifying and eliminating risk factors Early warning systems Informing learners Collaboration between learners Designing alternative learning materials Guiding learners/assisting them in making decisions Well-designed interface (creating an appropriate learning environment)	Increasing awareness Reflection Encouraging interaction Enabling someone to set personal goals Prompting someone to interact with his/her peers Instant feedback Allowing for comparison	Communicating with peers Encouraging someone to use different learning sources Prompting someone to consult experts Strategy training

Table 4.1 indicates different strategies that can be used for learners in the context of prevention, intervention, and postvention. Further, it is possible to employ some strategies in the context of prevention, intervention, and postvention. Besides, prevention, intervention, and postvention will support the self-regulation learning (SRL) skills of learners; this study reviews the SRL strategies too. There are different strategies in the literature such as goal setting, planning, monitoring, reflection, formative evaluation, summative evaluation, and time management (Schunk & Ertmer, 2000; Weinstein, 1994). The framework is developed based on the concepts that are identified by analyzing undesirable behaviors in online learning environments and the strategies that can be useful in these environments. Table 4.2 provides information on the framework.

Table 4.2 demonstrates the undesirable situations that may occur in online learning environments; the potential reasons for these situations; risky behaviors; and possible prevention, intervention, and postvention strategies. Below is the detailed information on the concepts in Table 4.2 under the relevant headings.

4.2.1 Dropout

Results of Levy's (2007) study suggest that in agreement with prior research, students' satisfaction from e-learning is a major factor in students' decision to complete or drop from such courses. Moreover, in contrast to prior correspondence courses and earlier types of e-learning courses, academic locus of control was not found to play a major role in predicting dropouts from the e-learning courses. Moreover, variables such as learner characteristics (age, gender, education), external factors (family issues, managerial support, financial problems), and internal factors (instructional design, assignment level, activity level, lack of motivation, academic integration, satisfaction) affect the students' decision to drop out (Park & Choi, 2009; Willging & Johnson, 2009).

Learners who are at risk of dropping out:

- May not interact with the system after logging to the system
- May interact with the system at first, but quit interacting with it later on
- May interact with the system at a low level with very long intervals

Determining whether students are at risk of dropping out and employing early warning systems can be included in the scope of prevention. Similarly, integrating different learning materials to online learning environments and allowing learners to choose between these materials can be considered as prevention activities. As for intervention, informing learners during the process about the fact that they will fail if they do not interact and presenting them learning dashboards that show their daily performance and in-group performance for comparison are some examples of activities for intervention. Prompting learners to communicate with the group and presenting them with the patterns of successful learners (so that they can see what successful learners did to succeed) can be included in the scope of postvention. Moreover, prompting learners to interact with the instructor is an example of postvention activities.

Table 4.2 Information about the proposed framework

Risky behaviors/ undesirable behaviors in online learning environments	Potential reasons	Risky behaviors	Prevention	Intervention	Postvention
Dropout	Satisfaction Locus of control Learner characteristics External factors Internal factors Academic success	Not doing anything else than logging to the system Low level of interaction with the system Failure to fulfill learning tasks	Early warning Alternative learning materials	Informing instructors Monitoring of learning performance	Prompting learners to communicate with the group Prompting learners to communicate with the instructor
Avoidance of Learning Activities	Learner characteristics Satisfaction Social anxiety	Failure to fulfill learning tasks. Lack of interaction with the system Interaction with only one interaction theme Decreasing weekly interaction	Alternative learning materials Guidance	Weekly interaction performance Interaction performances on a thematic basis	Prompting learners to communicate with the group Prompting learners to communicate with the instructor Strategy training
Failing learning performance	Lack of cognitive strategies Avoidance of interaction	Low quiz grades Failure to complete learning tasks on time Failing despite interaction with the system	Encouraging learners to study the subjects they are weak at Informing	Weekly interaction performance Comparing in-group interaction Predicting student success Weekly learning patterns	Prompting learners to communicate with the group Prompting learners to communicate with the instructor Strategy training Successful learning patterns Encouraging learners to refer to different sources
Locus of control	Internal factors External factors	Avoidance of interaction Low success in learning	Prompting learners to cooperate Informing	Individual performance Comparing in-group performance	Prompting learners to communicate with the group Prompting learners to communicate with the instructor
Academic procrastination	Fear of failure Stress Reluctance to complete the task Perception of competence	Submitting learning tasks at the last minute or not submitting at all Doing quizzes at the last minute or not doing at all	Reminder notification	Reminder notification In-group comparison	Notification In-group comparison

4.2.2 Avoidance of Learning Activities

Avoidance of learning activities is addressed in two main aspects. The first aspect is the lack of interaction with the system; the second aspect is the failure to complete learning tasks. Learner interactions in online learning environments fall under different themes as learner-learner, learner-instructor, learner-content, and learner-assessment (Şahin, Keskin, Özgür, & Yurdugül, 2017). Lack of interaction with the system includes the failure of learners to interact with the content, assessment, and discussion platforms. It also includes interacting with an interaction theme but failing to interact with another theme. For instance, a learner may interact with the content in an online learning environment but avoid interacting with the discussion platform in this environment. The failure to complete learning tasks refers to the failure to fulfill the assignments given to learners.

Integrating alternative learning materials to the system and guiding them in their decision-making process are some examples of prevention activities for the learners who avoid learning activities. As for intervention, learners can be individually informed about their weekly interaction performance to increase their awareness. It is believed that weekly performance graphs can enable learners to recognize their own performance and to do the necessary planning. Also, with the presentation of learner interactions based on interaction themes, learners can learn about their levels of interaction with themes and see with which theme they should interact more. Lastly, in relation to postvention, learners can be prompted to communicate with other learners and the instructor.

4.2.3 Failing Learning Performance

Failing learning performance can be discussed in two different ways: short-term and long-term failing learning performance. Short-term performances cover the results from quizzes at the end of each course unit. Encouraging learners to study the subjects they are weak at and informing them based on their results are some examples of prevention activities. Learners can be encouraged to study the subjects they are weak at through topic contingent feedback and also to use alternative learning materials on the same subject. Informing can be performed using textual feedbacks as well as the visual indicator of traffic signals. Studies demonstrate that learners hold positive views toward the feedbacks with the indicator of traffic signals (Arnold & Pistilli, 2012; Şahin & Yurdugül, 2019). As for intervention, the individual performances of learners can be compared with the group and learners can track where they are compared to the group. Furthermore, weekly performance graphs can enable learners to recognize their own performance. Also, predicting student success based on learner performance and interaction with the system helps learners make self-assessment and plan their learning. Besides, presenting learners with their weekly learning patterns in sequential analyzes allows them to identify their learning paths and to do the planning. Various postvention strategies can be employed for failing learning performance. One of them is to prompt learners to interact with the group and the instructor, which is also used in other cases. Conducting strategy training, showing successful learners' learning patterns, and encouraging learners to refer to different sources are some of these postvention strategies. Strategy training can be particularly offered to the learners who interact with the system at a high level and fulfill learning task but are not successful.

4.2.4 Locus of Control

Locus of control refers to a general expectation of the link between personal characteristics and the results of experiences (Lefcourt, 1991). There are two forms of locus of control: external and internal (Ajzen, 2002). The individuals with an internal locus of control associate their experiences with the behaviors that depend on their own responsibilities whereas those with an external locus of the control link these experiences to external factors, which are beyond their own control, such as luck, chance, fate, and coincidence (Rotter, 1975). The individuals with an internal locus of control strive to take the opportunities around them to achieve their goals, to attach more importance to their own achievement, and are prone to develop their own skills and ask more questions (Rotter, 1966; As cited in Loosemore & Lam, 2004).

Prompting learners to communicate with their peers is an example of prevention activities for the locus of control. As for intervention, informing learners with an internal locus of control of their performance, comparing learners with an external locus of control with the group, and encouraging them to learn in discussion environments are examples of practices. As a postvention activity, the system can be redesigned to prompt learners to interact with other learners and the instructor.

4.2.5 Academic Procrastination

Procrastination is defined as unnecessarily delaying a task that needs to be done or waiting until the last minute to do it (Knaus, 1998). Some of the possible reasons for procrastination are evaluation anxiety, difficulty in making decisions, lack of assertion, fear of the consequences of success, perceived aversiveness of the task, and competency (Solomon & Rothblum, 1984). Academic procrastination refers to putting academic tasks off to the last minute (Solomon & Rothblum, 1984). This study focuses on academic procrastination.

To deal with academic procrastination, different short-term and long-term notifications can be sent to learners. As for prevention, reminder e-mails or texts can be sent to learners before the deadlines for any learning task or quiz. Thus, learners are encouraged to complete learning tasks or quizzes. The long-term procrastination includes the situation where learners do not interact with the system for a certain time. To overcome this, reminder e-mails or texts can be sent to motivate learners as an intervention practice to ensure the interaction of the learners with the system. Also, learners can be presented with the group performance for the task as an intervention practice. As for postvention, if learners did not fulfill a learning task, encouraging notifications can be sent to learners to remind them to perform the next learning task. The system can be designed to send these notifications through e-mails or texts. Further, comparison graphs can be integrated into the system to enable the learners who fulfill and do not fulfill a learning task to track their status and to see where they are at compared to the group.

4.3 Conclusion and Discussion

Online learners are responsible for managing themselves and initiating, planning, and conducting their own work (Li et al., 2018). The learners who are successful in online learning environments have the following characteristics: (a) regularly accessing to lecture notes, (b) carefully reviewing the course content, (c) completing assignments on time, (d) making self-assessment about their learning, (e) asking questions when they need help, and (f) being active in communicating with others (You, 2016). Thus, online learning environments may be disadvantageous to learners who do not/are not able to take responsibility for their own learning (Demir, Yaşar, Sert, & Yurdugül, 2014). Yet, learning analytics has so much to offer to researchers to overcome such a disadvantage (Şahin, 2018). Learning analytics aims to optimize learning environments by focusing on educational challenges (Ferguson, 2012). Learning analytics contributes: (a) dashboard design (display the interaction data of the learners to them and to make awareness and reflection), (b) instructional design, (c) intervention engine (intervene to the individual) and adaptive engine (intervene to the system), (d) learning design, (e) learning experience design, and (f) content design. The initial studies on learning analytics were limited to the presentation of learner performance with the use of dashboards. It is thought that framework-based designs will come into prominence in the future research.

This study aims to develop a framework for prevention, intervention, and postvention for online learning environments based on learning analytics. To that end, this study explores the undesirable situations in online learning environments, and discusses and offers suggestions on what can be done in the context of prevention, intervention, and postvention. It is possible to identify the students who are at risk of dropping out and to make the necessary interventions through learning analytics (Xing & Du, 2019). Therefore, the proposed framework will potentially help to transfer the concepts of prevention, intervention, and postvention, which are psycho-educational constructs, to online learning environments based on learning analytics and benefit other researchers in the field. Looking at the future research directions of learning analytics, the following topics come into prominence: (a) acceptance of learning analytics and implementations, (b) early warning system and personalized learning, (c) ethics and data privacy, (d) learning design, (e) learning experience design, and (f) dashboard design (Bakharia et al., 2016; Ifenthaler, 2017; Mah, Yau, & Ifenthaler, 2019; Mangaroska & Giannakos, 2018; Siemens, 2013; Şahin & Yurdugül, 2020). In this context, it is thought that the framework put forward within the scope of this research will make important contributions for learning designers, learning experience designers, and instruction designers. Learning design is a methodology that enables tutorials and designers to make better decisions using appropriate resources and technologies for learning activities and intervention designs (Conole, 2012). Learning experience design includes support and guidance to learners in their learning experience rather than instructors and designers. The proposed framework is intended to provide tutorials and designers with tips on interventions, contents, and learning activities that should be included in the online learning environments. In addition, it is thought that this framework can lead to more effective learning designs.

The proposed framework particularly focuses on identifying the learners who are at risk or who show the signs of undesirable behaviors and offers possible measures taken for these learners for prevention. These measures include informing learners by providing them various feedbacks, identifying the learners who are at risk through early warning systems, and sending reminder notifications. Intervention activities can be carried out when undesirable behaviors manifest themselves, and these activities mostly include components such as dashboards. In this regard, the framework proposes numerous graphs to enable learners to compare themselves with the group and to allow for self-monitoring, self-awareness, and self-reflection. Postvention activities revolve around the activities that can be carried out after the onset of undesirable situations in an online learning environment. The framework contains different strategies such as prompting learners to interact with the instructor and other learners, strategy training, and encouraging them to use alternative sources.

A review of the prevention, intervention, and postvention components that are proposed in this study shows that these are closely related to the SRL development of learners. SRL is viewed as proactive processes that students use to acquire academic skills, such as setting goals, selecting and deploying strategies, and self-monitoring one's effectiveness (Zimmerman, 2008). Self-regulation is described as cyclical since feedback from the previous performance is integrated to make adjustments to current objectives (Zimmerman, 2000). In this regard, the proposed framework will potentially contribute to the SRL skills of learners. To fully recognize its contribution, it is necessary to integrate this framework into online learning environments and test it with real users. The next step of this study is to integrate the developed framework into a learning management system (LMS).

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Chapter 5
The LAVA Model: Learning Analytics Meets Visual Analytics

Mohamed Amine Chatti, Arham Muslim, Manpriya Guliani, and Mouadh Guesmi

5.1 Introduction

Despite the great enthusiasm currently surrounding the field of learning analytics (LA), we are still lacking evidence that LA has any obvious impact on learning (Ferguson & Clow, 2017; Gašević, Dawson, & Siemens, 2015). This hinders the acceptance and adoption of LA at scale in schools, universities, and workplaces. Along with technical research questions, there are more crucial pedagogical and methodological problem areas related to the design, deployment, and evaluation of LA. These include the lack of attention to the LA cycle; limited attention to validity, reliability, and generalizability; limited attention to ethics; and little evaluation of commercially available tools (Ferguson & Clow, 2017). But, the most important reason is that most LA solutions are not adopted by the end users because they are not well aligned with user needs. The solution – which has been lacking in the LA community until now – is to follow a human-centered LA (HCLA) approach that emphasizes the human factors in LA and truly meets user needs. Having the human in the loop is the key to increase value and drive forward the acceptance and adoption of LA (Chatti & Muslim, 2019).

Following a human in the loop approach, visual analytics (VA) – a data science research field that has lately been growing very rapidly – can play a significant role to support the acceptance of LA. VA refers to analytical reasoning facilitated by interactive visual interfaces and aims at making data and information processing transparent. It integrates the analytic capabilities of the computer and the abilities of

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the human analyst, thus allowing novel discoveries and empowering individuals to take control of the analytical process (Thomas & Cook, 2005; Keim, Mansmann, Schneidewind, & Ziegler, 2006).

Visualization has been widely considered as a crucial step in the LA process, and a variety of dashboards and indicators were proposed in the LA literature (Bakharia & Dawson, 2011; Bodily et al., 2018; Gašević et al., 2015; Jovanovic et al., 2008; Leony, Pardo, de la Fuente Valentín, de Castro, & Kloos, 2012; Verbert et al., 2013, 2014). These dashboards, although they employ some visualizations for representing data, are predominantly static and, in general, afford very little interaction. Ritsos and Roberts (2014) point out that VA can transform LA to go beyond mere analysis (confirmatory analysis) to gaining various insights from the data (exploratory analysis) with the aim of meeting the objectives of self-assessment, performance determination, awareness, and adaptation. However, the application of VA is still under-investigated in current LA research and practice.

The main focus of this work is to explore how blending LA and VA can achieve an effective HCLA approach and improve the acceptance of LA. To get at this, we present and discuss the Learning Analytics and Visual Analytics (LAVA) model as a conceptual framework through which VA can be seamlessly integrated into the LA process. As a proof of concept, we apply the LAVA model in the Open Learning Analytics Platform (OpenLAP) that collects learning activities data from multiple sources and allows different stakeholders of LA to dynamically generate custom indicators that meet their needs. Furthermore, we evaluate OpenLAP in terms of usefulness and usability based on the technology acceptance model (TAM).

5.2 Human-Centered Learning Analytics

Learning analytics (LA) focuses on the development of methods for analyzing and detecting patterns within this data and leverages those methods to support the learning experience. Chatti, Dyckhoff, Schroeder, & Thüs, (2012, 2014) propose a reference model for LA that provides a systematic overview on LA and fosters a common understanding of the key components of the LA ecosystem, based on four dimensions of the LA reference model, namely:

- What? What kind of data does the system gather, manage, and use for the analysis?
- Why? Why does the system analyze the collected data?
- Who? Who is targeted by the analysis?
- How? How does the system perform the analysis of the collected data?

In the ideal case, LA is a cyclical movement from data to analysis to action to learning (Chatti et al., 2014; Clow, 2012). LA is an iterative process generally carried out in six major stages, namely, *learning activities*, *data collection*, *data storage and processing*, *analysis*, *visualization*, and *action* (see Fig. 5.1). These steps are iterated, with each cycle yielding more effective learning activities.

Fig. 5.1 The learning analytics process (Chatti & Muslim, 2019)

User involvement in all stages of the LA process is the key to a wider acceptance and adoption of LA. It is vital to engage the various LA stakeholders (learners, teachers, institutions, researchers, developers, etc.) in the LA process. Especially, the learner should play an active role in the LA process, if LA tools are to serve the intended objective of improving learning (Chatti & Muslim, 2019). This is at the heart of HCLA. But how can an HCLA approach be implemented in practice? Visual analytics can help to face this challenge.

5.3 Visual Analytics

Computers have enormous storage capacity and computational power to support automated data analysis processes. By visualizing data, some patterns emerge which might not be noticeable in the raw form. Humans, on the other hand, have creativity, flexibility, background knowledge, sense of intuition, and the skills that help to extract meaningful insights from data. Interaction is the glue that binds analytics and visualization with the human analysts (Endert et al., 2014). Visual analytics (VA), a highly interdisciplinary research field, combines automated analysis techniques with human-interactive visualizations derived from a large amount of data, for effective understanding, reasoning, and decision-making (Keim, Mansmann, Stoffel, & Ziegler, 2009). The concept of VA can be better understood based on the sense-making loop for visual analytics, shown in Fig. 5.2. A

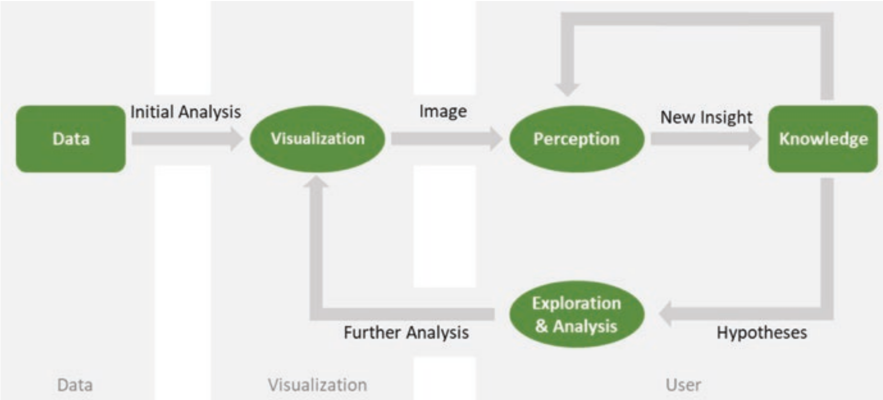

Fig. 5.2 The sense-making loop for visual analytics. (Adapted from Keim et al., 2008)

visualization is presented to the user based on the initial analysis of the dataset. The process then enters a loop, where the user drives the analysis process to draw new insights and accumulate knowledge through exploration. The user can interact with the visual representations to get a better understanding of the data through the different possible views or to eventually confirm hypotheses generated from previous iterations of analysis and interactions (Keim et al., 2008).

5.4 The LAVA Model

The main aim of LA is to turn educational data into insights, decisions, and actions in order to improve learning and teaching. However, in current LA implementations, human stakeholders are not actively involved in the LA process with its six stages, namely, learning activities, data collection, data storage and processing, analysis, visualization, and action. In order to achieve HCLA, there is a crucial need to involve humans throughout the whole LA process. This is where VA comes into play. Following a human in the loop approach, VA brings humans in the data analytics process to turn data into value. This paper proposes the Learning Analytics and Visual Analytics (LAVA) model, which incorporates VA into LA and enables stakeholders to control the LA process, making it human-centered through exploratory data analysis and visualization, as depicted in Fig. 5.3.

The LAVA model has been created by interweaving the reference model and the process of LA with the sense-making loop for VA. In this model, the four dimensions of LA (What?, Why?, Who?, How?) are revisited with VA concepts in the picture. The process of LA essentially remains the same, but it is enhanced by incorporating the human perspective in the Who? dimension and exploration in the How? dimension. In the following, we discuss the eight stages of the LAVA model.

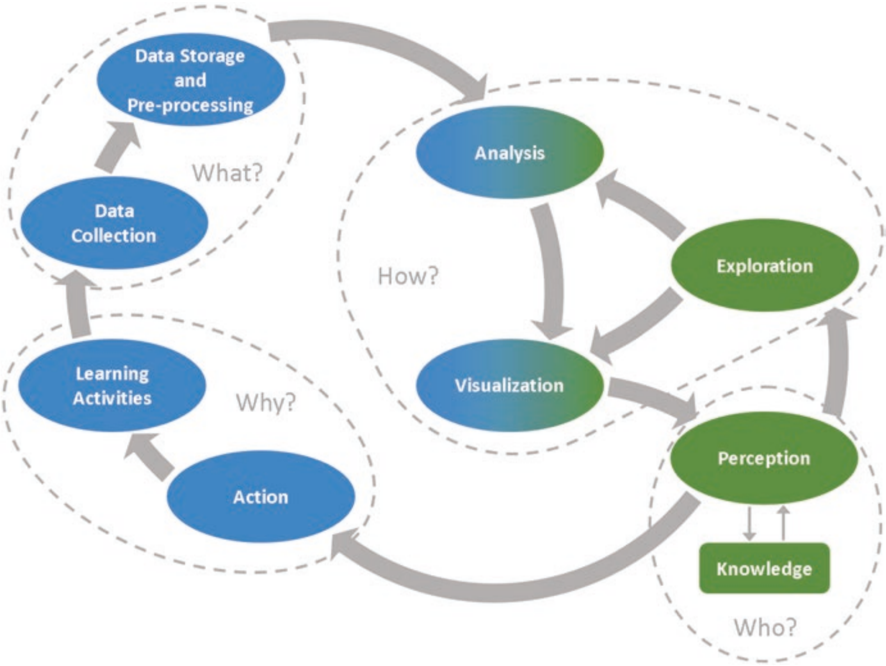

Fig. 5.3 The LAVA model – having the human in the loop

- *Learning Activities*: The LAVA model starts with concrete learning activities that can occur in different learning environments and generate a large amount of educational data.
- *Data Collection*: Collecting educational data is the foundation of the LAVA model. Today we have broad access to high-volume data from a variety of sources. The data can come from multiple, fragmented, often heterogeneous, formal, as well as informal learning channels. It can also come in different formats, distributed across space, time, and media.
- *Data Storage and Pre-processing*: The collected data needs to be systematically stored and processed to prepare data for further analysis.
- *Analysis*: After the data is collected and pre-processed, an initial analysis is performed before presenting any results to the users.
- *Visualization*: The analysis results are presented as indicators to the users in the form of visualizations that can help to understand and interpret the results as well as to infer conclusions from the data, which can improve the learning process. These visualizations should be interactive in nature allowing users to better understand the underlying data and analyze it further.
- *Perception and Knowledge*: Users play an important role in the LAVA model. Instead of automated analysis, the users drive the entire analysis process, and since every user is unique, there is no fixed path for this process. Users perceive a visualization, based on their previously acquired knowledge, the tasks which

need to be done, or the goal which is intended to be achieved. Different users might draw different insights from the exact same visualization. These insights may be completely new and augment the users' knowledge base. Based on these insights, the users can generate various hypotheses which require further exploration or taking actions.

- *Exploration*: The derived insights may not always be the end results. Users might also come up with further questions. The process then enters a loop, where users steer the analysis process to draw new insights through exploration, either by directly interacting with the visualizations or by modifying different parameters of the analysis. This process can go on for as long as required until the users find answers to prove or disprove their hypotheses.
- *Action*: Taking actions is the primary aim of the LAVA model. Based on the gained knowledge, different actions, such as intervention, feedback, and recommendation, may be performed with the aim of improving the learning activities.

5.5 The LAVA Model in Action

As a proof of concept, we applied the LAVA model in the Open Learning Analytics Platform (OpenLAP). OpenLAP is an ecosystem for Open Learning Analytics (OLA). The primary aim of OpenLAP is to collect heterogeneous data from multiple sources and support end users in defining custom indicators that meet their needs. An abstract architecture of OpenLAP is shown in Fig. 5.4. Based on the LAVA model, the "Indicator Editor" which is a component in the "Indicator Engine" of OpenLAP provides non-technical end users an intuitive and exploratory

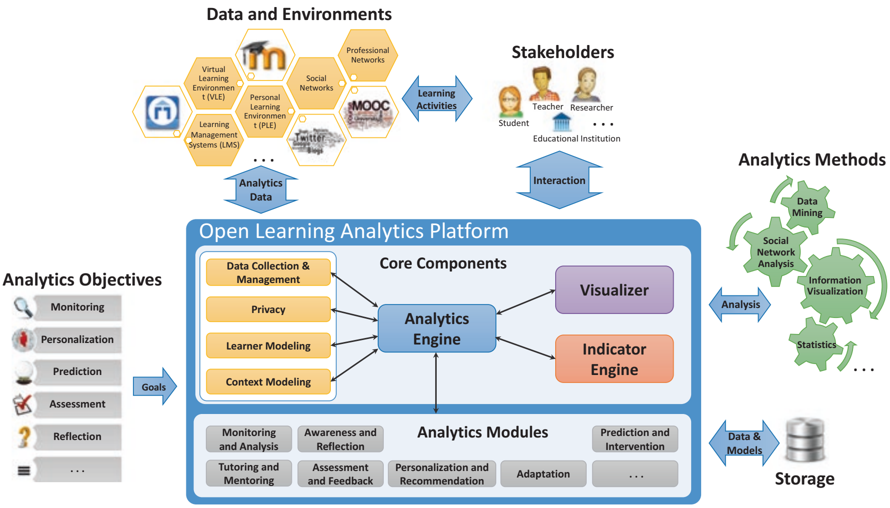

Fig. 5.4 The abstract architecture of OpenLAP. (Adapted from Chatti et al., 2017)

user interface (UI) that gives them control in defining their own indicators in a simple way. Following the Goal-Question-Indicator (GQI) approach proposed by Muslim, Chatti, Mughal, and Schroeder (2017), the "Indicator Editor" supports end users in a continuous LA process by setting appropriate analytics goal, formulating LA question, and defining indicators to answer the question. For each indicator, the user interacts with the "Indicator Editor" to explore the stored learning activity data, apply various data filters, specify an analytics method to analyze the data, and select an appropriate visualization technique to visualize the indicator. After finalizing the indicators, they are saved, and the HTML and JavaScript-based indicator request codes (IRC) are generated which can be embedded in any client application to provide analytics in context (Chatti, Muslim, & Schroeder, 2017; Muslim, Chatti, Mahapatra, & Schroeder, 2016; Muslim, Chatti, Bashir, Varela, & Schroeder, 2018).

The "Indicator Editor" supports three different types of indicators, namely, basic, composite, and multi-level analysis. The conceptual flow of each indicator type is shown in Fig. 5.5. The basic indicator is a simple indicator type that is precisely mapped to the GQI approach. The user generates a new indicator by defining a dataset, applying various filters, selecting an analytics method for analysis, and specifying the visualization technique to render the indicator. Using this type, simple statistical indicators can be easily generated, such as "activities of discussion forum per week" and "distribution of points in assignments." The composite indicator type allows the user to combine multiple basic indicators to form a composite indicator. Using this type, indicators like "my assignment points compared to an average of my peers" and "my learning resources views compared to the average of others" can be generated. The main condition for this type is that all the basic indicators to be combined should apply the same analytics method, whereas the dataset and filters can be different. The analysis results from each basic indicator are combined to provide a cumulative analyzed data which is rendered using the specified

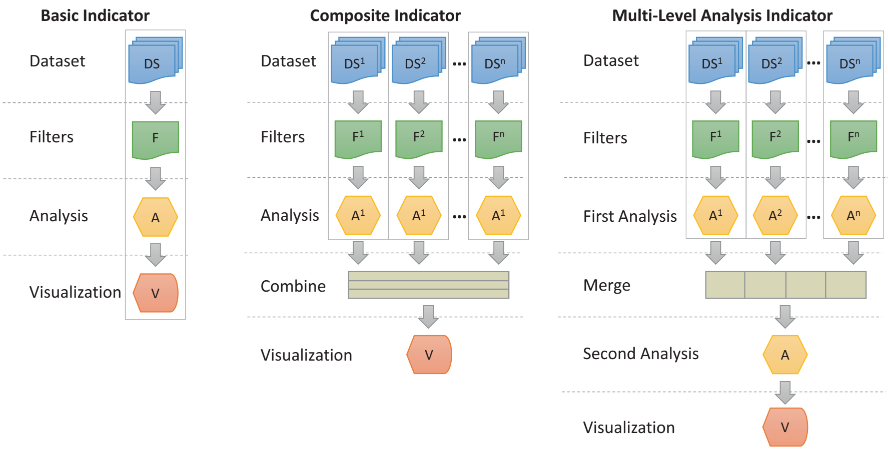

Fig. 5.5 Indicator types supported in the OpenLAP Indicator Editor

visualization technique. The multi-level analysis indicator type is used to generate complex indicators beyond simple statistical ones. These include indicators based on social network analysis or data mining methods, such as “cluster of students based on their learning resources views and average assignment points” and “predict students’ success rate” Similar to the composite indicator type, the multi-level analysis indicator allows the user to define multiple basic indicators to define the first-level analysis. However, the user does not have to apply the same analytics methods for the basic indicators. Then, the user has to specify an attribute common in all the basic indicators based on which the analyzed data is merged and passed on to the second-level analysis. Finally, the result of the second-level analysis is rendered using the selected visualization technique. Concrete examples of composite indicators and multi-level analysis indicators are discussed in Sect. 5.7.3. In the following, we discuss the implementation of the “Indicator Editor” in terms of the phases of the LAVA model.

5.5.1 Learning Activities

Learners generate a tremendous amount of interaction data while performing various activities in different learning environments. These activities include reading, writing, accessing and uploading learning material, taking tests, watching videos, and collaborating in wikis and discussion forums. Learners and teachers can use the “Indicator Editor” to get actionable insights from this interaction data.

5.5.2 Data Collection

OpenLAP provides mechanisms to collect interaction data from different learning environments. For each source, a data collection component (collector) needs to be developed. It can either be an integrated component in a source that gathers data and pushes it to OpenLAP or an intermediate component (adapter) that receives data from a source and transforms it into a required data format before sending it to OpenLAP.

5.5.3 Data Storage and Pre-processing

OpenLAP processes the heterogeneous data coming from different sources and stores it in the data model called Learning Context Data Model (LCDM) proposed by Thüs, Chatti, Greven, and Schroeder (2014). LCDM represents a user-centric, modular, and easy to understand data model that holds additional semantic information about the context in which a learning activity has happened (Lukarov et al., 2014).

The data storage mechanism in OpenLAP is flexible and can easily be modified to make OpenLAP work with other data models, such as xAPI and IMS Caliper (Muslim et al., 2016, 2017).

5.5.4 Analysis

OpenLAP adopts a modular and extensible architecture that allows the easy integration of new analytics methods, ranging from basic statistical methods to more advanced methods like clustering, classification, and social network analysis (Muslim et al., 2018).

5.5.5 Visualization

OpenLAP allows easy integration of new visualization techniques due to its modular and extensible architecture (Muslim et al., 2018). Currently, different visualization types are available in OpenLAP based on the "Google charts" and "C3.js" visualization libraries, such as bar, pie, line, box plot, and scatterplot. The "Indicator Editor" allows users to try out different visualizations during the indicator generation process and select the appropriate visualization according to their needs. Figure 5.6 shows sample visualization generated with the "Indicator Editor."

5.5.6 Perception and Knowledge

Selecting appropriate visualizations in the "Indicator Editor" can effectively help users find patterns and get actionable insights into the data. Users perceive a visualization based on their previously acquired knowledge. Based on the visualization,

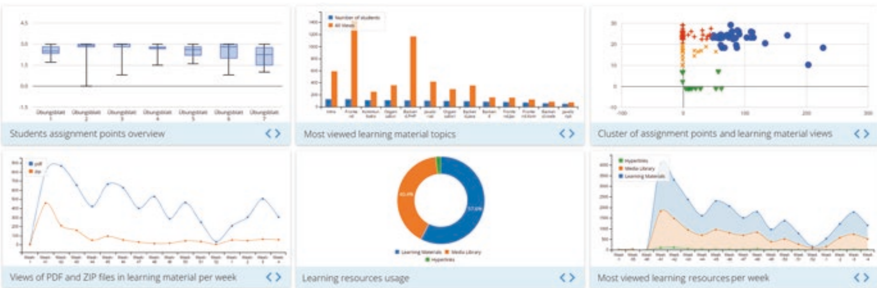

Fig. 5.6 Sample visualizations generated with the OpenLAP Indicator Editor

users can generate various hypotheses. The process then enters a loop, where the users drive the analysis process to accumulate new knowledge through exploration in order to prove or disprove their hypotheses. Newly drawn insights can add to the knowledge of the users.

5.5.7 *Exploration*

The "Indicator Editor" in OpenLAP is an interactive conversational component that enables users to control the indicator generation process, according to their needs. Following the GQI approach, the "Indicator Editor" allows end users to generate indicators by setting analytics goal, formulating questions, and defining indicators to answer these questions. The "Indicator Editor" supports users in exploring, analyzing, and visualizing the data through dynamic interactions, including filtering the data used for the indicator, selecting the analytics methods and visualization techniques, and changing the parameters of the data analysis algorithms. In the following, we present in detail the different sections of the "Indicator Editor" using an example of an instructor who wants to monitor the activities of her students in a specific course.

5.5.7.1 Goal

The first step in the indicator generation process is to select an appropriate LA goal, such as assessment, intervention, monitoring, prediction, or recommendation, as shown in Fig. 5.7. A predefined list of LA goals and their descriptions is provided to the users to help them in selecting an appropriate goal. However, if the provided list does not contain the required LA goal, the user has an option to request a new one, which will be reviewed by OpenLAP administrators and then added to the list. In our example of the instructor who wants to monitor the activities of her students, the "Monitoring" is selected as an appropriate LA goal.

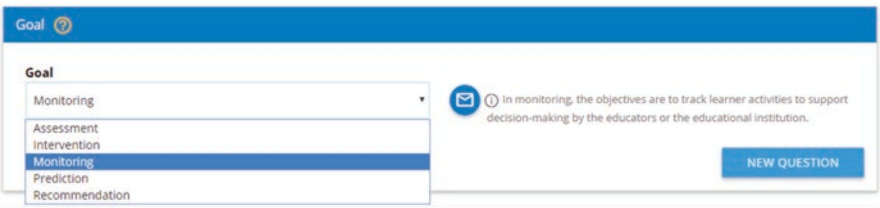

Fig. 5.7 The Goal section in the OpenLAP Indicator Editor

5.5.7.2 Question

After selecting an appropriate LA goal, the next step in the indicator generation process is to formulate a suitable LA question. Afterward, multiple indicators can be associated with the LA question either by loading an existing indicator generated by another user and modifying its parameters or defining a new basic, composite, or multi-level analysis indicator, as discussed in the next section. While a question might be asked in an abstract manner, an indicator is a concrete calculator with a corresponding visualization to answer the question. In our example, the instructor entered “How active are students in my class?” as the LA question and defined a set of four indicators to answer this question, namely, “Students weekly learning resources access,” “Students assignment points overview,” “Most viewed learning materials,” and “Correlation of assignment points and learning resources views,” as shown in Fig. 5.8. She can then view, delete, or select any associated indicator for editing again. Finally, she can visualize the question and the associated indicators in a dashboard format and save them to get the indicator request code (IRC) for the whole question as well as for each individual indicator, as shown in Fig. 5.9. The IRC is composed of HTML and JavaScript code which can be embedded in any client application that allows web content (e.g., dashboards, web pages).

5.5.7.3 Indicator

Three different indicator types, namely, basic indicator, composite indicator, and multi-level analysis indicator can be associated with an LA question.

Basic Indicator
In our example, the instructor associated her question with two basic indicators “Students weekly learning resources access” and “Students assignment points overview,” which are shown in blue (see Fig. 5.8). The process of defining a basic indicator consists of four main parts, namely, dataset, filters, analysis, and visualization.

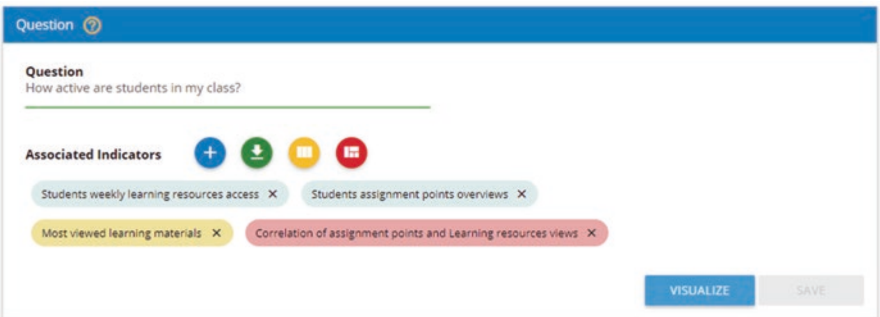

Fig. 5.8 The Question section in the OpenLAP Indicator Editor

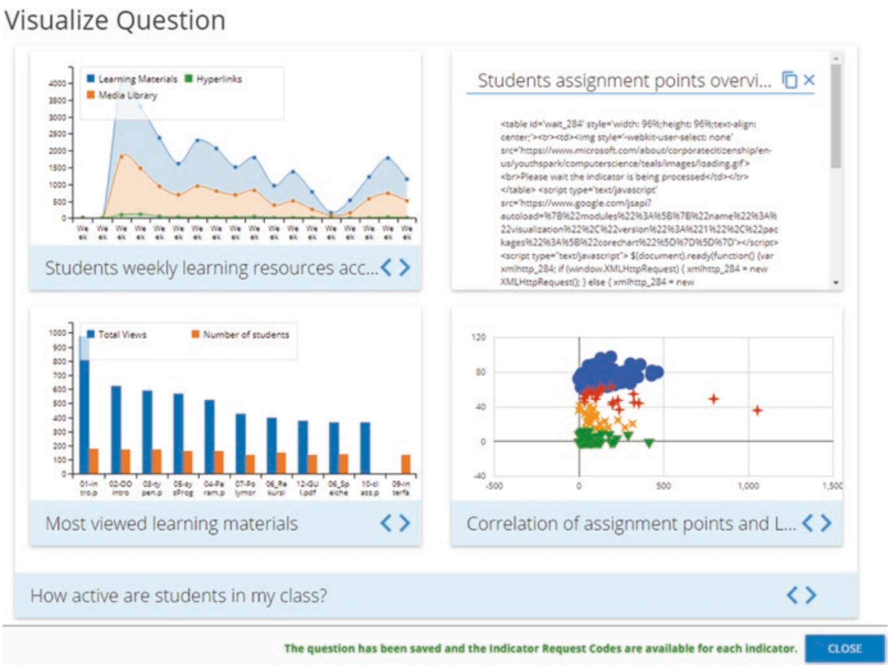

Fig. 5.9 The Visualize Question section in the OpenLAP Indicator Editor containing Indicator Request Code (IRC)

- *Dataset*: This part of the “Indicator Editor” allows the user to define the parameters for the indicator dataset. These include the list of data sources (e.g., Moodle, edX), platform types (e.g., web, mobile), performed actions (e.g., add, view, update, delete, post), and the category of objects on which the action is performed (e.g., wiki, discussion forum, assignments, learning materials). Figure 5.10 shows the dataset part of the “Indicator Editor” where the required parameters have been selected for the “students weekly learning resources access” indicator.
- *Filters*: This part allows the user to refine the selected dataset by applying various filters. Three different types of filters can be applied to the dataset, namely, “Attribute,” “Time,” and “User.” These filters are grouped under two tabs, as shown in Fig. 5.11. The “Attribute” filters are applied to the additional semantic information stored related to each category. For example, for “Learning Materials” category, attributes like “Name,” “File Extension,” and “Size (in Bytes)” are available, whereas for “Assignments” category, possible available attributes are “Title,” “Total Marks,” and “Due Date.” When multiple categories are selected, only the attributes common to all the selected categories are provided. The user can search for the possible values of the selected attribute and select one or more values. All the applied attribute filters are shown at the top, from where they can easily be removed. The “Time / User” tab is split into the “Time” and “User” sections. The “Time” filter section provides the possibility to specify the start and/or end date for which the dataset should be considered. In

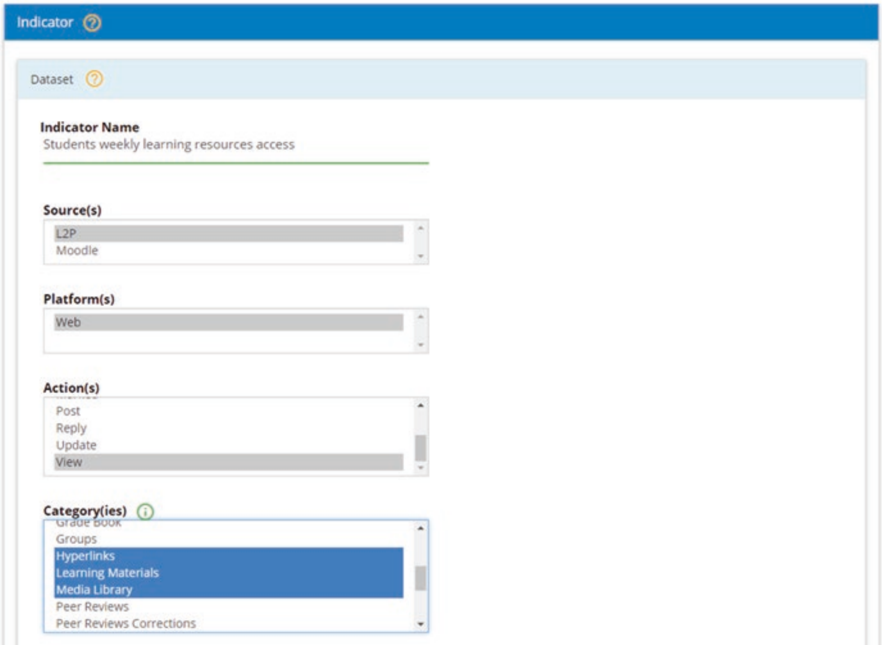

Fig. 5.10 The Dataset part in the OpenLAP Indicator Editor to define a Basic Indicator

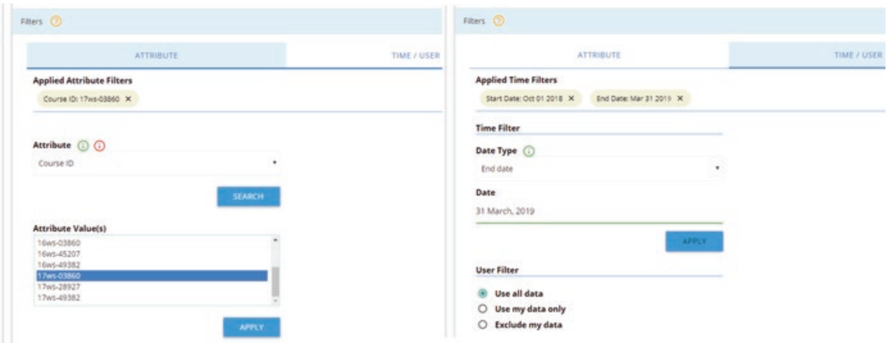

Fig. 5.11 The Filters part in the OpenLAP Indicator Editor to define a Basic Indicator

the "User" section, due to the privacy concerns, the user only has the option to use the anonymized data of everyone, use own data only, or use the anonymized data of everyone excluding own data.

- *Analysis*: After defining the dataset and applying the required filters, the user can specify which analytics method should be used to perform the analysis on the filtered dataset. The additional parameters required by the analytics methods are shown to the user with the default values pre-selected. The final step is to define the mappings between the filtered dataset and the selected analytics method by specifying which column of the dataset should be used for which input of the

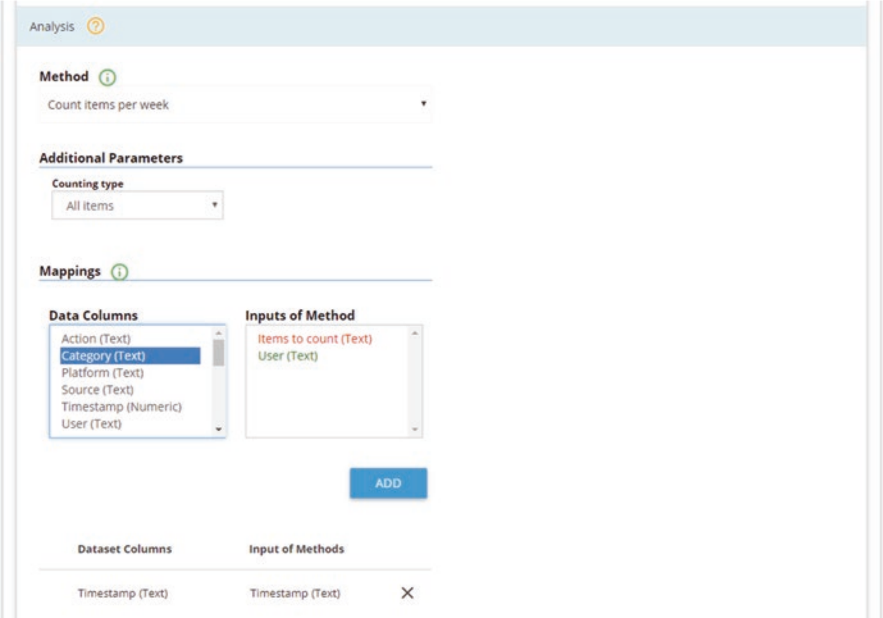

Fig. 5.12 The Analysis part in the OpenLAP Indicator Editor to define a Basic Indicator

selected analytics method. The mapping is performed by selecting an analytics method input as well as the dataset column that needs to be mapped to the selected input and clicking the "Add" button. The mapped analytics method inputs are removed from the selection and added to the list of mapped inputs. The red-colored analytics method inputs are required, and the green ones are optional. For the "students weekly learning resources access" example indicator, the instructor selected the analytics method "Count items per week," as shown in Fig. 5.12. This analytics method requires three inputs, namely, "Items to count," "User," and "Timestamp." The "(Text)" part attached to each input indicates that the specific input can only accept the data columns that are of "(Text)" type. The "Timestamp" input has already been mapped to the "Timestamp" data column, and it is no longer available in the analytics method inputs list.

- *Visualization*: The final step in the indicator generation process is to define the visualization of the indicator. In this part, the user selects an appropriate visualization library and visualization type for the indicator. Figure 5.13 shows the "Stacked Area Chart" visualization type of the "C3/D3.js" visualization library, which is used for the "students weekly learning resources access" example indicator. Similar to the analytics method part, the user defines the mapping between the outputs of the analytics method and the inputs of the selected visualization type. After defining all the parameters, the indicator can be previewed. The user can further explore by changing the dataset, applying different filters, and updating the specified mappings to come up with the indicator that fits her needs. Finally, the indicator can be associated with the LA question.

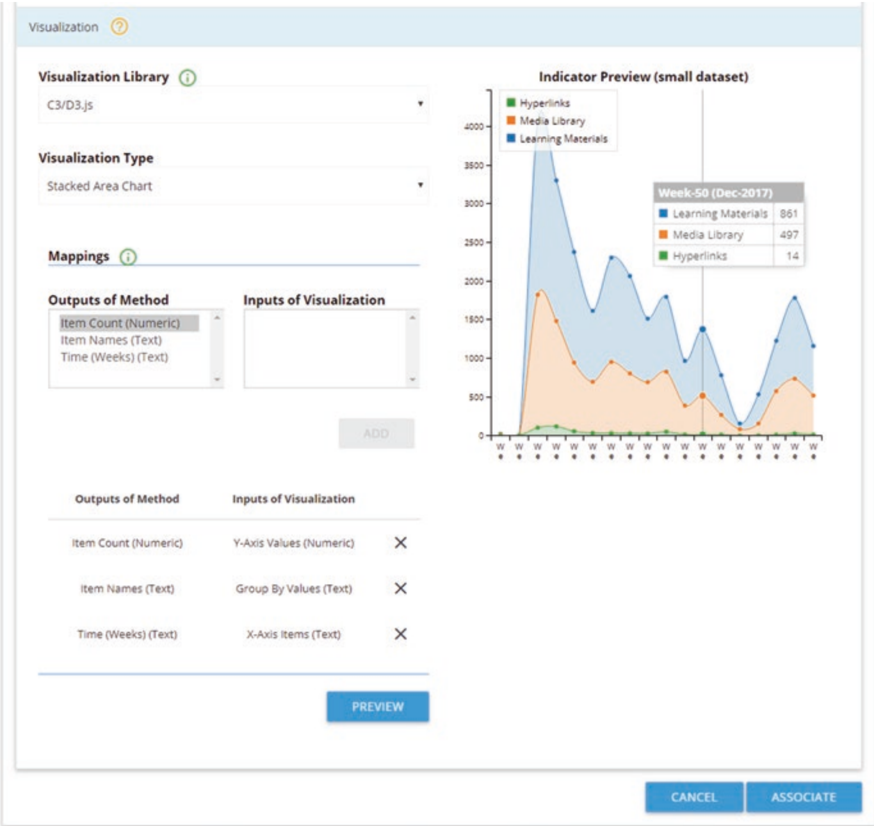

Fig. 5.13 The Visualization part in the OpenLAP Indicator Editor to define a Basic Indicator

Composite Indicator

A composite indicator can be generated by combining two or more basic indicators already associated with the LA question. The main condition for the composite indicator is that all the basic indicators to be combined should apply the same analytics method. For the example LA question "How active are students in my class?", the instructor defined a composite indicator called "Most viewed learning materials" using the "Number of students" and "Total Views" basic indicators, as shown in Fig. 5.14. Based on the analytics method of the first selected basic indicator, the UI notifies the user which basic indicators can be combined by highlighting them with green and disabling the others. In the example, the two basic indicators apply the analytics method "Count N most occurring items." The "Number of students" indicator counts the top 10 learning materials which are viewed by the highest number of students, and the "Total View" indicator counts the top 10 most viewed learning materials. After selecting the required indicators to combine, the user selects an appropriate visualization library and visualization type to preview the indicator. Finally, the composite indicator is associated with the LA question and shown in yellow (see Fig. 5.8).

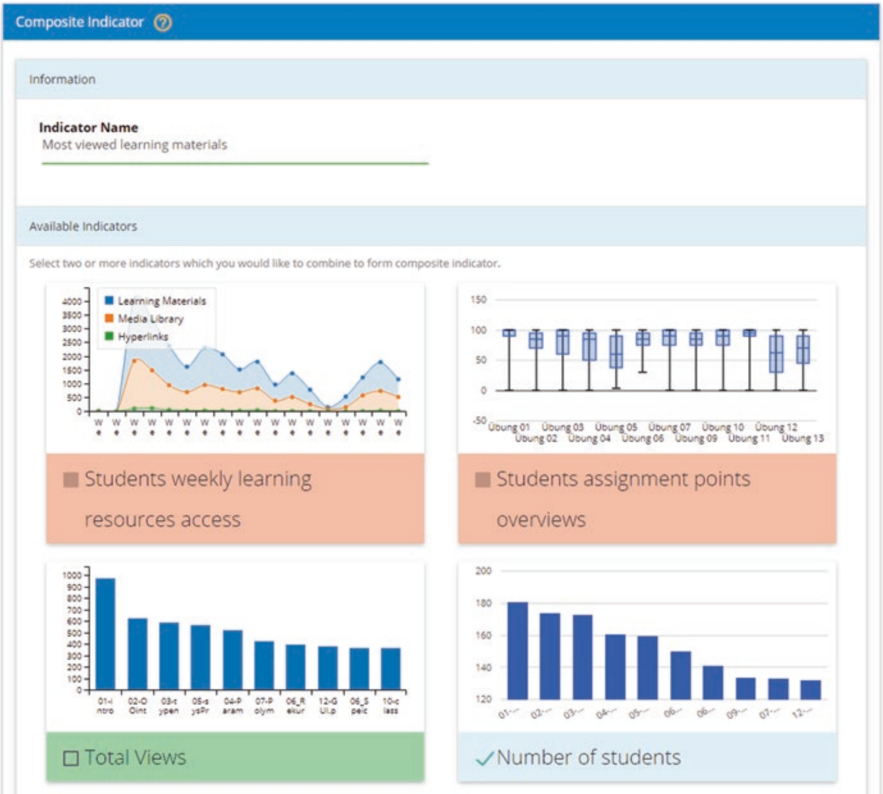

Fig. 5.14 The Composite Indicator section in the OpenLAP Indicator Editor

Multi-level Analysis Indicator

The multi-level analysis indicator consists of three parts, namely, first-level analysis, second-level analysis, and visualization. Figure 5.15 shows the UI for the first-level analysis part where the instructor selected two basic indicators, namely, "Views" and "Points" to create a multi-level analysis indicator "Correlation of assignment points and learning resources views." Next, the analyzed datasets from the basic indicators are merged by selecting a common attribute and passed on to the second-level analysis to identify clusters of students based on their assignment points and learning material views. The second-level analysis and the visualization parts are similar to the analysis and the visualization parts of the basic indicator. Finally, the multi-level analysis indicator is associated with the LA question and shown in red (see Fig. 5.8).

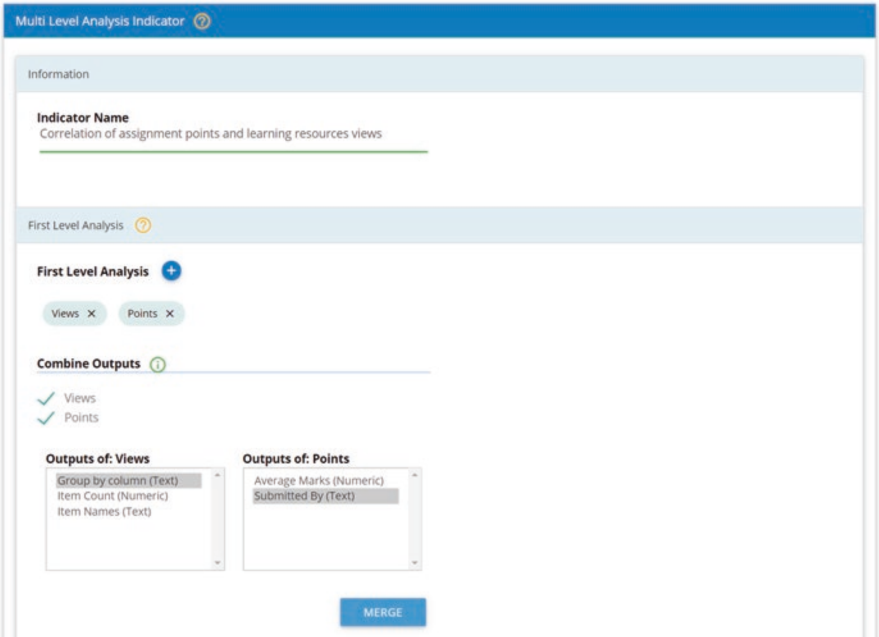

Fig. 5.15 The Multi-level Analysis Indicator section in the OpenLAP Indicator Editor

5.5.8 *Action*

The aim of the "Indicator Editor" is to help users turn data into decisions and actions (e.g., intervention, feedback, recommendation) by creating custom indicators, following the GQI approach. Since users are steering the indicator generation process, the insights drawn from these indicators will fit their needs and thus lead to useful actions. This is at the heart of LAVA model.

5.6 Evaluation

A thorough evaluation of the indicator generation process was conducted based on the technology acceptance model (TAM) to assess the user acceptance of the OpenLAP "Indicator Editor." Based on TAM, the two most important factors that influence the user's decision to use the system are perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, Bagozzi, & Warshaw, 1989). Therefore, the "Indicator Editor" is evaluated in terms of usefulness and usability.

5.6.1 Method

We employed various techniques to perform a quantitative and qualitative evaluation of the "Indicator Editor" in terms of usefulness and usability (Dix, Finlay, Abowd, & Beale, 2003). The cognitive walkthrough evaluation approach was used with the participants who were experts in the field of data analytics and LA, and the think aloud method was used with the students (Nielsen, 1994). The participants were asked to use the "Indicator Editor" and generate a set of different indicators. Moreover, a custom questionnaire was also filled out by the participants at the end of the interview sessions, which contained questions related to the overall usefulness of the "Indicator Editor" and its usability based on the System Usability Scale (SUS) (Brooke, 1996). These questions were also discussed with the participants in the interview sessions.

5.6.1.1 Setting

OpenLAP was seamlessly integrated as a third-party system in the university LMS and made available to the participants of three courses. Four hundred and fourteen students and twelve teachers volunteered to take part in the study. After a month of using the system, the participants were requested to take part in semi-structured interview sessions for the purpose of collecting detailed facts, opinions, and critiques about different aspects of using the "Indicator Editor." Each interview session lasted 30–60 minutes depending on the pace at which the participant performed the tasks and the amount of provided feedback. The audio, video, and screen recording for each interview session were captured. The data collected from each session was analyzed to improve the design of the questions for the next interview sessions. After all the sessions were finished, the next step was to clean, organize, and examine the results and draw conclusions. Thus, the audio recording of each interview was carefully transcribed. Additional information was extracted from the videos as well as from the screen recordings and embedded in the text. Afterward, the data from all the interview sessions were coded based on the coding process proposed by Corbin and Strauss (1990), combined, and analyzed to generate understanding and derive patterns.

5.6.1.2 Participants

The participants who volunteered for the semi-structured interview sessions included 34 students and 5 teachers. The students were enrolled in either a bachelor (70%) or a master (30%) degree program in computer science. About 28% of the participants told that they were not familiar with data analytics concepts, and about 51% were not familiar with LA concepts. About 54% and 36% of the participants mentioned that they were aware of the concepts of data analytics and LA, respectively.

5.6.2 *Usefulness*

The questionnaire contained the following questions to gauge the overall usefulness of the "Indicator Editor":

- Do you think that by using the "Indicator Editor" you can now generate the required indicators to support your learning/teaching activities?
- Do you think that the "Indicator Editor" is a useful tool to improve your teaching/learning experience?
- Do you think that the "Indicator Editor" provides the interaction possibilities that you expect from it?
- Are you satisfied with the level of interactivity to support indicator customization provided by the "Indicator Editor"?

Around 79% of the participants thought that they will be able to generate indicators that can support their learning/teaching activities, as shown in Fig. 5.16. All the teachers said that the "Indicator Editor" provides enough possibilities to generate the required indicators. One teacher further added that this is dependent on the quality and the amount of data available in OpenLAP. Most of the students also agreed that they can easily define the required indicators. However, they might need some time to try out different options and learn the system to be able to generate advanced indicators. Eighty-seven percent of the participants agreed that the "Indicator Editor" has the potential to be a useful analytics tool to improve their teaching/learning experience. One student said that "normally just the teachers have this information via the evaluations and now I am on this side and I can evaluate myself." In response to the question of the "Indicator Editor" providing the expected interaction possibilities, 78% of the participants replied positively. Around 76% of the participants agreed that the level of interactivity has a positive effect on the indicator customization. Some participants stated that the exploration options provided in the "Indicator Editor" would lead to customized indicators that meet their needs. However, some of the participants suggested to design

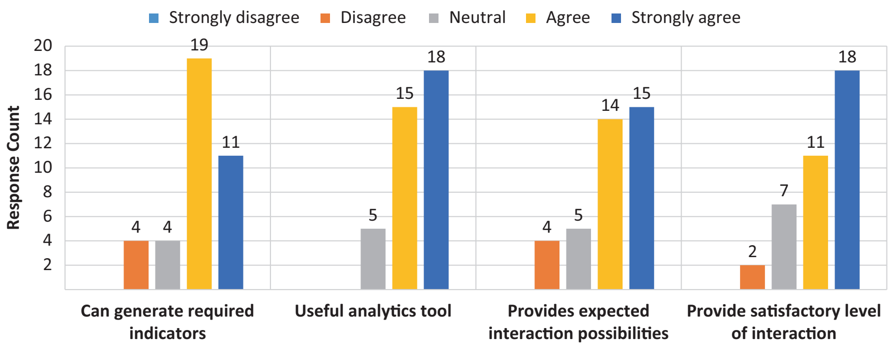

Fig. 5.16 Overall usefulness of the OpenLAP Indicator Editor

two separate modes of the UI, one with detailed customization possibilities for technical users and another one with just simple options for non-technical ones.

The interview sessions focused on the usefulness of the GQI approach in the "Indicator Editor." In general, the GQI approach was perceived as an intuitive way to structure the process of defining custom indicators. Some participants mentioned that the effect of selecting a specific LA goal on the overall indicator generation process was not clear. However, after explaining that as future work we are planning to extend the "Indicator Editor" with a feature that provides recommendations of questions and indicators based on the selected goal, almost everyone agreed on the importance of specifying a goal at the beginning of the indicator generation process. Some participants did not understand the relationship between the question and indicators. For example, a student said that "the goal is abstract that I understood … that was logical to me … I was not sure how a question is different from an indicator." As an improvement, some participants suggested to provide sample questions and related indicators in the "Indicator Editor."

5.6.3 Usability

The usability of the "Indicator Editor" is calculated using the System Usability Scale (SUS), which is a simple ten-item attitude Likert scale giving a global view of subjective assessments of usability (Brooke 1996). Based on the results of the custom questionnaire, the SUS score of the "Indicator Editor" is calculated to be approximately 61. The results of the overall usability evaluation are shown in Fig. 5.17. Seventy-four percent of the participants agreed that they would use the "Indicator Editor" frequently, e.g., at the beginning of a semester when the courses start, to set up their personal dashboards with the required indicators or when they might need an indicator which is not already available in the indicator catalog. However, there is relatively less agreement related to the ease of use of the system. According to the participants, this is mainly due to the unfamiliarity with the indicator generation process, the mapping steps, and the usage of some terms which might not be easy to understand by non-technical users, e.g., columns, mapping, and attributes. Some participants suggested again to have beginner and advanced modes of the UI. In terms of learnability, some participants stated that the system requires some effort and time to understand and start working with it and requested to provide video tutorials of different possible scenarios in the system.

The interview sessions revealed that defining mappings in the analysis and visualization parts of the indicator generation process (see Sect. 5.7.3) was the most complex task. For example, a student said that "this (mapping) is cool but I think it's really hard to do this on your own … especially for beginners." In order to improve the usability of the mapping steps, participants suggested to include automated mappings, e.g., "if I have 'Timestamp (Numeric)' as input and have the same column name then it's the obvious mapping … so at least it should be automatic and then if required I can change it" and "if you select something 'Text' based then you

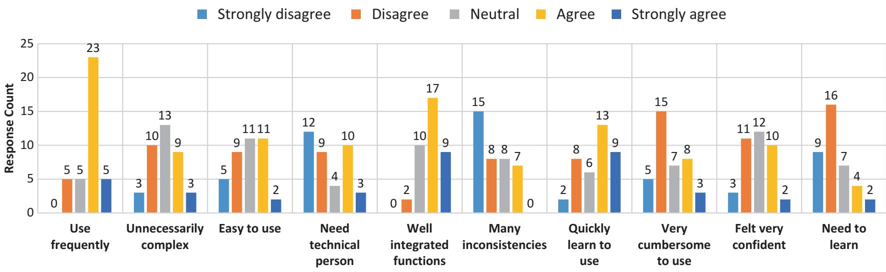

Fig. 5.17 Overall usability of the OpenLAP Indicator Editor

don't see 'Numeric' values in the other list ...." Participants also suggested to provide examples of the expected inputs/outputs, e.g., "I would prefer to directly add ... maybe in curly brackets after dataset column name, one or two examples ... like 'Source (Text) {edX, Moodle}' ... then it would be clear."

5.7 Conclusion

In this paper, we argued that adopting a human-centered learning analytics (HCLA) approach is vital to improve the acceptance and adoption of learning analytics. We proposed the Learning Analytics and Visual Analytics (LAVA) model as a possible implementation of the HCLA approach that, by having the human in the loop, has the potential to improve the acceptance of learning analytics. As a proof of concept, we applied the LAVA model in the Open Learning Analytics Platform (OpenLAP) to support learners and teachers in defining custom indicators that meet their needs. We conducted a mixed-method evaluation of the user acceptance of the OpenLAP "Indicator Editor" based on the technology acceptance model (TAM). The evaluation results showed that following a LAVA model-based approach has the potential to push forward the acceptance and adoption of learning analytics.

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Chapter 6
See You at the Intersection: Bringing Together Different Approaches to Uncover Deeper Analytics Insights

David Paul Fulcher, Margaret Wallace, and Maarten de Laat

6.1 Introduction

With an increased focus towards digital learning in higher education comes the proliferation of data generated by teachers and students in their day-to-day educational practice. More attention is being paid to the different ways in which this data can be used to support the goals of the student, the teacher and the institution. Learning analytics seeks to make this a reality through information and analysis in the context of key teaching and learning processes that result in decisions and actions to improve student outcomes. The educational drivers for learning analytics involve enriched student learning experiences. The economic drivers for learning analytics involve introducing efficiency and cost-effectiveness into education. These different framings create tensions when attempting to realize the potential of education to "help people to live well in a world worth living in" (Kemmis, 2014, p.21). In this chapter we describe the current practices at an Australian university six years into the implementation of learning analytics that covers both top-down and bottom-up aspects to try and maximize uptake by different stakeholders. Heath and Leinonen (2016) have already offered empirical insight into the implementation of learning analytics at this site. This chapter extends on this to explore the adoption of learning analytics that has unfolded since and so offer a useful source of ideas about ways of implementing institutional approaches to learning analytics along with a discussion of implications for future practice.

In their review of the various models informing adoption of large-scale learning analytics initiatives, Colvin, Dawson, Wade, and Gašević (2017) argue there are three broad focus areas: input models, process models and output models. Input models focus on first establishing the necessary elements to facilitate implementation

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of learning analytics programs. Process models focus on the "how" of learning analytics implementation, describing sequential steps to put in place. Output models focus on the outcomes associated with the implementation of learning analytics. Input and process models can be linear and non-linear, recognizing the complex and interrelated nature of learning analytics adoption. Output models tend to be linear with universal outcomes assumed based on different levels of implementation maturity. Common elements across these different models identified by Colvin et al. include: strategy, leadership, staff and institutional capacity, technological readiness and organizational culture. These models are often conceptual in nature and created out of data collected mostly from learning analytics specialists. To address this Colvin et al. (2015) set out to understand learning analytics implementation as enacted practice across the Australian higher education sector. The results of this study showed nuanced relationships between the various conceptions of learning analytics and its implementation. While some of the important features identified were consistent with the conceptual models, other important elements identified by the study were institutional context and the conception of learning analytics at the particular site. The study by Klein, Lester, Rangwala, and Johri (2019) reached a similar conclusion regarding institutional context, with the localized structures and resources seen to impact the adoption of learning analytics tools at a large public university in the United States. In terms of the way in which learning analytics is conceived at the local site, Colvin et al. (2015) found two broad clusters of learning analytics implementation. Either it was purely a tool focused on retaining students or it was partly this as well as targeted towards drawing out and informing teaching practice and student learning. Such nuance reflects the interplay of the different economic and educational drivers for learning analytics. It seems that in order to get large scale learning analytics initiatives off the ground student retention needs to be a key factor, no matter what.

6.2 The Story So Far

This chapter focuses on the use of learning analytics at the University of Wollongong (UOW). UOW is a regional university in eastern Australia with approximately 33,000 undergraduate and postgraduate students enrolled and approximately 2800 staff employed across five faculties and centralised services. UOW has a network of four regional campuses and three metropolitan campuses in the greater Sydney area. Beyond Australia UOW has campuses in the United Arab Emirates, Hong Kong and a presence in China, Malaysia and Singapore. A strategy for the roll out of learning analytics capabilities at the Australian campuses has been in place at UOW since 2013. To guard against the perception of learning analytics as a force outside an individual's control and as the sole factor influencing educational practice, a multifaceted approach has been taken to the use of learning analytics at UOW from an early stage. It is the academic endeavor, rather than technology and data that has driven learning analytics at UOW (Heath & Leinonen, 2016). Work has been undertaken under the executive sponsorship of the Deputy Vice-Chancellor (Academic), with a governance structure established to provide guidance so that ethics and privacy are treated, not just as problems to be overcome, but rather as opportunities to refine and improve learning analytics tools & processes (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013).

Few frameworks for large-scale adoption of learning analytics seem to draw on student perspectives (Colvin et al., 2017). At UOW a student survey was conducted to find out about the types of functionality desired from learning analytics, perspectives on privacy matters and preferences for interventions arising from learning analytics (Heath & Fulcher, 2017). The results informed both the strategy and accompanying learning analytics data use policy at UOW. Feedback was provided on the draft policy during consultation rounds with staff and students. The policy was also influenced by literature emerging at the time on these matters (JISC, 2015; Macfadyen, Dawson, Pardo, & Gašević, 2014; Prinsloo & Slade, 2013). The policy is primarily concerned with assisting UOW staff carry out learning analytics activities appropriately, effectively and responsibly. Guidelines for taking action from learning analytics insights were also developed in conjunction with the policy to provide a framework for integrating the process of interpreting and acting on learning analytics insights into the flow of existing learning, teaching and student support. UOW took the position that students could not opt out of learning analytics. This was debated at length by the governance committees, but was ultimately based on the university's duty of care to do what it can to maximize the likelihood of student success. In the interests of transparency, different communication channels have been used to ensure students awareness of learning analytics use. The learning analytics data use policy also states that students have the right to see their data used in learning analytics activities and to correct any inaccuracies about themselves.

The learning analytics team have been positioned as part of the centralized teaching and learning unit at UOW, which collaborates with staff and students to support sustainable improvements in teaching practice and student learning. This type of organizational structure for learning analytics meant budget and technology decisions were made at an institutional level. This created a top-down environment in which implementation of learning analytics tools were aligned with structures, resources and leadership across the institution. The focus here has been on early alert of students predicted to fail or withdraw from enrolled units. The learning analytics team distribute a series of reports at key points in the academic semester to coordinators of large first-year undergraduate units to help draw attention to patterns that may not be readily apparent. Unit coordinators are academic staff with specialist knowledge in the content area of the unit. They are responsible for the design of the unit, the sequencing and content of classes, the design of assessment tasks and the management of assessment marking and feedback. They have responsibilities for the quality of the teaching and learning in that unit and are required to monitor student performance and subject feedback to guide ongoing enhancement and development of the subject. Coordinators of other units have been able to opt in so that they can receive reports during semester for their units. Figure 6.1 below outlines the uptake of learning analytics at UOW by unit coordinators since initial

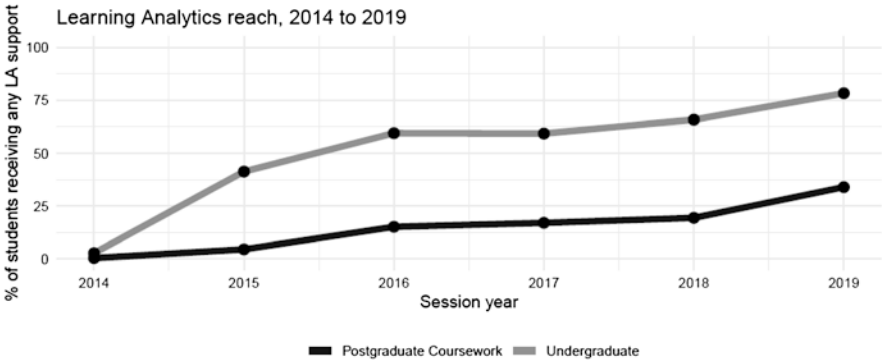

Fig. 6.1 Uptake of unit-level learning analytics at UOW

trials in 2014. By 2019, most undergraduate students (78%) at UOW were enrolled in at least one unit receiving learning analytics support. At the same time, 34% of postgraduate coursework students were in at least one unit with learning analytics support. This reflects the focus of learning analytics at UOW on helping undergraduates' transition into university study.

6.2.1 Centralized Support

It is our experience that the academic issues learning analytics identifies for UOW students and the interventions that stem from a student being identified on a learning analytics report are often general to the student and are not specific to the unit in which they are identified. In accordance with this, separate student support staff to the unit coordinators perform proactive outreach early in the academic semester in response to the insights generated by the learning analytics team. One of the ethical issues related to analytics about students is the danger of reducing each person to an individual metric (Ifenthaler & Schumacher, 2016; Roberts, Howell, Seaman, & Gibson, 2016). The data only ever tells you limited information about each student. What is important is that the purpose of the action taken with students who may be encountering difficulties with getting their studies underway is to better understand their particular situation and provide tailored support. Utilising separate student support staff in the faculty has also helped to address a common complaint from academic staff: the amount of time involved with making sense of the results and knowing what action to take with students (Howell, Roberts, Seaman, & Gibson, 2018; Klein et al., 2019). Given the contextual knowledge academic staff often have about the academic support needs for individual students they have still been encouraged to take action where appropriate. This has been complemented by the outreach performed by the central student support unit who have expertise in using positive reinforcement to help influence student behaviour and ensure a baseline of action has been taken with students who may be struggling.

6.2.2 System Generated Reports

The indicators used to identify students who may be at risk of dropping out are based on data warehouse infrastructure that brings together key components of the teaching and learning ecosystem at UOW (Heath & Leinonen, 2016). This includes data from the Learning Management System (LMS), library usage (aggregated), peer assisted supplemental instruction sessions and the student information system. While external software vendors have started offering similar functionality, the internal data warehouse has been used at UOW to drive this work as it brought together data missing from any single software component of the UOW learning platform. Having dedicated resources familiar with the local conditions responsible for the ongoing maintenance of the technical infrastructure used for learning analytics at UOW has ensured responsiveness to changes in the teaching and learning environment. It has also meant increased transparency in the techniques used to identify students who could benefit from additional assistance, which is another ethical concern of learning analytics (Lawson, Beer, Rossi, Moore, & Fleming, 2016; Lester, Klein, Rangwala, & Johri, 2017; Roberts et al., 2016; Slade & Prinsloo, 2013). Following guidance from the learning analytics ethical use of data advisory group, a deliberate effort was made to use indicators based on student behaviours rather than inherent student characteristics such as race, gender and socioeconomic background. Apart from yielding more accurate predictions about student outcomes, it has also helped reduce bias in the analytics techniques. Just because a student has a background not typically associated with higher education participation does not automatically put them at risk of early withdrawal (Gašević, Dawson, Rogers, & Gasevic, 2016; Lawson et al., 2016). Figure 6.2 below is a sample of a report provided to unit coordinators at the end of week 3 (out of a 13-week academic semester). This point in the academic semester was chosen because a few weeks had gone by to generate digital traces about student behaviour and it was still early enough for students to withdraw from units without incurring financial consequences. Students have been ranked on the report by the number of risk criteria they meet, the greater the number of risks the higher the student appeared on the report. Trials are underway at UOW to extend the information provided in this report with predictive modelling techniques, with a key challenge being to strike a balance between accuracy and transparency so that it is clear why a student has been identified (Hill, Fulcher, Sie, & de Laat, 2018).

The reports, such as the sample provided in Fig. 6.2, were designed with scalability in mind. Regardless of the unit taught, the coordinator received a similar looking report at the end of week 3 that displayed results specific to their student cohort. The reports have been formatted with a cover page describing their purpose and suggestions on how it can be used by the unit coordinator. An appendix has also been included with definitions for the unit coordinator of each of the risk criteria included in the report. These elements have served as nudges to assist unit coordinators to make sense of the report results in combination with their contextual awareness of the unit being taught to then decide what action to take (Dietz-Uhler &

									Criteria					
# of criteria met	Student Name	Student #	Tutorial Group	Campus	Contact #	Student Email	Disability	Weighted Average Mark	Has not logged into LMS	Has not logged into SIS	Student is late enrolment	Student not meeting minimum rate of progress	Student is repeating subject	Student not in a tutorial group
3	First, Surname	1234567		[Campus]	[Mobile]	abc123@uowmail.edu.au		49	X			X		X
3	First, Surname	1234567		[Campus]	[Mobile]	abc123@uowmail.edu.au		65	X	X				X
3	First, Surname	1234567		[Campus]	[Mobile]	abc123@uowmail.edu.au		49	X			X		X
3	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		52	X			X	X	
2	First, Surname	1234567		[Campus]	[Mobile]	abc123@uowmail.edu.au		65	X					X
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au	X	44				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		40				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		60				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		25				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au	X	51				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		55				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		57				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		61				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		52				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		66				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		52				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		61				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		56				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au	X	55				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		49				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		59				X	X	
2	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		57				X	X	
1	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		49				X		
1	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		51				X		
1	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		64					X	
1	First, Surname	1234567	[Tutorial Name]	[Campus]	[Mobile]	abc123@uowmail.edu.au		41				X		

Fig. 6.2 Sample learning analytics report sent to unit coordinators early in semester

Hurn, 2013; Gašević et al., 2016; Gašević, Dawson, & Siemens, 2015). By having "analytics products" such as the standard reports produced by the learning analytics team, a consistent experience has occurred for the recipients because the reports look and feel similar. While this has yielded capabilities that have been extended across UOW, it has limited the depth of potential insights generated from the data available on the student learning experience in a particular context. This exposes opportunities for further exploration to address bespoke information or information displayed in ways that are novel or address issues unique to particular cohorts of students. This is where the concept of "research sprints" have been implemented by the learning analytics team at UOW to help answer grassroots questions individuals have about their teaching and learning context.

6.3 Research Sprints

A common criticism of learning analytics is the mismatch between the analytics available and the front-line teaching and learning context (Ali, Asadi, Gašević, Jovanović, & Hatala, 2013; Gašević et al., 2016; Klein et al., 2019; Macfadyen & Dawson, 2012). This is consistent with observations made during the implementation of systematised learning analytics reports at UOW. In response to this, the learning analytics unit at UOW has developed an adapted version of the Research

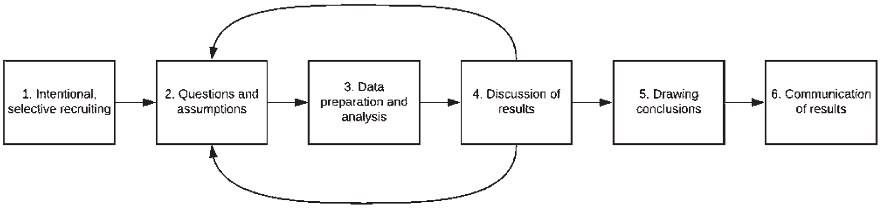

Fig. 6.3 Research sprint cycle. (Adapted from Rose (2016))

Sprint cycle (Rose, 2016). The Research Sprint process has aimed to uncover deeper insights in the available data to help answer particular pedagogical questions. It comprises six steps as outlined in Fig. 6.3:

1. *Intentional and selective recruiting*: this means making potential stakeholders (unit coordinators, instructional designers etc.) aware of the availability of a short burst of data science expertise (via the centralized learning analytics unit) and then selecting from a set of potential opportunities which align with and can be accommodated by the unit's staffing and resourcing;
2. *Identifying a set of questions and assumptions*: this step requires some close consultation with the stakeholder to refine and understand the problem they seek to solve, the question they seek to answer and the types of data they consider useful in providing insights;
3. *Data preparation and analysis*: this step requires good institutional and technical knowledge on the part of the data analyst so that they can advise on the type and nature of the available data and its propensity to generate a useful response to the query posed;
4. *Discussion of results*: the stakeholder and data analyst must undertake this step together. The data analyst can advise on the cleanliness and currency of the data, and on the descriptive and inferential statistics used or the models generated to help explain the results. Together with the stakeholder who draws on their more in-depth and personal knowledge of the context from which the raw data was taken there can be further refinements of the analysis and some 'meaning making' can take place;
5. *Drawing conclusions*: This step is an extension of the previous step, but it has a focus on working out what can and cannot be said about what the data shows and the level of confidence (and therefore trust and credibility) of those findings; and,
6. *Communication of results so that learnings can be applied to practice*: this step is highly reliant on the joint skills and effective collaboration of the data analyst and stakeholder. Together they jointly decide which forms of communication and methods of presentation (tables, graphs, dynamic or interactive displays, narrative forms) best communicate the findings of the sprint, and to whom should these findings be communicated.

The Research Sprint process requires an iterative approach so that the revelation of information and patterns guides the next step in the data analysis, as indicated by the backward arrows from Step 4 to Step 2 in Fig. 6.3. The term 'sprint' was used because the agreement between the learning analytics team and the commissioning unit has been a 2-week period. This has proven sufficient to find insights and short enough to adapt to new ideas as data exploration has unfolded. Even when there have been no insights, there have still been finished questions. This process has provided structure as well as flexibility to explore data and pose challenging questions using a grassroots approach so that analytics are immediately relevant for each particular context. Three examples of completed Research Sprints follow to show the range of uses of Research Sprints; explaining the ideas underpinning these steps and how they supported the sprint methodology. The examples also serve to highlight how the conduct of the sprints provided something not available through the routine system-generated reports described above, highly relevant to the requesting stakeholder, but not necessarily of immediate significance beyond the requesting unit. The first and second examples indicate the sorts of questions posed by academic units and the third, more detailed example, describes the response to a question from a central non-teaching unit. The examples are:

1. The First Year Chemistry Curriculum.
2. The French Language Curriculum.
3. The Analysis of Coursework Student Course Progress.

6.3.1 *The First Year Chemistry Curriculum*

The First Year Chemistry teaching team were interested in finding out the influence of Peer Assisted Study Sessions (PASS) on academic outcomes for students enrolled in first-year chemistry units (CHEM101 and CHEM 102) over the years 2015–2017. Peer Assisted Study Sessions (PASS) are an academic support program of supplemental instruction using successful later year students to facilitate peer-learning sessions in addition to the scheduled formal university classes (Dawson, van der Meer, Skalicky, & Cowley, 2014). The PASS program is often attached to what might be termed 'high risk' units. At UOW, the primary identification of 'high risk' is applied to those courses which have historically high rates of student failure or early withdrawal.

> The program integrates academic skills with course content in a series of peer-facilitated sessions that are voluntarily attended by students enrolled in these courses (Dawson et al., 2014, p. 610).

Each weekly PASS class is attended by a group of students enrolled in the target unit and is facilitated by a PASS Leader. PASS leaders are generally academically successful students with good interpersonal skills who recently successfully completed the unit. The PASS leader is responsible for facilitating,

> discussion around course content and related study skills, and for preparing learning activities such as worksheets, group work, problem-solving exercises, or mock exams for their students' (Dawson et al., 2014, p. 610).

The involvement of the First Year Chemistry team in a range of initiatives to re-develop the curriculum over the past several years, along with their sophisticated understanding of higher education pedagogy and the role of PASS, made this team ideal for their intentional and selective recruitment (Step 1 of the Research Sprint Process) to a Research Sprint. While the system-generated learning analytics products described in the first part of this chapter draw entirely on information applicable to all units (student attributes and student academic outcomes), this analysis differs from those because it used data only applicable to certain units. This involved data integration from a separate system that collected information on student participation in PASS. Therefore, an important part of Step 3 of this Research Sprint was the data preparation and analysis to ensure that the type of information that could inform the analysis was available and stored in a format that made it suitable for analysis.

Because Faculties resource aspects of the PASS programs for units within their disciplines, it is in their interests to evaluate the impact of such supports for students. In this analysis, only students who participated in both of the first-year chemistry units under consideration (CHEM101 and CHEM102) were included. These units were offered in consecutive academic semesters and it was student performance in the second of the two units that was the outcome considered (so at the end of each student's first academic year in Chemistry). Interestingly, a range of variables other than PASS attendance (such as the composite mark for CHEM101, online learning site access in the first semester, student age, markers of past and current academic aptitude) accounted for 74% of the variance in student marks for their second academic semester chemistry unit (CHEM102) final composite mark. There was a small, but significant effect associated with PASS attendance in second semester. This effect amounted to an increase of about 0.1 in the final composite mark for each week of PASS attended, that is, 10 weeks of PASS attendance was associated with an increase by one (1) in the final composite mark (a mark out of 100) for CHEM102. The analysts recognise that it cannot be said that these correlations were indicative of causation, especially because it is well recognised that PASS attendance may be a marker of other forms of engagement that are the true 'causative' factors. The conduct of this Research Sprint set the scene for the Research Sprint on the French Language Curriculum, which had undergone re-design with the aim of managing the risks that might be realised with, amongst other things, the reduction of access to PASS for French language students.

6.3.2 The French Language Curriculum

In 2018, the learning analytics team carried out a Research Sprint in collaboration with the French Language teaching team. There were cost pressures surrounding this context, including fewer teaching hours and the prospect of less Faculty financial support for supplemental instruction (PASS). This informed changes to the curriculum for the French major within the Bachelor of Arts, which involved students undertaking regular oral assessment hurdle tasks (through the LMS, Moodle). A hurdle assessment task is one which must be completed to a specified standard before the student can progress to the next learning activity or next assessment task. They function as a type of formative feedback and are helpful in enabling students to experience success through the iterative and sequential development of areas of skill. The course teaching team were interested in finding out more about online student activity. The curiosity of this teaching team and their openness to 'finding out' (even if that meant that their hopes were not realised), made this team another good candidate for Step 1 (the intentional and selective recruitment) of the Research Sprint process. The teaching team were particularly interested in finding out whether students interacted with each other as intended by the educational design of the units. A further question related to whether there was any relationship between online peer interactions and student academic performance. The teaching team's capacity to explain both the rationale for their inquires as well as the complex educational design of the core French language units greatly assisted in the identification of a set of questions and assumptions (Step 2 of the Research Sprint Process).

The principal source of formative feedback (using an online tool, Poodle) for these assessment tasks was peer feedback. The system was arranged so that first year students (those enrolled in 100-level units) received their feedback from second year and third year students (those enrolled in 200 and 300-level units), and those in second year (200-level students) received their feedback from students in their final year (300-level students). The analysis provided by this Research Sprint offered a range of useful information about student online interaction generally. Of particular interest was the connection between the number of online post counts (keeping in mind that students were posting online as a form of learning activity in units they were enrolled in and for students at 200- and 300-level, they were providing feedback to students in earlier year cohort's classes). Results of the Research Sprint showed those students who attained high marks in their French unit tended to have a broad range of audio post counts (from small to large counts). Those with low marks (including those with a fail grade) tended, almost exclusively, to have a pattern of low interaction. More generally, almost all students with a high number of online activity hours had good final marks, whereas all students who failed (achieved less than 50/100 as their final composite result) had a low number of activity hours. The French Language teaching team took this information to be indicative of the success of the peer-facilitated formative feedback approach and saw benefits of this approach both for those students giving peer feedback, as well as those receiving peer feedback.

In terms of the Research Sprint process, to undertake the appropriate data analysis outlined in Step 3 required access to an additional source of data beyond the data warehouse accessed for much of the routine learning analytics work. The source of this additional data included aspects of the LMS not already integrated into the data warehouse where students had uploaded their digital recordings of their own oral assessment tasks and (for 200-level and 300-level students) their peer feedback on those recordings using Poodle. Responding to this Research Sprint necessitated a new approach in order to gain access to the relevant data sources and turn that information into a form useful for analysis. The iterative nature of the Research Sprint process also came into play here with several cycles between question, data analysis and discussion of results. This Research Sprint is an example of analysis undertaken, based, at least partially, on the same data sets used to create the system-generated reports mentioned above; but designed to address questions that could not be answered by the standard system-generated reports.

6.3.3 The Analysis of Student Course Progress

The *Course Progress Policy* at UOW aims to support students to achieve success in their studies and to complete their qualification within a reasonable timeframe and without incurring unnecessary tuition fee debt. The Policy sets out the requirements for achieving satisfactory course progress (achieving passing grades in over 50% of the credit points in which the student is enrolled in each academic semester) and the processes for informing students of, and referring them to, intervention strategies to assist in the achievement of satisfactory course progress. While these are specific requirements of the Australian *National Code of Practice for Providers of Education and Training to Overseas Students 2018*, they are good practices to apply to the institution's support of all students.

The 2014 review of the Course Progress Policy resulted in some significant changes to the policy which, it was hoped, would have a positive impact on a student's ability to progress through a course of study. In early 2018 a Research Sprint conducted by the learning analytics team at the request of the Chair of the Coursework Exclusion Appeals Committee analysed the progression of the cohort of students who first enrolled in an award course at UOW in 2014. This was the first cohort to which the revised policy provisions applied. The aim of this Research Sprint was to gain insight into the effect of the Course Progress policy on student progress (and whether it was effective in achieving its objectives). The Research Sprint also served to inform the 2018 review of the UOW Course Progress Policy as well as the ongoing development of strategies to support students affected by the Course Progress Rules.

In terms of Step 3 of the Research Sprint process (data preparation and analysis) this Research Sprint was interesting because the same infrastructure used for the other two Research Sprints was used for a different purpose. Having the data warehouse infrastructure in place for a number of years meant historical data was available for a deeper analysis of student trajectories. Here, each student's pathway through their course was considered up to the point at which they either: (1) changed to a course at a different level (postgrad/undergrad), (2) completed their course or (3) their most recent enrolment status update. The Research Sprint found that outcomes worsen at each successive stage of the course status pathway, with completion rates roughly halved for students who did not achieve passing grades in over

50% of enrolled credit points compared to those who did. Completion rates halved again for students who did not achieve passing grades in over 50% of enrolled credit points in consecutive semesters.

The outcome of the First Year Chemistry Research Sprint demonstrated small effects of ‘interventions’ such as PASS. The French Language Curriculum Research Sprint demonstrated that the online peer interactions of students were taking place in the way anticipated and that there was a relationship between poor academic outcomes and low levels of online interaction. Each of these findings, while complex to analyse, were easy to interpret. For the Course Progress Research Sprint, Step 4 (discussion of the results) and Step 5 (drawing conclusions) required intense and close interaction between the data analyst and the key stakeholder. Underlying this were the procedures used to implement the Course Progress Policy (especially in relation to the changes in student course status from ‘active’, to ‘referral’, to ‘restricted’ and ‘excluded’). The meaning of the data was not immediately obvious. Ultimately, the Chair of the UOW Coursework Exclusion Appeal Committee was pleasantly surprised to find just how effectively the Course Progress Policy was working to assist students to return to a course status of ‘active’ and to eventually successfully complete their studies. Although failure to meet course progress requirements was indicative of a higher risk of student non-completion, the vast majority of students whose course status changed to ‘referral’ because of a lack of course progress in one academic semester, were eventually returned to the course status of ‘active’ and graduation. The evidence of this Research Sprint was used in tandem with the work of the Course Exclusion Appeal Committee to confirm effective implementation of Course Progress Policy. By supporting all students to successfully complete their studies in a timely way the University can help reduce the financial impact of higher education study for individual students and enhance their learning experience.

Step 6 (communication of results so that learnings can be applied to practice) of the Research Sprint process was important for this sprint because the range of stakeholders to the policy and to the process of managing students’ course progress was very diverse and they had a broad range of knowledge backgrounds and purposes. The provision of the data analysis in the form of a range of tables, and graphs enabled users of this information to quickly and easily interpret the meaning of the analysis, the conclusions reached and the implications for action. Since this report was produced aspects of it have been provided to the committee responsible for the review of the Course Progress Policy, the central unit responsible for implementing the procedures arising from the policy and the team leader of the central student support advisers.

6.4 Conclusion

Top-down aspects of learning analytics at UOW have generated scalable and sustainable practices. The governance structure has had oversight across the university, a data use policy has been put in place to help protect staff and students and the technical infrastructure has utilised a data warehouse that has catered for key aspects of the UOW learning platform. Frontline Research Sprints have helped address questions within particular teaching and learning contexts that learning analytics can help answer but are not addressed by the standard reports generated for unit coordinators in the top-down approach. The future direction for learning analytics at UOW will likely involve bringing these two different aspects closer together. Questions covered in Research Sprints will be used to develop and test new prototypes without the risk and resourcing implications of a full implementation. The intention here is to extend the learning analytics capabilities provided in the top-down approach with functionality shown to be useful for a number of academic staff. Key to this will be a collaborative design process with academic staff to better understand their needs related to learning analytics so that problems can be reframed, many ideas created and a hands-on approach adopted in prototyping and testing new learning analytics capabilities (Plattner, Meinel, & Leifer, 2010; Retna, 2016). Such an approach is consistent with findings from recent studies that reinforce the need for a greater emphasis on the human utilisation of learning analytics over the technical design aspects (Howell et al., 2018; Klein et al., 2019; Leitner, Ebner, & Ebner, 2019). The classroom, in its broadest sense, is where the majority of student retention opportunities lie and learning analytics is but one tool used in a variety of teaching and learning practices. This also rings true when casting the net wider than student retention and considering how learning analytics is best integrated into classroom practice to support innovations of any kind. Teaching staff are the gateway for this, so it is important we investigate and better understand their needs and practices associated with learning analytics. With a future mandate and resourcing to do so it would be possible to more systematically gather evidence through stakeholder evaluation. As they stand, the examples described in this chapter offer ideas about ways of implementing institutional learning analytics to complement existing "top down" approaches that offer ways to integrate stakeholders into the development process.

6.4.1 Future Directions

The growing use of data in other university aspects also poses implications for the future direction of learning analytics at UOW. Up until relatively recently the learning analytics work undertaken at UOW operated with a dual governance structure. As mentioned earlier, one governance committee focused on decision making and management of learning analytics and a separate group focused on ethical implications arising from secondary use of student data. Other initiatives at UOW are emerging that represent a broader focus akin to 'academic analytics' (Siemens & Long, 2011). The potential benefits for decisions informed by analysis of student data traverse different levels of the university: student, teacher, faculty, institution etc. (Ifenthaler, 2017). The number of insights to be derived from the available data will likely always outweigh what can be reasonably resourced when there is constant pressure to "do more with less". The rapid pace of technological change requires each of these initiatives based on student data to be treated as a living ecosystem in order to effectively address ethical considerations and ensure responsible use of data that protects all stakeholders: students, teachers, researchers, support staff and administrators. In recognition of this, the governance of all analytics initiatives based on student data at UOW is undergoing the changes necessary to guide future work.

Of relevance for a way forward at UOW is the approach taken at Open University UK, whereby cross-functional teams are established for each faculty comprising technical, pedagogical and stakeholder management expertise (Rienties, Cross, Marsh, & Ullmann, 2017). Findings from recent studies point to shortages in finding people with the diversity of practical data science skills as well as knowledge of learning and teaching (Gašević et al., 2016; Ifenthaler, 2017; Rienties, Herodotou, Olney, Schencks, & Boroowa, 2018). It is unlikely that all of these capabilities will reside in any one individual. In recognition of this, decision making needs to be approached in a collaborative way with a variety of expertise to develop evidence-based solutions implemented in ways that meet student needs and facilitate their success (Klein et al., 2019). This is consonant with broader trends in data science whereby a range of diverse talents are required to ask smart questions and communicate insights and what they mean for practice (Berinato, 2019).

The experience at UOW is consistent with the finding of Colvin et al. (2015) which suggests that the situated practice of learning analytics implementations generates future capacity. It is worth considering one perspective on how that works by reflecting on Boud and Brew's (2013) work on academic development where they suggest that,

> a conscious focus on academic practice *qua* practice can fundamentally shift one's perspectives on professional learning. It moves from the consideration of learning as something that individuals do, to seeing learning as a social process occurring within the context of practice. Viewing learning as a constructed and emergent phenomenon arising in and from academic work positions academic development as a process of working with opportunities for learning created by work itself. Some aspects of this work foster, and others inhibit, learning, and an important task for the academic developer is to work with academics to engage with helpful and unhelpful facets of work in relation to their learning (pp. 209 – 210).

The work reported on in this chapter casts the work, particularly, but not only the Research Sprints, undertaken by the learning analytics team in close collaboration with teaching and other staff, as an approach which 'fosters' learning by staff by engaging one another in a social process within the context of their practice. In other words, each of these Research Sprint projects was itself a form of peer learning taking place in the situated practice of the stakeholders themselves, and therefore enhancing the development of future capacity of both the learning analytics team and the stakeholders with whom they collaborate. This builds trust in the practice of learning analytics by making it relevant to academic practice (or university governance practice) itself. It is not clear whether the use of Research Sprints will be sustainable and scalable, or whether the findings from such sprints are applicable beyond the small specialist work group involved in each sprint. What is clear is that this type of endeavor connects with the 'lived experience' of teaching and other staff and works to build trust in the practice of learning analytics. Building trust in the use of 'big data' will in turn result in more consistent uptake of learning analytics tools.

At UOW, an initial focus on the near real time provision of reports through the lens of retaining students resulted in system-generated reports scaled across the institution. Other system-generated reports aimed at identifying overall patterns of student engagement with learning opportunities in each unit have also supplemented this. This gave stakeholders a certain understanding of the conceptualisation of learning analytics at UOW, which in turn revealed constraints in the depth of insights provided to teachers in the context of their practice. Research Sprints were formulated in response to this observation as a way to uncover important questions about student learning in particular settings; conduct customised analyses for these questions; and co-construct new knowledge claims that informed practice. This reinforces the importance of putting in place iterative processes that continually refine the development and implementation of learning analytics. Future work aims to bring the top-down and bottom-up elements closer together so that students and teachers have more nuanced, contextualised and thus more trusted tools to enhance educational practice.

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Chapter 7
"Trust the Process!": Implementing Learning Analytics in Higher Education Institutions

Steps Towards an Evolutionary Adoption of Data Analytics

Armin Egetenmeier and Miriam Hommel

7.1 Introduction

The further development of higher education institutions (HEIs) based on data is getting more and more important. Therefore, analytics in the educational context is used in order to ensure, for example, the quality assurance in teaching or to improve organizational efficiency. Especially the institutional quality management (QM) uses analytics to provide the HEI administration as well as faculty and course facilitators with relevant information to meet regulatory requirements (cf. Heesen, 2005). This information contains, for example, results from surveys or ratio analyses. The results of the analyses are often summarized in reports and used as a basis for educational decision-making at the HEIs. Furthermore, lecture evaluations are carried out at most HEIs and provide information for teachers in order to reflect and ensure their teaching quality (Kauffeld & Zorn, 2019). That grants an insight into learner's experience and can be a starting point for the targeted improvement of lessons. This shows that institutional, administrational, and teaching staff at many universities uses data-based analytics already to gain insights into organizational or learning processes. However, the focus is often limited on their individual objectives (e.g., administrative tasks) due to the various responsibilities and duties. Thus, research in the single departments is shaped by a pragmatic approach on the tasks (cf. Ansmann & Seyfried, 2018) and often remains in a particular course, group of stakeholders, or learning environment.

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In recent years, new technologies resulted in more data being available in the field of higher education (e.g., user data from learning management systems). Furthermore, the demand on accountability, reporting, and the proof of effectiveness increased. Both together offer new possibilities in terms of data analytics and make them more essential (cf. Oblinger, 2012; Petersen, 2012), for example, in order to gain insights into still unresolved questions in education like student success or effective teaching methods. Thus, research fields like learning analytics (LA) emerged. In contrast to the well-established data analytics mentioned above, which are understood to mean the general investigation of data sets in order to draw conclusions from the information, LA offers a more holistic approach and focuses more on the learning environment, the individual students, and their learning processes. The goal of LA is to support stakeholders (institutional and administrative staff, educators, learners, and researchers) of different levels (from micro- to mega-level) with valuable information (Greller & Drachsler, 2012; Ifenthaler, 2015; Romero & Ventura, 2013) like real-time feedback, predictions, or information about learning processes. In this way, LA can be a beneficial addition to existing data analytics used at universities. However, despite the great potential LA offers, the development of especially institution-wide (large-scale) implementations, which can impact the educational sector, is slow. Research is mostly based on developing LA applications in individual courses or for a specific task (small-scale). Therefore, the adoption of LA in higher education, i.e., the strategic and systematic large-scale introduction, and the question of how it can be guided are important topics.

This contribution describes the implementation of LA at Aalen University of Applied Sciences (UAS) as a case study which encouraged an adoption process. It starts with a literature review in Sect. 7.2 on current issues and challenges concerning LA and its adoption. The present progress of the adoption process is discussed and a closer look at the leadership approaches of LA adoption is given. Finally, models developed to support the adoption of LA are presented. Section 7.3 introduces a well-known LA adoption model originally developed for top-down approaches. Afterwards, an adapted version of this model is proposed that shows potential to guide the evolutionary bottom-up development process. Section 7.4 presents important milestones of the adoption process at the Study Support Center (SSC) of Aalen UAS. Three major development stages outline the evolution of an institution-wide LA framework used at the SSC in detail. The development of the framework occurred in a bottom-up approach, which is regarded in terms of the adapted model. Furthermore, possible implications from this adapted model approach are discussed. The contribution ends with a short summary of the experiences of the case study, an outlook on still existing challenges of the process, and a conclusion (Sect. 7.5).

7.2 Adoption of Learning Analytics

In the early days of LA research, the predicted time-to-adopt of a “mainstream use” of LA lay within a few years (Johnson, Smith, Willis, Levine, & Haywood, 2011). This prediction was justified due to the compelling promises of the field (to be effective), the emergence of (successful) applications in the context of LA (cf. Arnold & Pistilli, 2012), and the increasing emphasis to demonstrate student success (Brown, 2011). Summing up, Siemens (2012, p. 7) stated in 2012 that in theory “LA has potential to dramatically impact the existing models of education and to generate new insights into what works and what does not work in teaching and learning.” However, in 2019 Dawson, Joksimovic, Poquet, and Siemens (2019, p. 454) come to the conclusion that in practice “LA research has not yet reached its potential, [but] it is advancing and is on the right path to fulfil its stated promise of generating sector wide transformations.”

The growing interest in LA leads to the development of LA implementations around the world. Wong (2017) presents several case studies of LA applications and implementations sorted by the intended goals (e.g., support decision-making, give feedback, or provide assistance to students). These examples are for the most part located in educational institutions in the United States, Australia, Canada, and the United Kingdom (Sclater, Peasgood, & Mullan, 2016). Although these case studies show the success and potential of LA systems, the state of adoption even in those countries is mostly in a nascent stage (Tsai & Gašević, 2017). This shows that interest in implementing and using LA is given, but only in a few cases it is a major priority (Arroway, Morgan, O’Keefe, & Yanosky, 2016). One reason that the adoption of LA at HEIs has slowed down after the emerging and promising start (Papamitsiou & Economides, 2014) is due to arising concerns and issues (Drachsler & Greller, 2016). In order to encourage the adoption of LA by addressing common problems in this field, nationwide education initiatives were founded like SoLAR[1], LACE[2], or SHEILA[3]. The foundation of these initiatives helped to promote the exchange of results and common issues and, thus, raise the awareness of LA at HEIs. In addition, organizations like EDUCAUSE[4], JISC (cf. Sclater et al., 2016), or SURFnet (cf. Baas et al., 2015) are also dealing with questions around LA and spread their results to increase the knowledge in this field.

7.2.1 Issues and Challenges of LA Adoption

The introduction and use of LA reveals some challenges that need to be overcome in order to adopt it successfully. These challenges either lie in the research area of LA itself or relate to the adoption process. Both are part of this subsection. The challenges within the research field of LA are mentioned because they also show relevance to LA adoption but not discussed further, as this has already been done extensively in the literature. However, issues related to the adoption process are discussed in more detail.

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[1] SoLAR: Society for Learning Analytics Research (https://www.solaresearch.org)

[2] LACE: Learning Analytics Community Exchange (http://www.laceproject.eu)

[3] SHEILA: Supporting Higher Education to Integrate Learning Analytics (https://sheilaproject.eu)

[4] EDUCAUSE: https://www.educause.edu

An overview on issues within the field of LA itself can be found, for example, in (Avella, Kebritchi, Nunn, & Kanai, 2016). *Data collection and analysis*; *legal, ethical, and privacy concerns*; or *connections to pedagogy* are some of the mentioned ones. Prinsloo, Slade, and Khalil (2018) discuss factors and issues affecting the implementation of LA with respect to the different stakeholder levels. Balancing these impacting elements may lead to a situation where LA gets "stuck in the middle," which may hinder the further development of an LA implementation on a small scale.

Due to the lack of maturity of the field, concerns about the usefulness and the impact arise (Greller & Drachsler, 2012). Although there are numerous LA implementations (Sclater et al., 2016; Wong, 2017), *evidences of impact*, e.g., to student success are rare (Ifenthaler, Mah, & Yau, 2019). Therefore, a shortage of studies empirically validating the impact exists (Tsai & Gašević, 2017). In a literature review by Dawson et al. (2019), the authors investigated the impact of LA according to five dimensions (study focus, data types, purpose, institutional setting, and scale of research and implementation). They identified a limited impact on practice, theory, and frameworks due to the focus of LA research in small-scale experimental studies or individual courses. Currently, LA "remains mired within a phase of exploratory analyzes" (Dawson et al., 2019, p. 452), but in future impact research should be standard on LA implementations.

In addition to the challenges within the research field of LA, the adoption process itself can be challenging. Concerning this process, Tsai, Moreno-Marcos, Tammets, Kollom, & Gašević, (2018) identified the most frequent issues as *demand on resources*, *challenges on privacy and ethics*, as well as *stakeholder engagement*. These three main issues are discussed in the following.

The *availability of resources* includes financial investments, the technological requirements (e.g., infrastructure to access the data), and the required staff capacity and expertise. Especially the first two are antecedent affordances needed to start an implementation of LA and the adoption process at a university. However, a shortage of sufficient training for the staff should also be avoided to reach the full potential of LA (Tsai & Gašević, 2017). But since LA is more an interest than a need at HEIs (Arroway et al., 2016), a lack of investment in resources is not excluded.

Ethical, privacy, and legal concerns are relevant issues for LA since the emergence of the field (Drachsler & Greller, 2016). Thus, the need to think ethically has been a subject of research for many years (cf. Slade & Tait, 2019; Willis, Slade, & Prinsloo, 2016). Due to a low level of transparency, students as a main group of stakeholders remain worried about the surveillance possible by some data analytics systems (Slade, Prinsloo, & Khalil, 2019). This includes data collection, the variety of purposes to use data, and the implications of the analysis. All these concerns may lead to a lack of trust in the system or in the acceptance of the results, which may hamper impact and can cause failure. As trust is a key component of a solid analytics program (Petersen, 2012), Drachsler & Greller (2016, p.89) summarized these items in "an eight-point checklist named DELICATE that can be applied by researchers, policy makers and institutional managers to facilitate a trusted implementation of Learning Analytics."

The *stakeholders and their engagement* are also crucial for the adoption process and the success of LA. Thus, understanding the stakeholders, their needs and concerns, is fundamental to implement data analytics successfully (Campbell & Oblinger, 2007). This involves, for example, the development of pedagogical interventions (Wise, 2014), pedagogy-based approaches to analytics (Tsai & Gašević, 2017), or the preparation and design of the results so that the respective stakeholder group can easily understand them (Clow, 2012).

While every university initiating an LA adoption process provides at least necessary resources and clarifies important privacy issues, the stakeholder engagement still remains critical. To exploit the full potential of an LA system, each group of stakeholders should be involved in order to avoid a focus on a single group and to reach an equal engagement. Especially institutional leaders should be included, since they promote further development of the university and can therefore more easily stimulate (necessary) changes within the institution. In this way they can even help to develop and deploy an LA tailored policy (Tsai & Gašević, 2017). Tsai et al. (2018) generally propose to implement such a specific LA policy in order to address the challenges and to conduct the adoption process in a structured way. Consequently, involving the institutional leaders can be crucial for a successful adoption of LA at a larger scale.

7.2.2 Leadership of LA Adoption

The provision and usage of single small-scale LA implementations at an institution are often not enough to achieve an institution-wide adoption. As mentioned above, developing an institutional LA policy can support the adoption process, e.g., by formalizing the intended changes or by maintaining the essential communication within the stakeholders (Tsai & Gašević, 2017). For the development of such a policy, the institutional leadership plays an important role. In order to frame the LA adoption in complex leadership theory, Dawson et al. (2018) conducted an interview study at Australian universities. As a result, two classes of leadership approaches (*top-down* and *bottom-up*) were identified among the institutions. Both approaches have a unique set of characteristics.

The *top-down approach* for adoption follows an "instrumental approach," in which the implementation of LA is often regarded as a technical solution. Assigning LA to an administrative level promotes progress in terms of an establishment of infrastructure but may ignore the building of staff capacity. Thus, awareness and uptake among the involved persons can be difficult to achieve. Communication, support (Tsai & Gašević, 2017), and understanding the concerns of each stakeholder group (Campbell & Oblinger, 2007) are essential elements for this approach.

The *bottom-up approach* cultivates the adoption with "emergent innovators" and small-scale projects. This more practice-oriented approach focuses on the holistic concept of LA to improve teaching and learning within the learning environment. Many examples of small-scale LA implementations fulfill a specific task within the institution successfully (cf. Wong, 2017), but these case studies often lack a concept to scale up among the HEI. Thus, the adoption process starting with these innovative projects can be undirected, and a realization of change in HEI administration can be difficult. Building a common cause among the stakeholders can stimulate the adoption process.

Based on the kind of leadership approach, the strategy of the university to adopt LA should be chosen accordingly, since each class of approach has to focus on specific aspects and deal with different issues. Therefore, knowing if a *top-down* or a *bottom-up* approach is used at the HEI can promote an appropriate adoption process.

But even if the leadership approach is clear, the development of a policy needs assistance. Therefore, models were developed for LA adoption, formulating implementation strategies that can support the deployment of an institutional policy, counteract upcoming issues, and thus promote the adoption on a large scale. Such models are presented in the following.

7.2.3 Models of LA Adoption

The implementation or adoption of any data analytics system (especially LA systems) in a university is a comprehensive task, because "institutions are stable systems, resistant to change" (Ferguson et al., 2014, p. 120). Furthermore, they build a complex structure as "loosely coupled systems" (Weick, 1976). Due to the complexity of the HEIs, an "ad hoc" or a disconnected (analytics) project has often limited impact or will eventually fail (Dawson et al., 2018). Therefore, a thoughtful approach on adoption is crucial to be successful and sustainable. As a result, several authors developed models of LA adoption in order to overcome common issues and concerns and to provide the HEIs with a guide to the adoption process.

Colvin, Dawson, Wade, and Gašević (2017) classified the literature of LA adoption models into three primary groups: *input*, *output*, and *process models*. All of these model types reveal insight into specific factors that induce the dissemination of LA. Common elements in almost all models include "technological readiness, leadership, organizational culture, staff and institutional capacity for learning analytics, and learning analytics strategy" (Colvin et al., 2017, p. 285). These elements summarize the main aspects of a successful LA adoption.

Concerning the model types, *input models* support institutions at the beginning of the adoption process with a focus on antecedent affordances and requirements influencing the adoption process. These models help to indicate critical dimensions that need to be considered (Greller & Drachsler, 2012) or to identify deficient areas hampering the development and deployment of LA, e.g., with the Learning Analytics Readiness Instrument (Arnold, Lonn, & Pistilli, 2014). After a promising implementation of an LA system in the first place, the overall adoption is often ongoing. One problem of input models is that advances of the systems may be missed because the focus is on starting conditions.

Output models describe the progression of LA deployment in an organization over time. This involves a description of the maturity stages of LA deployment. Siemens, Dawson, and Lynch (2013) outlined five stages in their Learning Analytics Sophistication Model, beginning from simple awareness (by reporting to a small group of stakeholders) and advancing to a transformation in the organization and the educational sector. Describing the maturity stage of a system offers a reference point to work on the next steps but may fail to provide deeper insight into overcoming obstacles or limiting factors to progress.

Finally, *process models* try to map a sequence of processes (in form of operational tasks) to adopt data analytics. Focusing on the way of implementing LA provides organizations with iterative, step-by-step approaches to deploy LA on a large scale. In contrast to input and output models, process models focus more on further development and can serve as a practical guide for adopting LA at HEIs. The stepwise approach seems particularly suitable for large-scale adoption. Therefore, in the following the focus is on process models.

As an example for an elaborated process model coping typical obstacles like the diversity of stakeholders and the complexity of HEIs, the RAPID Outcome Mapping Approach (ROMA) (Ferguson et al., 2014; Macfadyen, Dawson, Pardo, & Gašević, 2014) is mentioned here. Originally, the ROMA model was designed to support policy and strategy processes in complex contexts (Young & Mendizabal, 2009). Ferguson et al. (2014) adapted it lightly for the context of LA. In the following, the term *ROMA model* always refers to this adapted model.

Several case studies underpin the successful deployment of LA reached with the *ROMA model* (Ferguson et al., 2014). But although the model is proposed as an iterative approach, the presented case studies show primarily only the first iteration. Especially, encountered obstacles and resulting developments – handled by the institutions – are not mentioned in detail.

Based on the *ROMA model* combined with results from an institutional survey at several European universities, the project team SHEILA developed a policy framework (Tsai et al., 2018) as a first output of their ongoing research. The so-called SHEILA framework includes a list of actions, challenges, and policy advices aligned to the *ROMA model* dimensions to promote the adoption. Furthermore, the framework could be used to evaluate the readiness of HEIs for LA. In several case studies, Tsai et al. (2018) analyzed the adoption approach using the framework with universities located across Europe. As a result, a set of reflective questions was formulated based on the local actions and challenges as policy prompts for institutions.

Regarding the leadership of LA adoption, *top-down* and *bottom-up* approaches are distinguished (cf. Sect. 7.2.2). The *ROMA model* and the SHEILA framework support mainly an institutional *top-down* adoption process for which they are undoubtedly suitable. However, developments in LA are also often driven by emerging innovators. Nevertheless, there is no further discussion in literature if the models are also suitable as a basis for a *bottom-up* approach. Therefore, the following section deals with this question and explains how the *ROMA model* can be adapted for this purpose.

7.3 Adapted Roma Model for Bottom-Up Adoption

At many HEIs, the introduction of LA starts within small-scale projects focusing on individual courses. The (further) development of these small LA projects within the university is initially difficult to estimate because innovations cannot be forced. Furthermore, if developments are only driven by innovators, they can be uncoordinated, and especially stakeholders at higher institutional levels may receive too little information about them. Therefore, there is no reason for these decision-makers to expand the projects and scale them up to the institution or university. This lack of a strategic concept (cf. Sect. 7.2.2) to scale up such projects can in turn be a reason why small-scale LA implementations frequently do not result in institution-wide adoptions. If the decision for an institution-wide (large-scale) adoption starting from a small project is made consciously, a process model can help to address this in a structured manner. Therefore, the following describes how the *ROMA model* can be adapted to be suitable for a bottom-up adoption of LA.

The *ROMA model* consists of a seven-step iterative cycle, which can guide the systematic institutional implementation of LA. The following list contains the seven steps together with questions that need to be answered for using the model (Ferguson et al., 2014, p. 128):

1. Define a clear set of overarching policy objectives: What are the objectives of LA? What changes should be achieved?
2. Map the context: Which given framework conditions exist? Which are conducive and where are barriers?
3. Identify the key stakeholders: Who should benefit?
4. Identify learning analytics purposes: What are the needs of the stakeholders? What are the purposes?
5. Develop a strategy: What needs to be done in order to meet the desired outcomes?
6. Analyze capacity; develop human resources: Does the institution have the capacity to implement the planned strategy? Do the respective individuals have the necessary skills?
7. Develop a monitoring and learning system (evaluation): Are the original policy objectives and vision still accurate and relevant in the light of the assessment of context, purposes, and capacity? Were the desired changes achieved?

Although the *ROMA model* guides the adoption primarily on an institutional level (top-down) rather than an upscaling implementation (bottom-up), it contains all relevant dimensions of a bottom-up adoption process. Thus, a slight adaptation focusing more on the stakeholders can help to use it for a bottom-up adoption of LA. Concerning the order of the single processing steps, we therefore suggest for the adapted (bottom-up) model to identify the key stakeholders (step 3) immediately after defining the overarching objectives in order to highlight the (potential) impact for the stakeholders. Subsequently, the learning analytics purposes can be identified for them. Only then the context should be mapped, whereas it is important to clarify the given conditions, barriers, etc. with regard to the stakeholder group. In this way, the context can be specified more precisely to the current situation. In summary, this means that step 2 ("Map the context") from the *ROMA model* described above is pushed behind step 4 ("Identify learning analytics purposes").

The iterative use of the model is of crucial importance here in order to exploit the full potential of the LA system. Every iteration step provides evidence-based knowledge centered on one additional group of stakeholders, which increases the stakeholder engagement gradually. This stepwise transition of key findings through the stakeholder levels can promote awareness and trust in the system. The following section presents a case study of an evolutionary bottom-up adoption resulting in an institution-wide LA framework.

7.4 Adoption of Learning Analytics at Aalen UAS

At Aalen UAS an institution-wide LA framework supporting different levels of stakeholders has been installed in a bottom-up process starting from a small project over the last few years. The architecture of the framework and the benefits for the stakeholders are presented in detail in Hommel, Egetenmeier, and Maier, (2019). The following Sects. 7.4.1, 7.4.2, and 7.4.3 describe the single processing steps which were necessary for its installation. In addition, results of each major development milestone are discussed. Section 7.4.4 sums up the bottom-up installation of the framework regarding the adapted *ROMA model* for bottom-up adoption described in Sect. 7.3 and mentions associated implications.

7.4.1 A Small Project as Starting Point

In order to improve quality in teaching and learning, the German Federal Ministry of Education and Research has supported different educational projects like the "AkaMikon" project (see Acknowledgments) at Aalen UAS. It started at the end of 2011 with the establishment of the Study Support Center (SSC) as a central unit.

The overall objective of the "AkaMikon" project is the reduction of study-dropouts especially those caused by subject-related reasons. As many students drop out during the first two or three semesters because of problems in mathematical subjects (Heublein et al., 2017), the SSC developed measures to support students during the study entry phase in improving their basic mathematical skills. These measures are mathematical prep courses held before the beginning of the first semester, lecture-accompanying tutorials during the first two semesters, as well as measures to level the heterogeneity in the initial mathematical knowledge like a mathematical online course (Nagengast, Hommel, & Löffler, 2013; Nagengast, Hommel, Maier, Egetenmeier, & Löffler, 2017).

In order to evaluate the effect of these measures, an accompanying scientific research has started immediately at the beginning of the project. The aim of this research was to gain insights into the development of students' initial mathematical knowledge and learning progress and, therefore, in the effectiveness of the measures. Based on the evaluation results, the measures should be adapted accordingly in order to get more effective. Here, the SSC appears in a dual role. On the one hand, it provides the analysis results; on the other hand, it uses them to adapt and further develop its measures (as teachers) and to get insights into the learning process (as researchers).

The basis of the scientific research is a comprehensive data collection described in detail in Hommel, Egetenmeier, and Maier (2019). In each semester, the following data are collected:

- Attendance data for the prep course and the lecture-accompanying tutorials
- Tests (pretest before the prep course, posttest after the prep course, follow-up test 4–6 weeks after the beginning of the lectures) querying mathematical foundations that are covered by the prep course
- Self-assessments of the students on the topics of the prep course queried before each test
- Sociodemographic data from the student information system (SIS), e.g., specific exam results or type and grade of the university entrance qualification (UEQ) allowing students to enter a UAS (cf. Dürrschnabel & Wurth, 2015), which represents the educational biography including different school types (cf. Eckhardt, 2017)

Using personal data is essential for the data analyses carried out for evaluating the measures. This means that data protection issues are concerned. Therefore, a data protection safeguarding is necessary, which was developed at the SSC with the support of responsible institutions (Egetenmeier et al., 2016). For this purpose, various questions had to be answered already in 2012, such as:

- Which analyses should be carried out?
- Why should they be carried out?
- Which data are needed for this purpose?
- How are the data collected and stored?
- Who is allowed to access the data?

As the collection of personal data requires the written consent of the students, the process resulted in a data privacy statement developed for the SSC (SSC DPS). Note that only data of students having given their consent by signing the SSC DPS may be stored and analyzed. Therefore, it is very important to convince as many students as possible to sign the SSC DPS.

If a high transparency can be gained, the trust in the analyses and the willingness to participate in the data collection grow. In order to avoid inference on individual persons the data are therefore pseudonymized and analyzed only for aggregated data sets. Furthermore, students need to have the possibility to opt out. This shows that the data protection process of the SSC covers various items of the DELICATE

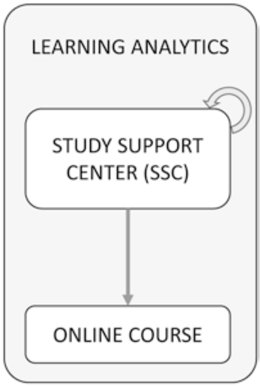

Fig. 7.1 Initial state of the LA framework at Aalen UAS

checklist of Drachsler and Greller (2016) who also emphasize the importance of trust into the process and system (cf. Sect. 7.2.1). With the data protection process of the SSC, this trust of students can be significantly promoted.

First evaluation results showed a positive effect of the prep course (Nagengast et al., 2013). However, they also revealed that the basic mathematical knowledge could not be improved as sustainably as it would be desirable (Neumann, Heinze, & Pigge, 2017). Consequently, the SSC measures were adapted in two ways in order to improve their quality. On the one hand, the prep course was extended by one week, in which the mathematical basics were repeated once again. On the other hand, a mathematical online course was developed allowing students to repeat the mathematical basics ubiquitously (Egetenmeier, Krieg, Hommel, Maier, & Löffler, 2018; Krieg, Egetenmeier, Maier, & Löffler, 2017). Of course, the impact of the adaptions had to be evaluated again. This happened by continuing the existing analyses as well as by long-term studies. Until this point the first milestone of the LA framework of Aalen UAS has been reached. It is presented in Fig. 7.1.

7.4.2 Closing the Gap Between Teachers and Learners

After the implementation of the first basic LA framework (cf. Fig. 7.1), further analyses were carried out. These analyses showed for learners and for teachers discrepancies between their assumptions and reality (cf. Hommel, Egetenmeier, Maier, & Löffler, 2019). Learners often have a wrong assumption about their mathematical knowledge. This is especially evident when comparing test results with self-assessments. This comparison shows that learners are convinced that they master mathematical fundamentals much better than they actually do. Teachers on the other hand assume that their students know the mathematical basics (cf. Neumann et al., 2017) and that they use offered support measures. But in addition to the deficient basic mathematical knowledge already mentioned above, analyses showed that voluntary support offers are rarely used in some study courses. Moreover, teachers are unaware of the heterogeneity of the group of students especially in educational biographies. This is a crucial point since some mathematical topics are not taught obligatory in certain school types (Dürrschnabel & Wurth, 2015).

These discrepancies lead to a gap between teachers and learners. Students have difficulties to follow the lecture because the teacher requires basic mathematical knowledge that the students lack. However, since students are unaware of their mathematical deficits, they have no intention to improve their mathematical foundations. In order to close this gap, the idea arose to reflect the actual situation to students and teachers and make them aware of existing deficits or specific circumstances of the group of students.

As different stakeholders have specific needs for their information, the types of reports were chosen accordingly. For students feedback emails were selected in order to provide them with information about their actual state of knowledge and their learning progress. These emails are sent twice a semester. Besides the results of the mathematical tests, the emails contain topics that are mastered only insufficiently and should therefore be repeated. In order to help students with this repetition, links to support offers are included. Thus, ideally, students are intended to improve their mathematical knowledge on their own, for example, by using the mathematical online course of the SSC.

Teachers should be made aware of the heterogeneity of their group of students to cause an adjustment of their lectures to the concerns of their students. To facilitate this adjustment, the teachers of mathematical basic lectures receive so-called study course reports containing evaluations on the composition of the group of first-semester students of their study course regarding their educational biography, their initial mathematical knowledge, and their self-assessment as well as their attendance in voluntary support measures. The results for the regarded study course are compared to those for the entire university. The teachers receive the report twice a semester. The first report is sent to them at the beginning of the semester, the second one at the beginning of the following semester including the correlation between the results of the exams and the participation in support measures.

Altogether, the intended changes of the actors should lead to a better understanding of the students in the lecture and thus improve teaching quality. For a detailed explanation of the content of the feedback emails and the study course reports, see Hommel et al. (2019); Maier, Hommel, and Egetenmeier (2018); or Hommel et al. (2019). The introduction of this feedback system leads to an extension of the initial LA framework (Fig. 7.1). In this extended framework, teachers and learners were added as stakeholders as shown in Fig. 7.2.

The individual feedback creates benefits for both added stakeholders. This increases the willingness of participating in the process and the trust in the system which is crucial concerning LA adoption (cf. Sect. 7.2.1). Among other things, the increased number of students signing the SSC DPS reflects this improvement since the introduction of the feedback emails. For teachers, the additional information increases the willingness to support the data collection, for example, by providing lecture time for writing the follow-up tests.

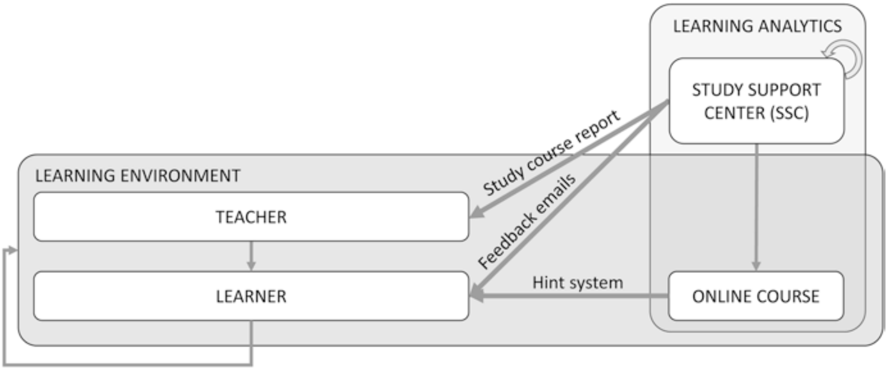

Fig. 7.2 LA framework after the integration of the feedback system

Of course, the impact of the feedback instruments should also be validated quantitatively, which is another challenge of LA adoption (cf. Sect. 7.2.1). For the impact of the emails, user data of the online course could be used to evaluate if students are actually using the online course to repeat the topics listed in the email. However, privacy issues concerning e-learning have not yet been clarified at Aalen UAS, so personal data may not be used for this purpose. Quantifying the extent to which teachers adapt their lectures based on the reports is also difficult. For teachers themselves the classical lecture evaluations (cf. Sect. 7.1) or study course reports of following semesters form a possibility for examination. Unfortunately, for privacy reasons, the lecture evaluations may not be used for systematic analyses by the SSC. However, some teachers admitted that the reports led to changes, such as the introduction of admission exams.

7.4.3 Extension to Higher Levels

After positive feedback from the teachers on the study course reports, reporting should also be extended to the faculty and course facilitators as well as to the institutional level. While the study course facilitators should receive the same reports as the lecturers, aggregated reports should be generated for the faculties. However, it turned out that the study courses of a faculty are sometimes very heterogeneous. Therefore, it made more sense to send all reports of the individual study courses of the faculty to those responsible, instead of summarizing them. On the one hand, this makes it possible to compare single study courses of the faculty and adjust their curricula individually. For example, students in one study course may need obligatory measures rather than others. On the other hand, it also allows the observation of the development and trends of individual study courses over several semesters. This can also support the curriculum and learning design.

Concerning the support of decision-makers of the institution in strategic planning, institution-wide analyses are helpful. Thus, in a next step, further analyses were carried out examining not only individual courses but also institution-wide relationships. For example, correlations between the UEQ type (cf. Eckhardt, 2017) and the results in the tests of the SSC and those in the first math exam, respectively, were examined (Nagengast et al., 2017). It was found that the initial mathematical knowledge depends on the educational biographies. This was also confirmed when looking at the correlations in a long-term study. Furthermore, the development of the composition of the group of first-year students shows a decrease in the number of students with educational biographies having better results in the mathematical tests. This is a valuable information for further strategic planning.

Moreover, different characteristics of specific groups of students were further investigated. For instance, attendance data or UEQs were compared for students who passed the first math exam with those who failed (Hommel et al., 2019). Besides, a long-term study of the follow-up test results for prep course participants and non-participants visualized that the prep course has a positive effect, but this is not enough in order to consolidate the knowledge as sustainably as desired (Maier et al., 2019). Whether this is due to voluntary participation or the relatively short prep course duration remains an open question.

The university administration receives the information gained in these analyses in form of institution reports and presentations. As a result of all these analyses, the university administration decided to continue developing and redesigning a package of supporting measures to address the problem of unsatisfactory initial mathematical knowledge. This package is to be used throughout the university. Summing up, this serves as one example how institution-wide analytics can support educational decision-making.

Adding the faculty as well as the institutional level to the existing framework results in the full LA framework in Fig. 7.3.

7.4.4 Summary of the Adoption Process

The case study described above shows the evolution from a small-scale implementation to an institution-wide LA framework at Aalen UAS. The focus of development lays on the iterative integration of new stakeholders and supporting them according to their specific needs by means of results from the data analysis. In this way, the impact was increased with each iteration.

This evolutionary development process can be understood in terms of the adapted *ROMA model* for bottom-up adoption described in Sect. 7.3. In contrast to other case studies regarding the *ROMA model* (top-down) which carry out only one iteration (cf. Ferguson et al., 2014), at Aalen UAS the adapted (bottom-up) model was run through three times in order to develop the full LA framework in Fig. 7.3. The individual steps of this adapted (bottom-up) model are essential parts of each evolution stage and can be identified in the case study. Table 7.1 summarizes them for

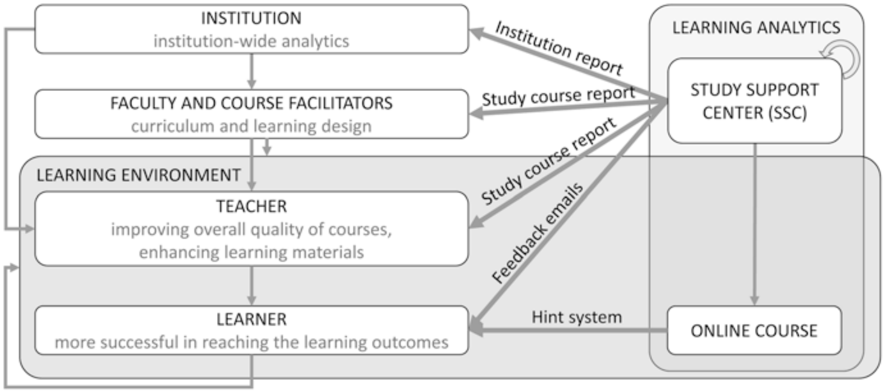

Fig. 7.3 Current state of the LA framework at Aalen UAS (cf. Hommel et al., 2019)

each iteration (note the changed order of steps 2–4 compared to the top-down *ROMA model*).

The case study shows clearly that the systematic iterative approach of the adapted *ROMA model* is suitable for a large-scale bottom-up LA adoption. In theory, this adapted model for bottom-up adoption can further expand the potential usage of process models, so that small projects can be scaled up. In particular, the (theoretically founded) *ROMA model* can already serve as a practical guide for a bottom-up adoption process if minor adjustments are made. This not only confirms the theoretical approach of the *ROMA model* but increases also its practical value.

The methodical approach of iterative process management offers the advantage of further development based on the results of previous iteration steps. Taken together with the addition of new stakeholder groups, transparency and trust can be increased. Nevertheless, by focusing on each stakeholder group individually, tailor-made developments are promoted. This leads to an increase in acceptance and fully exploits the potential of LA for the stakeholders.

7.5 Outlook and Conclusion

The previous sections show how the adoption of LA in a higher education institution can be realized using a bottom-up approach and how the results of the data analyses can support educational decision-making as well as the further development of the HEI. The adoption process starting from a small project and resulting in an institution-wide LA framework was furthermore regarded in terms of the process model ROMA. In order to focus more on the stakeholders and their needs, the original *ROMA model* for LA adoption was adapted to be suitable for a bottom-up adoption and three iterations were carried out.

Concerning the successful adoption of LA on a large scale, several main issues were mentioned in Sect. 7.2.1. The following list summarizes the conditions that

Table 7.1 Adoption process of LA at Aalen UAS with the adapted *ROMA model*

Step	Iteration 1 (cf. Sect. 7.4.1)	Iteration 2 (cf. Sect. 7.4.2)	Iteration 3 (cf. Sect. 7.4.3)
1. Define overarching objectives	Enhance SSC measures for better support of students	Increase awareness to close the gap between teachers and learners	Support educational decision-making
2*. Identify key stakeholders	SSC members as • Teachers • Researchers	• Teachers of mathematical lectures • Students	• Faculty and course facilitators • Institutional leaders
3*. Identify LA purposes	• Get more insights into students' initial mathematical knowledge and a better understanding of learning processes • Evaluate effectiveness of support measure	• Provide teachers and learners with evidence-based results from the evaluation to increase their awareness concerning existing deficits or specific circumstances	• Provide faculty and university administration with evidence-based results to support educational decision-making, strategic planning, and curriculum design
4*. Map the context	• Installation of the SSC as central unit • Specifications of the third-party funded project, e.g., financial and human resources • Requirements due to German privacy policy	• Evidence of deficits and specific circumstances available from analyses of iteration 1 • Problem: How can teachers and learners be made to change their behavior?	• Availability of study course specific and institution-wide evidence-based results • Problem: How can stakeholders of higher levels be reached and convinced?
5. Develop a strategy	• Clarification of data protection concerns • Definition of data base and evaluation approach	• Definition of type and content of reports for the different stakeholders (feedback emails, study course reports) • Selection of sending times • Consideration of specific needs of the stakeholders	• Definition of type and content of reports for the different stakeholders • Selection of the sending times • Consideration of specific needs of the stakeholders
6. Analyze capacity; develop human resources	• Definition of data acquisition (which data, when, how, participating departments like IT or student department) • Handling of big amounts of data • Understanding the structure of data from the SIS	• Development of simple, easily understandable visualizations of the results in order to avoid misinterpretations • Finding a suitable way to provide information • Help stakeholders with questions	• Development of simple, easily understandable visualizations of the results in order to avoid misinterpretations • Finding a suitable way to provide information • Help stakeholders with questions

(continued)

Table 7.1 (continued)

Step	Iteration 1 (cf. Sect. 7.4.1)	Iteration 2 (cf. Sect. 7.4.2)	Iteration 3 (cf. Sect. 7.4.3)
7. Develop a monitoring and learning system (evaluation)	• Adaption and extension of support measures of the SSC based on the evaluation results • Evaluation of the effects of these changes, e.g., with long-term studies	• Increased number of students signing the SSC DPS • Lecture evaluations and following reports offer a possibility for teachers to evaluate adaptions • Planned: Evaluation of the impact of feedback emails via user data of the online course	• Further development of institution-wide support measures • Curriculum adaption in study courses • Introduction of admission requirements • Evaluation of the effects of these changes with following reports and long-term studies

* Different order compared to the top-down *ROMA model*

have contributed to mastering them at Aalen UAS and, thus, being conducive to success:

1. Demand on resources (financial, human, technological): Financial and human resources were available due to the small third-party funded project the process started from.
2. Privacy, ethical, and legal concerns: Data protection regulation could take place right at the start realizing a high level of transparency by informing students in detail and giving the possibility to opt out.
3. Create trust into the system: Benefits could be delivered to more and more stakeholders, increasing their trust into the process and their willingness to support data collection.
4. Engagement of stakeholders: The provision of information was adapted to the needs of the stakeholders. Furthermore, stakeholders of all levels were integrated. Especially the institutional leaders showed interest in the evaluations already at a very early stage and promoted them. In this way, a common cause was built among the stakeholders. Thus, the development was directed to the goals of the university, which encouraged the adoption process.
5. Evaluation of usefulness and impact: An evaluation of the effects of the changes due to the data analytics is carried out within the accompanying research of the SSC, e.g., with long-term studies.

Nevertheless, there are still several challenges requiring further work in the future. Firstly, due to the changing in regulation, privacy and legal concerns are still relevant. Unfortunately, in all analyses of the SSC, only data of those students having signed the SSC DPS may be investigated. In order to achieve a systematic evaluation of the data of all students, the evaluation statute of Aalen UAS was revised. In addition, an evaluation statute for e-learning is in process, in order to allow the evaluation of data collected in this way. This should offer the possibility for further analytics and evaluations, e.g., of the impact of the feedback emails (cf. Sect. 7.4.2).

Secondly, concerning the often missing pedagogical grounding of LA technologies (e.g., Tsai et al., 2018), the integration of pedagogical advice for the teachers is regarded as an open challenge. In a first step, further integration of the existing didactic advisory at the university into the data analytics is considered. Based on these experiences, the development of a pedagogical guideline for teachers seems reasonable. As a result, the culture of the university may be changed.

Finally, another challenge lies in the impact of and the trust in LA (cf. Sect. 7.2.1). Only when the results matter for all stakeholders, data analysis can achieve its full potential. Since results from well-established data analytics processes are often better accepted than newly introduced ones, putting the newly introduced ones together with existing ones seems to be reasonable. As the evidence-oriented accompanying research of the SSC building the basis for the LA framework fulfills the demands made on a quality management of the study entrance phase (Maier, Hommel, & Egetenmeier, 2018), an integration into current, well-established QM processes is possible. Therefore, an intensified exchange is ongoing to explore the possibilities of integrating relevant results from the framework as a supplement to the current standard QM processes.

From the experience gained in the case study, we draw the following conclusions regarding a successful institution-wide adoption of LA. In general, it is difficult to deploy a large-scale LA system one-to-one to another HEI since every institution has a different context. Although the adoption of LA often shares common issues (cf. Sect. 7.2.1), every institution has to resolve them at least partially on its own. An LA adoption model can help here by providing a framework, which is then filled by the respective institution. Using a bottom-up approach offers the opportunity to involve stakeholders early in the process and to enhance their trust into the system incrementally by generating benefits for them. This focus on benefits for each group of stakeholders ensures the practical usage of the LA system and increases its impact. The adapted *ROMA model* for bottom-up adoption presented in this contribution can serve as guide for other HEIs to achieve this goal. Future research in adoption of LA should focus on the transferability and the practical use of this model. Among other things, it should be investigated if this bottom-up approach can also be used successfully at other universities or if further adjustments are necessary.

All in all, implementing LA on a large scale is an elaborate process that requires time and persuasiveness. The most important thing is to be patient, to be persistent, and to trust the process.

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Part II
Focussing the Learner and Teacher in the Adoption Process

Chapter 8
Students' Adoption of Learner Analytics

Carly Palmer Foster

8.1 Introduction

Learner analytics is defined as 'the direct-to-student communication and visualisation of personalised insights derived from the educational data mining process for the purpose of positively influencing learning behaviour' (Foster & Francis, 2019, p. 3). This differentiates it from other types of institution-facing analytics models where the data are not directly available to students; examples of the latter include predictive early warning systems to mitigate retention risks (Arnold & Pistilli, 2012; Jayaprakash, Moody, Laurana, Regan, & Baron, 2014) and curriculum development tools (Grant, 2012). In a learner analytics model, data are often communicated directly to students through dashboards, reports and apps without intervention or mediation by academic or support staff. Studies have evidenced that students do have a general interest in analytics systems and seeing their data (Sun, Mhaidli, Watel, Brooks, & Schaub, 2019) with results showing a positive correlation between students' propensity to share their data and their perceptions of its benefits (Ifenthaler & Schumacher, 2015). Students are usually expected to derive their own narrative and meaning from the data (Davis, Chen, Jivet, Hauff, & Houben, 2016). There are two types of learner analytics (Wise, Zhao, & Hausknecht, 2014):

- Embedded learner analytics integrates data directly into the learning environment or learning activity to influence participation, engagement or achievement. An example of embedded analytics is an eye-tracking study (Sharma, Davis, & Coulthard, 2016) which used gaze-based alerts to improve students' in-video attention.

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- Extracted learner analytics provides students with data that is not directly embedded within a specific learning activity but supports general participation in the learning experience. It presents individualised learning data and summarises engagement and achievement across a range of activities. An example of extracted analytics is *Learning Tracker* (Davis et al., 2016) which allows students to view and compare data on their engagement with online resources.

This chapter is concerned with extracted learner analytics, *Connect Analytics*, and the factors influencing its adoption during a live research project at Northumbria University in the United Kingdom. The predominant model of delivery is traditional on-campus teaching supported by a modularised virtual learning environment (VLE) and large on-campus library. Connect Analytics is a smartphone widget which sits within an existing university platform called Connect. The add-in was designed specifically for this project. It combines extracted analytics[1] with the functionality to self-capture data.[2] Data are presented either numerically or graphically across three screens: my modules, my course and my goals. When students log in, this generates trace data.

Digital technologies and analytics are located within a changing sector looking to harness technology to improve students' experiences and outcomes (Francis, Broughan, Foster, & Wilson, 2019). Learner analytics methods are generally reported to be effective relative to improving students' outcomes; for student-facing models, improved student engagement is the most commonly desired outcome of learner analytics (Foster & Francis, 2019). Studies often use historical data (e.g. grades, historical engagement with resources) to motivate future engagement and activities (see Aljohani & Davis, 2013; Brusilovsky, Hsiao, & Folajimi, 2011; Charleer, Klerkx, Santos, & Duval, 2013; Davis et al., 2016; Kitto, Lupton, Davis, & Waters, 2017; McNely, Gestwicki, Holden Hill, Parli-Horne, & Johnson, 2012; Sharma et al., 2016; Wise et al., 2014). The *Connected Learning Analytics (CLA)* toolkit (Kitto et al., 2017) is an example of analytics as a reflective aid whereby students 'explore data describing their past behaviour patterns and think about how they could change to achieve a data trace that fits more closely with identified goals' (Kitto et al., 2017, p. 166). The evaluation of *CLA*'s efficacy was inconclusive with one of the three trials specifically reporting adoption issues. It was suggested that this was due to a lack of alignment between analytics and assessment; the notion that students may not want to mimic idealised 'data traces' in their behaviour was

[1] Analytics was available on students' individual log-ins to the virtual learning environment by module compared to the class average. Module grades compared to the class average were also included. Automatically captured data from the virtual learning environment were updated every night with the previous day's activities. Grades data were updated when new grades had been validated on the student's record.

[2] Students may log the number of hours they have studied and measure this relative to their notional workload or track the progress they feel they have made in a module as a percentage. Students can also capture how difficult and stimulating they find each module and their progress relative to eight predefined 'personal goals'; 'Money & Finance', 'Physical wellbeing', 'Employability', 'Mental Well-being', 'Relationships', 'Fun & Social', 'Academia' and 'Living Space'. Self-captured data update instantly.

not challenged nor was there an analysis of whether there was a predisposition to adopt based on the attributes of the students involved in the study. Considering another tool, *Coach2* (Brouwer, Bredeweg, Latour, Berg, & van der Huizen, 2016) their study noted:

> The hypothesis was that the DB enables learners to explore and reflect upon statistical relations between current study behaviour and future result, based on experiences of learners in the past […] it was expected that the DB provides an actionable tool for reflection. (Brouwer et al., 2016, p. 366).

The study did not however attempt to understand what level of data literacy was required to digest 'statistical relations', what types of students would be comfortable comparing their behaviour to others and what the dashboard should include to be considered 'actionable' by students. In some cases, such as the *Navi Badgeboard* (Charleer et al., 2013), learner analytics goes as far as to actively penalise students for a lack of engagement by awarding negative badges for inactivity. It seems that whilst the majority of empirical studies in this space acknowledge an educational theory underpinning the change in students' experiences, few articulate how these theories are adapted to the specific context of learner analytics.

There is substantial evidence to support the assertion that digital behaviour can be used to infer personality (Lambiotte & Kosinski, 2014) with studies finding relationships between personality and university students' information literacy (Aharony & Gur, 2019), use of mobile technology (Ehrenberg, Juckes, White, & Walsh, 2008) and willingness to try out new technology (Nov & Ye, 2008). Moreover, there are studies which find that students' intentions to use technology for learning is influenced by the intersection between their personality and their learning style (Balakrishnan & Lay, 2016). These are almost non-existent considerations in the literature which evaluate the effectiveness of learner analytics. Most studies start with an existing theory of change and assess impact within that frame of reference rather than starting with the student and their thoughts, values, motivations and behaviours regarding personalised data and its presentation. Often, 'self-regulated learning' is a theory underpinning learner analytics design without an understanding of how or why students' access to or engagement with analytics supports any change in behaviour. Studies have gone as far as to deploy advanced statistical methods on population sizes of over 10,000 MOOC learners to quantify the positive impact of learner analytics on engagement and final grade (Davis et al., 2016). There remains however an unsatiated appetite for more meaningful critique and understanding if and how these results may be replicated in traditional higher education settings.

Moreover, Prinsloo and Slade (2016) argue that students are not necessarily aware of the data mining activities taking place in their learning environment nor the controls in place and are unclear how it is of benefit to them. Unsurprisingly then, as the operationalisation of analytical approaches develops, educational data mining and, by extension, learner analytics are often scrutinised regarding data ownership, value and control in platformised academies (Robertson, 2019). Left unaddressed, this may impact wider scale implementation by institutions and adoption by students.

Establishing some core principles for learner analytics, adoption will provide structure for future approaches by contributing insight into the underlying causal relationship at play. This understanding is critical to progress; even if learner analytics tools are, as evidence suggests, effective in improving students' attitudes and behaviours, the consequential impact on transforming learning and attainment are impossible to realise if tools cannot be systematically implemented, adopted or maintained. The aim of this chapter is to investigate students' predispositions to data and analytics and offer insights on how they perceive its value relative to their existing educational and digital experiences. The setting is a large UK university. There are two guiding research questions:

RQ1: What do students expect from a learner analytics platform? How and why does this influence adoption?
RQ2: With what purpose do students engage with a learner analytics platform? How and why does this influence adoption?

8.2 Methodology

The research methodology deployed in this study was Critical Realist Grounded Theory (Blunt, 2018; Hoddy, 2018; Oliver, 2012), a hybrid approach which accommodates mixed methods and acknowledges that at the outset of the research it was not fully known if, when, why or how students would engage with the learner analytics platform or what factors would bring about the phenomena. Grounded Theory (Glaser & Strauss, 1967), on the one hand, offers the opportunity to 'address "why" questions while preserving the complexity of social life' (Charmaz, 2008, p. 397). Critical Realism, on the other hand, highlights the importance of the senses, perception and causality within scientifically significant experience (Bhaskar, 1978). Critical Realist Grounded Theory recognises a compromise for both the abductive philosophy of critical realism and the inductive emphasis of grounded theory methods and allows for a distillation of emerging themes influencing adoption. Consequently, this chapter offers results and discussion which seek to get as close as possible to the reality of students' adoption of analytics whilst acknowledging that it will never be the actual experience of every or any individual wholly.

The predominant method of data collection was capturing student sentiment through pre- and post-project surveys plus semi-structured focus groups and interviews. Some quantitative and statistical methods were used with respect to survey data and trace data to aid a contextual understanding of the research environment. As Eaves articulates, the process of grounded theory is 'a recursive rather than linear one' (Eaves, 2001, p. 657) and so it is important to at least convey the chronology of data collection and analysis across the academic year 2018/19 (Fig. 8.1).

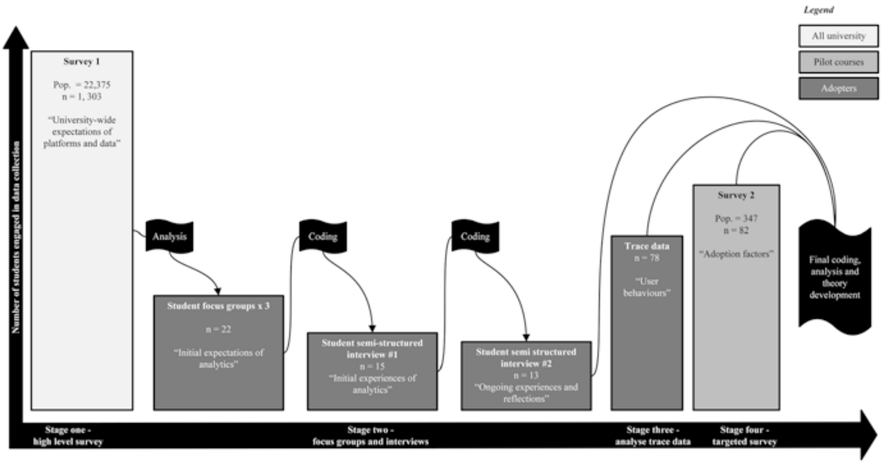

Fig. 8.1 High-level overview of the research process

After each stage there was a period of theoretical sampling (Hodkinson, 2008) to inform, design and refine the subsequent data collection activity. Sample sizes from the first survey were large enough to utilise two-proportions Z-testing; where sample sizes were too small in the later survey, Barnard's exact test was used in R software. This is a critical realist, mixed methods approach which posits the value of all data in the appropriate context. Small samples sizes coupled with the process of theoretical sampling limit the extent to which the quantitative results of the second survey may be considered categorically and in isolation; nevertheless these results are offered to you here in a documented context with the hope that that they are either replicated with greater ease or disproven with greater clarity. Ultimately the analysis herein prescribes to the notion that there exists 'a world where researchers are free to treat "p = 0.051" and "p = 0.049" as not being categorically different' (Wasserstein, Schirm, & Lazar, 2019) and asserts that this chapter presents only a signpost in the journey towards learner analytics theory. A summary of each stage follows.

The first survey sought a university-wide understanding of students' expectations for using data about themselves within their learning environment. To maximise feedback and gain a high level of confidence in the results, the first survey was sent to all students on campus (n = 21, 799). It had 1303 responses (6.0%) despite 17,164 students (78.7%) opening the email invitation to complete the survey and 1607 students (7.4%) clicking on the link to the survey. The majority of survey respondents (n = 1051, 84.1%) were already users of the Connect platform; this proportion of users to non-users is comparable with the general population for that period in the academic calendar. Male students were significantly less likely to participate in this survey (p = 0.00).

From both practical and operational perspectives, the live project was restricted to certain programmes and cohorts to allow for ongoing development of the platform and limit the risk of technological failure. From an ethical perspective and being cognisant of projects which had encountered negative effects of learner analytics (Beheshitha, Hatala, Gasevic, & Joksimovic, 2016), the project took an informed consent approach meaning students had to sign up to access Connect Analytics on their smartphone.[3] An invitation to sign up was sent to students enrolled on specified courses as well as a group of student representatives (the total number of invited students = 347). The semi-structured focus groups took place at the beginning of a 15-week semester followed by individual interviews with users in the middle and end of the semester. Participants were users with access to Connect Analytics granted a week prior. Activities were transcribed and coded in the interim weeks (see Fig. 8.1) and then thematically analysed. The end of project survey was targeted to the eligible population for the pilot including non-users; it had a response rate of 24% (n = 82) and tested the emerging themes, not just from the interviews but the whole research journey. Sample sizes were small in this survey and so findings are somewhat limited. The crux of the survey played back to students the personality traits which were, during focus groups and surveys, most frequently hypothesized as being important factors influencing the adoption. This is at the expense of using an existing recognized personality framework such as the 'big five' (Goldberg, 1990). It also relies on students' perceptions of their personality and academic standing rather than a diagnostic or statistical assessment thereof. These were conscious decisions made to preserve the recursion of the grounded theory process, acknowledge the limitations of the researchers' expertise in the field of personality trait psychology and present a foundation upon which a variety of disciplines may build.

Trace data was analysed based on the student ID, activity type and timestamps. Students were grouped into user types based on their *frequency of use* and their *regularity of use*. Frequency of use is a quartile-based position derived from the product of a) discrete weeks of platform usage and b) the volume of activities. Regularity of use was derived from the quartile position of the maximum count of weeks that a student went without any usage.

8.3 Results

This section begins by summarising the findings of the university-wide survey which investigated students' propensity to use data about themselves and others as well as the impact and benefits that they expected such an implementation would have. Data are then presented from the live research project; results here include quantitative counts of students who signed up to access Connect Analytics supported by qualitative data on their motivations and experiences.

[3] The project also had to comply with General Data Protection Regulations which are significant if not somewhat ambiguous in the space of operational learning analytics.

8.3.1 Implementation of a Learner Analytics Platform

The results show that 66% of students (n = 862 / 1303) agreed that 'they use data and information about themselves to make decisions' but less than half said they used data about other people (n = 621 / 1303). Students in Computer and Information Sciences (p = 0.01) were more likely to state that they used data and information both types of data; the only group of students statistically less likely to do so were those who chose not to disclose their demographic data (p = 0.01).

Students were asked, would it be useful if the university presented data and information about their engagement with their studies? 84% of respondents said yes (n = 901 / 1069). Figure 8.2 shows that grades data was deemed to be the single most useful piece of information.

Students of applied sciences were particularly more likely to want to see grade data (p = 0.02) whereas a significant proportion of social work and education students disagreed with this (p = 0.00). Accounting and finance students notably favoured VLE login data (p = 0.00) but design students were unlikely to expect that it would be useful to them (p = 0.01). Psychology, social work and education students were significantly more interested in attendance data (p = 0.00) which was the opposite of architecture and built environment students (p = 0.01). Students in humanities favoured data on library activity (p = 0.01,) but not one of the 59 art students surveyed said this data would be the most useful data to them.

Seventy-three percent of students wanted to compare their data to another data point; the choice of the majority, when given multiple choices to select from the most popular combination, was comparing to the class average and self-set or university-set targets (n = 183/1069). Comparing their data to students in the top of the class from either their current cohort or the cohorts from previous academic years was unpopular and was more likely to be a preferred option for male students

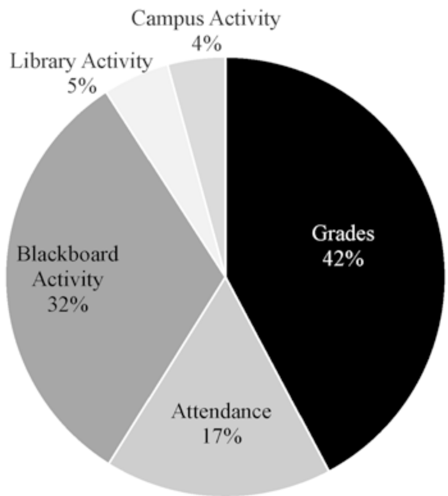

Fig. 8.2 "Of the data or information below, pick the one that you think would be most useful to you"

Table 8.1 The expected impact on the student experience of presenting data and information

Question	% Agree	Commentary
Access to data and information about my studies would impact what I do during my university experience	80% agree (753 agree; 249 strongly agree)	Students in applied sciences were significantly more likely ($p = 0.00$) to expect an impact on what they do as a result of the data. None of the 51 design respondents disagreed that the data would impact their actions ($p = 0.04$).
Access to data and information about my studies would impact what I know about my university experience	75% agree (682 agree; 250 strongly agree)	Students in computer and information sciences and design were significantly more likely to expect an impact on what they know as a result of the data ($p = 0.02$ and 0.03 respectively).
Access to data and information about my studies would impact what I think about my university experience	65% agree (654 agree; 161 strongly agree)	Students in both applied sciences and Law were significantly more likely to expect an impact on what they think as a result of the data ($p = 0.01$ and 0.04 respectively).
Access to data and information about my studies would impact what I feel about my university experience	64% agree (618 agree; 179 strongly agree)	Students in computer and information sciences were significantly more likely ($p = 0.02$) to expect an impact on what they feel as a result of the data. Psychology students were the only subject group to significantly disagree ($p = 0.02$) with the idea that data would impact how they feel.

(35% versus 27%, $p = 0.00$) and international students (44% versus 27%, $p = 0.00$). Table 8.1 shows the results of questions which asked students whether their data would influence what they do, know, think or feel whilst at university. Students were significantly more likely ($p = 0.00$) to expect that data and information would impact their actions rather than their emotions.

Some students anonymously, through the free text commentary, raised concerns that data analytics may introduce an unhealthy nature of competition into their community; ‘It could cause anxiety for some students who are not as confident or academic. As I am studying nursing, which should be about working as a team and supporting each other, rating people could discourage this thinking. It also encourages people to judge themselves and others on their academic achievements alone’. These sentiments were countered in equal measure with positive comments; ‘I would like to see analytics of my library usage, with a rundown of the amount of books I have used and the amount of journals I have accessed in order to see if there was a correlation between the amount of time I spend in the library and my eventual grades’.

8.3.2 *Adoption of Connect Analytics in the Live Pilot*

The invitation to sign up to the Connect Analytics widget was sent in the first teaching week of the second semester. Twenty-two percentage (78 of 347) of eligible students signed up using an online form in an email invitation from the programme leader over a period of 10 days. No students signed up after this point even though the ability to join the project was open throughout the whole semester. The sign up invitation was not effective as the sole method of capturing students' propensity to adopt the technology with students reporting that they did not pursue analytics because 'they did not receive the email' or they 'forgot about it'. This limits the findings somewhat.

Of the 78 students who did sign up via the invitation, 22 took part in one of three focus groups. When asked about their expectations for using analytics, many students perceived its purpose as being intrinsically linked to academic support. This was as a formative intervention based on historical performance:

> I thought it would be if you haven't performed well in your exams and how you can perform better. So automatically we will get some emails or links to library skills sessions and it would prompt you if you haven't done good in this part of the exam last semester or so it would say do this and you can improve on that. [Focus Group 1]

For others it was more future-focused with students' expecting data summaries and functionality to plan various scenarios; 'I wanted to see where I am up to academically and what pass marks I need to get certain grades' [Focus Group 2]. A major appeal was that students expected it to integrate with and collate information from multiple platforms to relieve the burden of navigating them separately; 'the thing that definitely drew me to this app was seeing the scores that I have up to now because [the virtual learning environment] really isn't conducive to having an overall idea of what your grade is up to this point' [Focus Group 1]. It was expected that analytics would extract data to track their experience. Some students wanted their Wi-Fi usage and library access data presented as a proxy for their on-campus engagement; others questioned whether it could link to apps they were using for study such as *Toggl,* the time tracking and reporting application, and *Forest,* an application designed to improve users' focus on their physical surroundings by encouraging smartphone hiatus.

In total, Connect Analytics was accessed 1121 times; 222 of these occasions were just to view the analytics with no logging activity or 'clicks', e.g. data interrogation recorded. Figure 8.3 shows that usage fluctuated over the semester. For context focus groups took place in week 1 and interviews were conducted in weeks 8 and 14; whilst the intrusion of the data collection activities will certainly have impacted the weekly login statistics, the chart shows that analytics engagement is more active during teaching time.

Fifteen students engaged with part one of the interviews and thirteen went on to engage with part two. Fifty-six percentage ($n = 44 / 78$) of students who signed up to Connect Analytics engaged with the self-capture data functionality at least once. Table 8.2 summarises individual student activity as per their frequency and regularity of using the platform.

For brevity those students with no logging activity whatsoever are not included in Table 8.2 but are discussed alongside sporadic users in (see 8.3.2.5). Table 8.3 shows that the most frequent users were studying business but were the least regular in terms of their activity pattern. Design students appear to have above average fre-

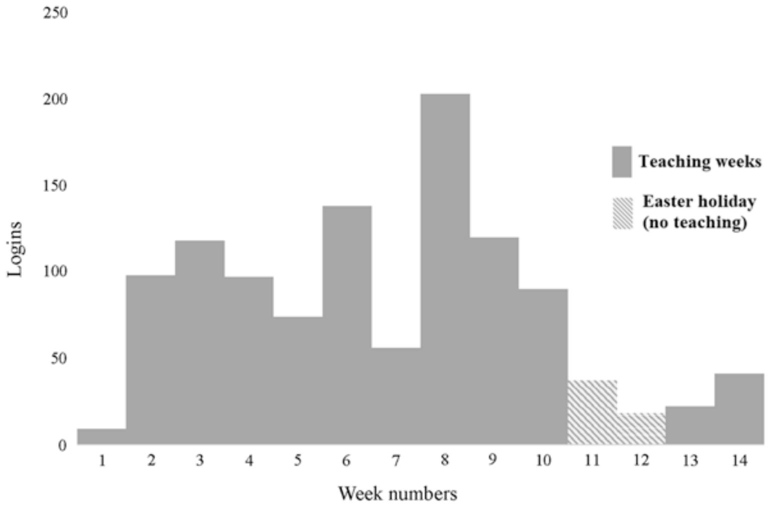

Fig. 8.3 Students logins to Connect Analytics by week of semester

quency of use however this was due to 'Student15' exhibiting excessive logging behaviour (z = 5.3) compared to the rest of the group which inflated the results. Removing Student15 from the cohort as an outlier shows that design students were the least frequent users of the platform.

Individual students were grouped based on their frequency and regularity of Connect Analytics activities. The typologies which emerged in the trace data provided a useful structure for triangulating and synthesising the focus group and interview transcripts to highlight patterns and trends. They are discussed hereafter.

8.3.2.1 Somewhat Active but Irregular Users (N = 12)

These students mainly cited that their adoption of analytics was driven by a desire to see their grades and track comparative academic progress. Several hypothesised that engagement with and commitment to university would influence analytics usage; 'I think there could be a correlation, not between intelligence, but those who do well by engaging with their material and those who engage with the app' [Interviewee 2]. These students were disappointed that the grade average only updated with summative module assessment marks; this caused them to use the app less as the semester progressed stating that the grade information did not change frequently enough for it to be useful. Capturing and tracking their own data was generally deemed to be too subjective to be useful but they did try it; 'it didn't really mean anything to me' [Interviewee 5]. These students were not negative about analytics or their irregular usage because they took an individualised perspective towards its utility:

Table 8.2 Users grouped by frequency and regularity of self-data capture

Student	Frequency (*z*)	Regularity (*z*)	Type
Student1	−0.3	0.8	Somewhat active, irregular
Student2	0.4	−2.3	Active, regular
Student3	−0.2	−0.2	Somewhat active, irregular
Student4	−0.5	1.4	Sporadic
Student5	0.0	0.1	Active, irregular
Student6	−0.4	0.8	Somewhat active, irregular
Student7	−0.4	0.8	Somewhat active, irregular
Student8	−0.5	0.4	Sporadic
Student9	1.2	−1.9	Active, regular
Student10	1.3	−1.6	Active, regular
Student11	−0.1	0.4	Somewhat active, irregular
Student12	0.1	−0.2	Active, irregular
Student13	0.4	−0.2	Active, irregular
Student14	2.6	−0.6	Active, regular
Student15	5.3	−1.9	Active, regular
Student16	−0.2	0.4	Somewhat active, irregular
Student17	−0.1	−1.6	Somewhat active, regular
Student18	0.3	0.1	Active, irregular
Student19	0.7	0.1	Active, irregular
Student20	−0.5	0.1	Somewhat active, irregular
Student21	−0.2	−0.9	Somewhat active, regular
Student22	0.0	−0.9	Active, regular
Student23	−0.2	1.4	Sporadic
Student24	−0.3	−1.3	Somewhat active, regular
Student25	−0.5	1.1	Sporadic
Student26	−0.5	−0.2	Sporadic
Student27	−0.4	1.1	Sporadic
Student28	−0.4	0.8	Somewhat active, irregular
Student29	−0.4	−0.6	Somewhat active, regular
Student30	−0.4	1.4	Sporadic
Student31	−0.5	−0.6	Inactive, regular
Student32	−0.4	−0.6	Somewhat active, regular
Student33	−0.5	−1.3	Inactive, regular
Student34	−0.5	0.4	Sporadic
Student35	−0.4	−0.2	Somewhat active, irregular
Student36	−0.1	−1.3	Somewhat active, regular
Student37	−0.5	0.4	Sporadic
Student38	−0.5	1.1	Sporadic
Student39	−0.5	1.1	Sporadic
Student40	−0.3	0.8	Somewhat active, irregular
Student41	−0.4	0.4	Somewhat active, irregular
Student42	−0.5	1.1	Sporadic
Student43	−0.3	1.4	Sporadic
Student44	−0.4	0.4	Somewhat active, irregular

Table 8.3 Average and range frequency and regularity of use by subject

Subject	Frequency average	Frequency range	Regularity average	Regularity range
Business	0.2	1.2	−0.7	0.8
Other	0.0	0.4	−0.5	1.4
Design	0.1	5.3	0.2	1.4
Sport	−0.3	0.7	0.1	1.4
Computer science	0.0	2.6	0.1	1.1

> We spent about ten hours in the library because we left an essay until the last minute […] that's personally not something I even thought about logging because it didn't feel like time well spent. It just seemed like a last-minute rush and that's not something I want to log. It's not ten hours that I'm proud of [Interviewee 4].

This group also challenged the usefulness of automatically captured data without local context. Saying of comparative data on VLE logins: 'It makes no difference because for some classes the lecture slides are online. It makes sense that the data isn't the same and so it wouldn't really help me do anything' [Focus Group 2]. Design students did not see VLE data as being a metric for their success: 'once we've downloaded the thing we need, we don't need to use it again, with everything being more sketch-booky' [Interviewee 7]. This student went on to elaborate on the library loans feature; 'I'm not bothered about data on my library books. Sometimes it just depends on how many I can carry not how many I want to read'.

8.3.2.2 Active and Regular Users ($N = 6$)

When asked what they hoped to achieve from the platform, these students focussed on two areas: improving organisation and quickly accessing high-level grade information. 'I use this app to create a balanced academic life across all modules. It has allowed me to be confident in the organisation of my time. Especially in the exam window' [Interviewee 13]. Students in Group 2 also acknowledged that self-capturing data was subjective but their overriding focus on planning rather than benchmarking meant this positively translated to their needs. These students believed that simplifying and centralising their data was a bonus and that it had an aspect of fun about it.

> This just takes all the information and puts it all in one place. It makes it really easy to flick through, look at it and plan. I find the other stuff fun. How many books you have on loan, how many times you've logged in to the VLE aren't really useful per se. They don't really motivate you because they don't really log your progress or anything but they're just really fun to check out [Interviewee 5].

Speaking of the goals section, this student also commented: 'It's very subjective as it's just 1–10 and nobody really knows what you would call a 1 and what you'd call a 10. But that's the fun in it'. These students were the biggest users of other types of apps for studying. Three of the six cited previous experience in designing and coding apps, and all had a clear understanding of how data could be structured and personalised to specific settings:

> One student might log 100 hours for this part, 100 hours for the other part. For somebody else in design it might sketchbook phases. So we might already know that we want around 100 pages, so they might say that, 'I don't care if it's 25 research pages, or 25 development pages, I just want 50 pages.' [Interviewee 10]

8.3.2.3 Somewhat Active and Regular Users (*N* = 6)

These students placed less initial emphasis on the organisation and management of their study habits and behaviours. They differ from Group 1 in their perception of the other non-grade data. Instead of disengaging with the platform when they realised that grades did not update regularly, they switched to using self-captured data with the consensus that it was fun and 'some data is better than no data' [Interviewee 3]. This meant their usage persisted consistently but not in the manner they originally intended. The subjectivity of self-captured data was actively managed through self-reflection: 'I like logging progress. I've adjusted the way I look at it' [Interviewee 11]. These students were ambitious and keen to use multiple methods and tools to achieve their goals; commonly this included daily pen-and-paper to do lists to visualise their plans. Most students admitted that, despite its advantages, analytics complemented but did not replace their handwritten task lists fearing that digital task lists would overcomplicate the process and become less bespoke to them by standardising rules and categories.

8.3.2.4 Active but Irregular Users (*N* = 5)

These five users had a distinct and differentiating focus: self-tracking in the goals section. The high volume of activity for this group is mainly due to the level of data points created when interacting with the eight different goals and as such their activity counts are inflated compared to the other groups. Students who tracked their goals typically did not engage with other sections of the app and had little interest in the data of others. They used it only when they perceived their circumstances required them to rather than habitually: 'It is good to reflect on my goals. Although I change a lot and am very much in flux I think where I want to be is pretty much consistent, so I keep them there to stay on track' [Interviewee 9].

8.3.2.5 Sporadics and Users with No Logging Activity (*N* = 49)

The only way to understand the usage behaviours of students with little or no trace activity is through qualitative enquiry. However these students are typically harder to engage; only a few students signed up for the focus groups and none attended the interviews. Their non-adoption of specific elements of learner analytics is difficult to ascertain without further research. Those who did attend focus groups reported that the self-tracking features did not integrate enough into their experiences to be worthwhile: ‘the reason I’m not using it is I feel it is very subjective. I could drag that thing back and forth all I want but it doesn’t really mean anything’ [Sporadic user in Focus Group 1]. Design students were notably positive about the concept of logging their study hours to prove when they were in the studio; however, in reality, this did not materialise for the majority. During the interviews some said they found using their phones in the studio for *any* purpose ‘too distracting’ and were actively avoiding it. Checking their data sporadically was useful for maintaining a feeling of motivation, but they felt that comparative data, which had perceived risks to personal and community wellbeing, should be optional and customisable.

8.3.3 Students’ Feedback on Connect Analytics After the Live Pilot

Of the 72 students who signed up to access Connect Analytics, 45.8% ($n = 33$) completed the end of project survey; of the 275 students who did not sign up to Connect Analytics, 17.8% ($n = 49$) completed the survey. The completion of the post-project survey was low amongst those who signed up but did not use the platform ($n = 8$). These students thought it was ‘too crowded’ or said they ‘forgot about it’. One student remarked in the free text field, ‘I was expecting personality type tests, advice and mementos of when and what to do’, which corroborated sentiments from the focus groups. Respondents who did not sign up to access Connect Analytics cited a variety of reasons such as they did not notice or receive an email invitation, they forgot to sign up or they did not want to use more of their phone’s memory. Only one student cited privacy concerns as the reason for not signing up.

Tables 8.4 and 8.5 summarise the results of questions which sought to understand whether students’ perception of their personality and relative academic performance correlated with their adoption and use of Connect Analytics.

Students who felt ‘organised’ were less likely to sign up citing that they did not feel they needed to track themselves. Conversely there are directional data to suggest that students who perceived themselves as being ‘forgetful’ were more likely than not to sign up; this had no impact on their adoption of the platform over the semester and may be due to small sample sizes. “This does however align with the topic of ‘forgetfulness’ which emerged in the interviews; ‘reminders is the main thing I thought that this app should do’ (somewhat active but irregular user, Interviewee 4). Ongoing usage was significantly lower for students who perceived themselves to be shy, and there is evidence to suggest that a perceived creativity may also be an influencing factor although half of these students were designers. Despite much discussion in both the focus groups and interviews about using data to positively drive competition, no meaningful statistical relationship could be quantified in terms of its influence on adoption.

Table 8.4 Self-stated personality style versus initial platform adoption and ongoing usage

Self-stated personality	Sign up	Didn't sign up	*p* One-tailed	*p* Two-tailed	Used	Didn't use	*p* One-tailed	*p* Two-tailed
Organised	4/33	14/49	0.04*	0.09	4/25	0/8	0.15	0.29
Forgetful	7/33	4/49	0.07·	0.10	6/25	1/8	0.33	0.58
Reliable	5/33	13/49	0.19	0.26	5/25	0/8	0.12	0.19
Consistent	7/33	6/49	0.19	0.34	7/25	0/8	0.12	0.12
Eratic	4/33	2/49	0.11	0.21	2/25	2/8	0.14	0.24
Engaged	8/33	8/49	0.25	0.46	6/25	2/8	0.50	1.00
Confident	9/33	10/49	0.33	0.57	7/25	2/8	0.50	0.90
Focused	5/33	11/49	0.33	0.57	5/25	0/8	0.12	0.19
Motivated	11/33	18/49	0.40	0.77	8/25	3/8	0.48	0.84
Collaborative	4/33	9/49	0.33	0.57	2/25	2/8	0.14	0.24
Shy	4/33	9/49	0.33	0.57	1/25	3/8	0.02*	0.02*
Creative	8/33	10/49	0.36	0.70	4/25	4/8	0.04*	0.06 ·
Competitive	7/33	9/49	0.40	0.77	7/25	0/8	0.12	0.12
Introverted	6/33	7/49	0.36	0.65	4/25	2/8	0.48	0.73
Balanced	3/33	7/49	0.33	0.57	1/25	2/8	0.06·	0.07 ·
Pessimistic	1/33	4/49	0.21	0.37	1/25	0/8	0.48	0.73
Diligent	2/33	2/49	0.37	0.71	2/25	0/8	0.32	0.57
Stimulated	1/33	0/49	0.19	0.24	0/25	1/8	0.12	0.12

*Significance code: *** p < 0.001, ** p < 0.01, *p < 0.05, ·p < 0.1*
Barnard's exact test

Table 8.5 Perceived academic performance versus initial platform adoption and ongoing usage

Self-stated personality	Sign up	Didn't sign up	*p* One-tailed	*p* Two-tailed	Used	Didn't use	*p* One-tailed	*p* Two-tailed
Top of the class	12/33	11/49	0.10	0.19	11/25	1/8	0.12	0.13
Around average for my class	19/33	37/49	0.07·	0.09·	13/25	6/8	0.15	0.29
Below average for my class	2/33	1/49	0.24	0.43	1/25	1/8	0.26	0.47

*Significance code: *** p < 0.001, ** p < 0.01, *p < 0.05, ·p < 0.1*

No significant relationships were found between students' perceptions of their academic performance and their propensity to adopt analytics; however, students who felt they were top of the class were more likely to use the grade average function (11/12 users) and cite their reasons for using analytics as being for comparative academic reasons: 'it's motivation to be better than others' and 'it has allowed me to have clear comparisons between my own work and others in my class'. This is in contrast to the students who felt they were around or below average academically who reported lower usage of grade functions (13/21, $p = 0.03$) and were more likely to use the app to keep themselves on track for their modules.

In order to explore the idea of 'signposting and support', students were asked whether accessing analytics had led them to engage with academic staff or support services. Only two students said that it had, both of which said it made them seek the advice of their tutor on how to improve their grades.

8.4 Discussion: Understanding Students' Adoption of Learner Analytics

Two thirds of students reported in the first survey that they used data about themselves to make decisions. Students most likely expect data to affect their actions rather than thoughts or feelings. The focus groups offered further insights that students expected the analytics platform to triage issues and signpost to support services. It was, on a basic level, expected to encourage positive study actions. Only two students reported that they sought help from a tutor as a result of the data and generally it was not the case that analytics had a direct widespread impact on students engaging in new activities. Accessing analytics helped to inform the frequency or focus of students' existing activities. It is argued that analytics may only have the reach to motivate new actions and behaviours for a small subgroup of regular and confident adopters.

The first survey highlighted that grades were expected to be the most useful dataset with qualitative analysis, later providing insight that this is both to evaluate previous performance and plan future academic improvement. Students who perceived themselves to be successful academically were more likely to use grades data which suggests it is affirming rather than inspiring. VLE was also expected to be useful and previous research suggests that the outcomes of MOOC and blended learners can be improved by sharing online engagement data. However, in an on-campus setting, VLE data seem less valuable; in reality the users of certain disciplines were less sure how to interpret it meaningfully and questioned its appropriateness as a proxy for their learning style. This is an important finding as it demonstrates how learner analytics, particularly extracted models, may increase adoption by adapting to modes of teaching and learning styles.

The results suggest that the perceived usefulness of different datasets differ by subject; good proxies for engagement are different for designers who may gauge a successful day in terms of sketch book pages or time spent in the studio versus subjects with a greater emphasis on essay progress or time spent in the library. Furthermore, students of vocational subjects such as nursing, social work and education were hesitant to engage with analytics around academic performance because of the impact on community spirit. This does not necessarily mean that learner analytics only has traction for certain subject areas only that students adopt and respond to data differently based on their discipline. This may mean different datasets and comparator groups within an agile learner analytics model. Catering to the personality differences and values which manifest in academic tribes presents challenges for multidisciplinary institutions which want to offer a standard analytics solution to all students.

By consolidating data from hard-to-navigate platforms, analytics can allow students to locate themselves on their educational journey; for some this is relative to their goals whereas others are keen to orientate themselves relative to peers. As such data and analytics are merely stimuli within the students' experience helping them to reflect and react. Unexpectedly, as stimuli it was also found to be fun. Contrary to the expectations reported in the university-wide survey, adopting learner analytics leads many users to think and feel differently; this is an interesting juxtaposition of expectations and actual experiences. Those who accessed Connect Analytics often discussed how it made them feel in terms of their motivation, sense of control and performance; debating implications that comparative data could have on emotions was particularly prevalent. Although it was popular for students to want a second dataset with which to compare, it was found that male students and international students had the greatest appetite for comparing their data to top of the class.

The cadence of data updates was also found to influence adoption based on students' appetite for new information. More granular data such as module component marks which are often available earlier in the semester may have increased adoption amongst users in this study but may also have hindered it by making the platform 'busy'. It is important to recognise that students do not all engage with analytics regularly and consistently. A minority of students will habitually engage with analytics but the majority will naturally fluctuate. These peaks and troughs are in line with their changing perceptions and goals, their teaching schedules and the key points in the academic calendar such as exams. A deeper understanding of these factors will help to encourage a positive model of engagement rather than penalising students for their lack of use. There is no reason to believe that periods of inactivity mean analytics has failed to be adopted; even sporadic users engage at points they feel are appropriate and relevant for them.

One of the most definitive factors influencing students' adoption of data and analytics is its role in the organisation and management of study habits and behaviours; unlike embedded analytics, this is core to extracted analytics because the data presented are not of any academic value but instead support study holistically. Specifically, they support an existing and prevalent culture of tasklisting amongst students and add detail and precision to their plans. Most students admitted that analytics complimented but did not and was unlikely to ever replace their handwritten task lists. Conversely, there were students who wanted to use analytics but could not organise themselves to do so.

Whilst it is encouraging for the field of learner analytics that the majority of students in this study were open about the possibilities of using data analytics, the self-selection of students to the surveys, focus groups and interviews may have exaggerated this finding. Students who chose not to actively disclose their demographic data felt less certain that they would use analytics to make decisions. This is a demonstration of the findings of Ifenthaler and Schumacher's (2015) research on student's propensity to divulge personal data which correlates with their conservative perception of the benefits of doing so (Ifenthaler & Schumacher, 2015).

There will always be a subsection of the population for whom personalised data raise concerns although these students generally represent a small percentage of the community. There are opportunities for more open and transparent communication around learner analytics including the opportunities articulated by students in this research. These may alleviate apprehension and positively promote students as active agents in learner analytics rather than as passive consumers of data.

Students' adoption of learner analytics is found to be similar to that of other digital pedagogies such as game-based learning, in that it intersects with their expectations, level of interest and engagement (Eseryel, Law, Ifenthaler, Ge, & Miller, 2014). It is argued that students' propensity to adopt analytics is influenced by their existing relationship with data, their discipline, their perception of self and the connections between these factors and the following four expected benefits:

1. Improved knowledge of academic standing (e.g. compared to personal goals or class benchmark)
2. Better informed organization and study management
3. In situ signposting to relevant support services
4. Curiosity and fun

Learner analytics emerges as a vastly more personalised process than has previously been presented and so it follows that it has drawn the attention of literature on capitalist higher education platforms which often criticise the deployment of analytics for personalised services. Hall (2016) argues that educational data platforms facilitate a Foucauldian model of experience whereby students are microentrepreneurs; for learner analytics this implies a movement away from institutional and faculty led initiatives towards the self-service and self-support model. This study argues that data, extracted from one platform and presented in another, are capable of impacting students' behaviours and perceptions; the platform can facilitate and empower students to impose their individualities and experiences on to data in a way which becomes personalised and thus meaningful. It is therefore asserted that to assume learner analytics could ever be a ubiquitous tool for self-regulation is an oversimplification. Zimmermanm (1989) argues that self-regulation relies on students' strategies, perceptions of self and goals; undoubtedly there are elements of that in learner analytics. This study finds that learner analytics supports and refines but also disrupts and is disrupted by this process. Some students may positively regulate their learning as a result of analytics, but there are personality types and learning styles which do not orientate using data alone and so it is not generally applicable. Students' perceptions of self and others fluctuate throughout the semester; even personal goals are not constant. Students may change tactics, but their overarching strategies are rarely moved by data.

Students should be supported to use learner analytics. Designated materials and resources which introduce the process of extracted analytics may mitigate negative consequences arising in isolation such as confusion over an engagement metric or disappointment at a bad grade. The ability to tailor comparator sets and customise data may alleviate anxiety; however, customisation may also lead to certain subgroups 'hiding' from data. Allowing data to be hidden does not support students to deal with situations or empower them to take agency in their academic development; providing all data and encouraging them to cherry-pick may prove the best balance.

In spite of the complexities at play in the adoption of learner analytics, there is a lighter side to data and one which is underplayed in learner analytics literature to date; most users enjoy consuming their data. Fun is particularly important for learner analytics adoption because the lack of an intermediary to make sense of the data has the risk of disengaging or demotivating students. That their engagement with analytics can be classified as 'a bit of fun' acknowledges that there are equally important non-quantifiable aspects of their experiences as students. It also helps practitioners to better appreciate the relative value of extracted data within a far broader context that varies for each individual student.

8.5 Conclusions

At the beginning of the academic year, data were gathered across a broad range of subjects to understand students' expectations of personalised data and analytics; this was followed by a smaller study to observe those expectations in reality and contextualize adoption. The research, although modest in scope and accepting of its limitations, has been successful in gathering a wide variety of data which have herein been presented as exploratory insights into students' adoption and usage of extracted data analytics in their learning environment. It has established that students' propensity to adopt analytics is influenced by their existing relationship with data, their discipline, their perception of self and the connections between these factors and the following four benefits: analytics for orientating oneself academically; analytics for improved organization and management; analytics for signposting to support; analytics for fun.

Students are overwhelmingly of the opinion that analytics should better link with university resources to ensure that their data have purpose and therefore what can be asserted is that extracted analytics has a burden to be interconnected with the support fabric of a university in the same way that embedded analytics should marry with pedagogy. Whilst this is the initial articulation of the factors influencing learner analytics adoption, the underlying theory for behavioural change as well as a deeper understanding of students' rejection of analytics requires further refinement. The complexity of students' engagement with analytics has implications for many fields of research not just educational studies. From demographic and disciplinary differences to emerging styles derived from perceptions of self and data about self, it is clear that extracted learner analytics has some way to go to reach a state of general adoption and is unlikely to ever be ubiquitous. We must continue to engage with students to understand the ways in which both their adoption and rejection of analytics may influence the growing industry of 'edtech'.

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Chapter 9
Learning Analytics and the Measurement of Learning Engagement

Dirk Tempelaar, Quan Nguyen, and Bart Rienties

9.1 Introduction

The topic of student engagement is of crucial importance because of its close connection to self-regulated learning, the condition sine qua non for all learning, and learning in technology-enhanced learning environments in specific (Ifenthaler, Gibson, & Zheng, 2018a, 2018b). Nevertheless, beyond a general agreement on the importance of the construct, *engagement could be described as the holy grail of learning*, (Sinatra, Heddy, & Lombardi, 2015, p. 1), research literature demonstrates a lack of agreement on how to operationalize learning engagement. Traditional educational research applies survey instruments to investigate the role that engagement plays in the learning process. One of the instruments broadly validated in empirical research is the motivation and engagement scale (MES), based on the 'motivation and engagement wheel' framework (Martin, 2007). This instrument distinguishes cognitive or motivational and behavioural or engagement facets, and within each category, adaptive and maladaptive facets. Of more recent times is the data analytics–inspired research tradition of investigating traces in digital learning environments to operationalize learning engagement (see, e.g., Azevedo, 2015; Ifenthaler et al., 2018a, 2018b). Some proponents of the data analytics tradition base the choice for engagement measures generated by logs on a total denial of the validity of survey type of data. However, more in general, one can observe that empirical studies in

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learning engagement are typically based on survey data, or log data, but nearly never attempting to integrate both approaches (Christenson, Reschly, & Wylie, 2006).

The aim of this chapter is to provide such 'multi-modal data'-based contribution to the research of student engagement in learning. In this study, not only quantitative aspects of engagement are investigated in terms of measured or self-reported intensity of learning activities but also qualitative aspects of engagement. For example, learners make conscious choices of what type of learning activity to engage, such as using un-tutored and tutored problem-solving as well as worked examples (Aleven, McLaren, & Koedinger, 2006; Aleven, McLaren, Roll, & Koedinger, 2004; Aleven, Roll, McLaren, & Koedinger, 2016; McLaren, van Gog, Ganoe, Karabinos, & Yaron, 2016). This line of research investigates learning behaviours and student's preferences for feedback formats in their learning. Traditionally, research on the use of worked examples and other instructional formats of problem-solving took place in the non-authentic settings of labs, along the lines of an experimental design with the different instructional formats as different treatments, in search for differences in efficiency and effectivity of learning. The introduction of learning analytics (Ifenthaler, 2015; Ifenthaler, Yau, & Mah, 2019), and, more in general, the use of technology-enhanced instruction, created new opportunities for the research of students' preferences for different formats of learning feedback. It made it possible to move from the lab to authentic educational setting, to move from the experimental design to observational settings, investigating individual differences in preferences for feedback formats rather than the efficiency or effectivity of them. This development led to a convergence of learning analytics-based studies in the use of feedback by students, such as Ifenthaler (2012), and instructional design-based research, such as Aleven et al. (2004, 2006, 2016) and McLaren et al. (2016). Our current study is aligned with this development, adding an extra dimension to the research of student's preferences: the temporal dimension (Rienties, Cross, & Zdrahal, 2017). Our study builds on previous research by the authors (Nguyen, Tempelaar, Rienties, & Giesbers, 2016; Rienties, Tempelaar, Nguyen, & Littlejohn, 2019; Tempelaar, Rienties, & Giesbers, 2015; Tempelaar, Rienties, Mittelmeier, & Nguyen, 2018; Tempelaar, Rienties, & Nguyen, 2017; Tempelaar, Rienties, & Nguyen, 2018) that focused on the issue of early prediction of drop-out or low performance.

9.2 This Study

The integration of the two approaches of operationalizing learning engagement, the survey approach and the data analytics approach, is the primary goal of this empirical study. The integration of both approaches is enabled by the dispositional learning analytics context of the course we investigate. The instructional format is that of blended or hybrid learning, which generates a rich set of log variables that are indicators of learning engagement. Examples of such indicators are overall student activity in the digital learning tool as measured by the number of attempts to solve problems and time-on-task, next to more specific indicators as the number of worked examples studied and the number of hints called for or, very specific to this context, the number of finished packages. Problems are offered to students in the format of small sets of related problems, called a package. A finished package is when a student studies all problems of such a set in one run. All of the measurements of these indicators are dynamic in nature: they are measured in each of the eight sequential, weekly learning cycles. The dispositional aspect of our research refers to the administration of several self-report surveys that measure learning dispositions of students, both at the start of the course and during the course.

9.2.1 Context

This study takes place in a large-scale introduction course in mathematics and statistics for first-year students of a business administration and economics program in the Netherlands. The educational system can best be described as 'blended' or 'hybrid'. The most important component is face-to-face: problem-based learning (PBL), in small groups (14 students), coached by expert tutors (in parallel tutor groups). Participation in the tutor group meetings is required. The online component of the blend is optional: the use of the two e-tutorial platforms SOWISO (https://sowiso.nl/) and MyStatLab (MSL). This design is based on the philosophy of student-centred education, in which the responsibility for making educational choices lies primarily with the student. Since most of the learning takes place outside the classroom during self-study through the e-tutorials or other learning materials, the class time is used to discuss how to solve advanced problems. The educational format, therefore, has most of the characteristics of the flipped-classroom design in common. The intensive use of the e-tutorials and achievement of good scores in the e-tutorial practice modes is encouraged by giving performance bonus points in quizzes that are taken every 2 weeks and consist of items drawn from the same item pools that are used in the practice mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials.

In the use of the e-tutorials, three different learning phases can be distinguished. In Phase 1, students prepare for the next tutorial session. Knowing that they will face the discussion of 'advanced' maths problems in that tutorial session, students are expected to prepare by self-study outside class, e.g., by studying the literature together with some peers, or practising in the e-tutorials. Phase 1 was not formally assessed, other than that such preparation allowed students to actively participate in the discussion of the problem tasks in the tutorial session. Phase 2 was the preparation of the quiz session, one or 2 weeks after the respective tutorial. The three quizzes were taken every 2 weeks in 'controlled' computer labs and consisted of test items that were drawn from the same item pools applied in the practising mode. Although the assessment through quizzes was primarily for formative purposes, students can score a bonus point in each quiz that is added to their written exam score. Phase 3 consisted of the preparation of the final exam, at the end of the course. The written exam was a multiple-choice test of 20 questions on mathematics,

Table 9.1 The three learning phases: preparing the tutorial session as Phase 1 (light grey), preparing the quiz session as Phase 2 (grey), and preparing the exam as Phase 3 (dark grey)

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Topic Week 1	Phase 1	Phase 2	Phase 2	Phase 3	Phase 3	Phase 3	Phase 3	Phase 3
Topic Week 2		Phase 1	Phase 2	Phase 3	Phase 3	Phase 3	Phase 3	Phase 3
Topic Week 3			Phase 1	Phase 2	Phase 2	Phase 3	Phase 3	Phase 3
Topic Week 4				Phase 1	Phase 2	Phase 3	Phase 3	Phase 3
Topic Week 5					Phase 1	Phase 2	Phase 2	Phase 3
Topic Week 6						Phase 1	Phase 2	Phase 3
Topic Week 7							Phase 1	Phase 3

as well as 20 questions on statistics. These questions could be practised using textbook materials and e-tutorial modes. The final exam is mostly summative of nature and has by far the largest share in the course score (86%). Students' timing decisions, therefore, are related to the amount of preparation in each of the three consecutive phases and are summarized in Table 9.1.

The subject of this study is the full cohort of students 2018/2019 (1072 students). The diversity of the student population was large: only 21% of the student population was educated in the Dutch secondary school system, compared to 79% educated in foreign systems, with 50 nationalities. A large part of the students had European nationality, with only 4.0% of the students from outside Europe. Secondary education systems in Europe differ widely, particularly in the fields of mathematics and statistics. It is, therefore, crucial that this introductory module is flexible and allows for individual learning paths. On average, students spend 27 hours connect time in SOWISO and 32 hours in MSL, which is 30% to 40% of the 80 hours available to learn both subjects. Although students work in two e-tutorial platforms, this analysis will focus on student activity in one of them, SOWISO, because of the availability of fine-grained and time-stamped log data.

9.2.2 Instrument and Procedure

Both e-tutorial systems SOWISO and MSL follow a test-driven learning and practice approach. Each step in the learning process is initiated by a problem and students are encouraged to (try to) solve each problem. If a student has not (fully) mastered a problem, he or she can ask for hints to solve the problem step by step or ask for a fully worked out example. Upon receipt of feedback, a new version of the problem is loaded (parameter based) to enable the student to demonstrate his or her newly acquired mastery. The alternative feedback strategies that students can choose for are:

- Check: the unstructured problem-solving approach, which only provides correctness feedback after solving a problem

- Hint: the tutored problem-solving approach, with feedback and tips to help the student with the different problem-solving steps
- Solution: the worked examples approach
- Theory: asking for a short explanation of the mathematical principle

Our study combines log data from the SOWISO e-tutorial with self-report data that measure learning dispositions, and course performance data. Azevedo (2015) distinguishes between log data of product type and process type, where click data is part of the process data category. In this study, we will focus on process data only, such as the clicks to initiate the learning support mentioned above of Check, Hint, Solution and Theory, since those represent the engagement of students with learning in the e-tutorial. SOWISO reporting options for log data are very broad, which requires making selections from the data. All dynamic log data were assigned to the three consecutive learning phases in line with the scheme depicted in Table 9.1, next aggregated over time, to arrive at static, full course period accounts of log data. For all three learning phases, six log variables were selected:

- #Attempts: the total number of attempts at individual exercises
- #Examples: the number of worked examples called
- #Hints: the number of hints called
- #Views: the number of theory pages in which a mathematical principle is explained, called
- #Packages: the number of sets of related exercises that all correspond to one mathematical principle a student finishes
- TimeOnTask: total time on task in problem-solving

Survey-based engagement indicators are taken from the MES-instrument, derived from ‘Motivation and Engagement Wheel’ framework by Martin (2007). Martin breaks down learning cognitions and learning behaviours into four categories of adaptive versus maladaptive types and cognitive versus behavioural types. The classification is based on the theory that thoughts and behaviours can either enable learning and act as boosters or hinder learning by acting as mufflers and guzzlers. The instrument Motivation and Engagement Wheel (Martin, 2007) provides an operationalization of the four higher-order factors into 11 lower-order factors. Self-belief, Value of School, and Learning Focus shape the adaptive, cognitive factors, as cognitive boosters. Planning, Task Management, and Persistence shape the behavioural boosters. The mufflers, maladaptive cognitive factors are Anxiety, Failure Avoidance, and Uncertain Control, while Self-Sabotage and Disengagement are the maladaptive, behavioural factors or guzzlers. Cognitive factors are best interpreted as learning motivations, whereas the behavioural factors represent facets of learning engagement. In this study, we apply student scores administered in the first week of the course so that these survey-based engagement scores can be taken as antecedents of the log-based engagement indicators.

9.2.3 Data Analysis

Given the purpose of connecting the data analysis with student feedback and interventions, we opt for person-centred methods rather than variable-centred methods in the data analysis phase. Person-centred methods result in profiles of students demonstrating similar learning behaviours. These profiles are constructed by two-step clustering. The subsequent step in the analysis is to investigate profile differences with regard to the antecedents of these profiles, the student learning dispositions, and with regard to the consequences of these profiles, the learning outcomes. Inputs for the clustering step are all learning engagement indicators of log type: the number of Attempts, Examples, Hints, Views, and Packages plus TimeOnTask to prepare the tutorial sessions, to prepare the quiz sessions, and to prepare the final exam, in total 18 engagement indicators. As a next step in the analysis, differences between profiles were investigated with ANOVA, and prediction equations were estimated with hierarchical regression models. In the derivation of these prediction models, special attention was given to the issue of collinearity, also coined as multicollinearity. Collinearity arises when predictors in a regression model are correlated, what is typically the case in many learning analytics applications, where prediction models are estimated with learning logs as predictor variables. As a result of collinearity, regression coefficients are not stable but can take surprising values, with large standard errors. When collinearity is strong, a rule of thumb being the variance inflation factor exceeding the value of five, the model needs to be adapted, e.g., by eliminating one of the highly correlated predictor variables. Ethics approval for this study was achieved by the Ethical Review Committee Inner City faculties (ERCIC) of the Maastricht University, as file ERCIC_044_14_07_2017.

9.3 Results

9.3.1 Descriptive Statistics of Survey-Based Measures

Survey-based measures of engagement that follow the ‘Motivation and Engagement Wheel’ framework are administered with a Likert 1…7 scale having the value four as the neutral anchor. Descriptive statistics are provided in Table 9.2.

Mean scores of adaptive cognitions and behaviours are all beyond the neutral score. Most scores are quite high, with the exception of Planning: students perceive their proficiency in planning their study at a rather modest level. Maladaptive cognitions score, with one exception, below the neutral score. That exception is Anxiety: students express high levels of anxiety, relative to the other maladaptive constructs.

Standard deviations are low for variables with extreme scores, both in the high end of the scale (the adaptive constructs) and the low end of the scale (Disengagement),

Table 9.2 Descriptive statistics of engagement measures from the 'Motivation and Engagement Wheel' framework

Variable	Scale	Mean	Standard deviation	Cronbach alpha
Self-belief	Adaptive cognitions	5.98	0.74	0.78
Valuing school		6.03	0.63	0.64
Learning focus		6.34	0.60	0.74
Planning	Adaptive behaviours	4.84	1.06	0.78
Task management		5.62	0.94	0.76
Persistence		5.58	0.79	0.77
Anxiety	Maladaptive cognitions	4.63	1.29	0.84
Failure avoidance		2.49	1.27	0.84
Uncertain control		3.42	1.17	0.80
Self-sabotage	Maladaptive behaviours	2.18	1.02	0.80
Disengagement		1.73	0.73	0.65

with higher standard deviations found in variables ending up in the middle of the scale.

Reliability scores range from satisfactory to good, with two exceptions: those for Valuing School and Disengagement are weaker.

9.3.2 *Cluster-Based Learning Profiles*

The cluster analysis results in four different learning profiles, similar to previous research when applying cluster analysis to longitudinal log data (Rienties et al., 2019). The temporal aspect of the log data contributes strongly to distinguishing the four profiles, much stronger than the aspect of different instructional formats. That is students of different profiles first and for all concentrate on different learning phases. The labelling of the clusters we have opted for is based on these temporal aspects of learning processes:

- Profile Inactive students: The 257 students in this cluster demonstrate low engagement levels in the e-tutorial. These students 'opt-out' with regard to the digital learning environment and prepare themselves in different ways, or not at all. The few learning activities in the digital mode are mostly in the second learning phase, the preparation of the quizzes.
- Profile Exam preparation: This smallest cluster counting 69 students prepares in both the second and third learning phases. As the next cluster, their preparations in the digital mode are primarily assessment based.
- Profile Quiz preparation: The largest cluster with 468 students shares with the previous profile that preparations are directed at assessments but differs in timing: they focus completely on learning in the second phase, preparing the quiz sessions.

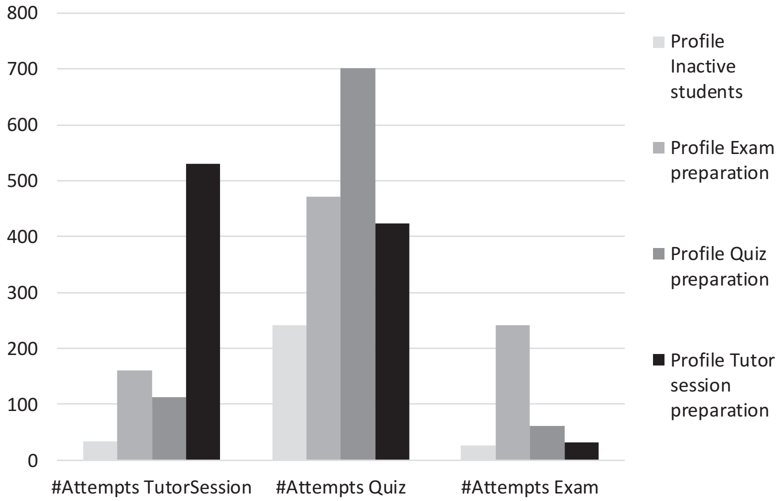

Fig. 9.1 Number of Attempts, for each of the three learning phases, and all four learning profiles

- Profile Tutor session preparation: These 315 students are the 'ideal' students in a PBL-based curriculum: they seriously prepare the tutorial sessions by learning and practising in the e-tutorial and finish their preparations in the second learning phase, rehearsing to prepare the quizzes. They seem not to need any further preparation in the third learning phase.

Figure 9.1 describes the differences between these four learning profiles graphically by means of the distribution of the number of Attempts over the three learning phases, for each cluster. Other engagement indicators, as #Examples or TimeOnTask, generate very similar patterns, due to the collinearity of engagement indicators.

Figure 9.1 makes clear that most students postpone learning until after the tutorial session. It is only the approach of an assessment, first the quiz and later the final examination, that creates sufficient stimulus to do most of the learning for students in the first three clusters. Most of their learning takes place in the second learning phase and is finished in the third learning phase. The exception to this pattern of postponing the learning process is found in the last cluster, labelled as the profile directed at the preparation of the tutorial session. Most of their learning takes place in the first phase, and learning is finished in the second phase, leaving little to study in the preparation of the final examination.

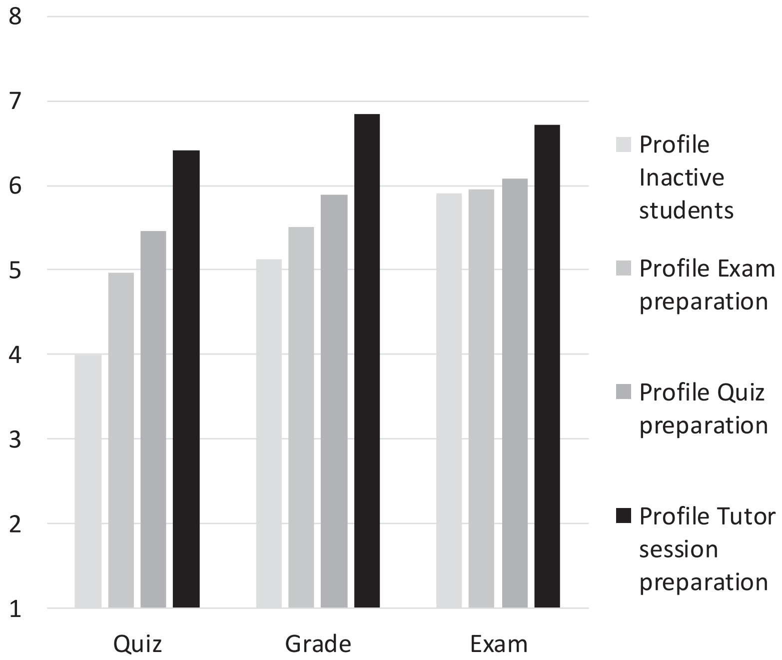

Fig. 9.2 Means of course performance indicators Quiz, Grade and Exam, standardized to the grading range 1…10, for the four different cluster-based learning profiles

9.3.3 Learning Profiles and Course Performance

The relevance of engagement indicators and student profiles based on these engagement indicators is in the relationship with course performance variables. Figure 9.2 provides an impression of that relationship. There is indeed a consistent relationship between profiles, ordered from less to more adaptive learning behaviours, and course performance, where all course performance variables are re-expressed as school grades (1…10). Differences between profiles are even larger when performance is expressed in a pass or fail, because the typical passing benchmark is at 5.5. Effect sizes of profile differences calculated by ANOVA analyses are 18.7%, 9.5%, and 4.0% for Quiz, Grade, and Exam, respectively.

All three ANOVA analyses are statistically significant with significance levels below 0.001. Post-hoc analyses indicate that differences in mean quiz scores are statistically significant for all four clusters, whereas statistical significant differences in grades and exam scores refer to the differences between the fourth cluster of students with the profile of preparing the tutor session, and the three other clusters.

9.3.4 Bivariate Relationships Between Engagement Indicators and Course Performance

Although the several engagement indicators are collinear, bivariate relationships with course performance variables demonstrate characteristic differences in patterns (see Fig. 9.3). All correlations in Fig. 9.3 equal to 0.1 or larger are statistically significant at significance levels of 0.001; correlations of absolute size of 0.075 or larger are statistically significant at significance levels of .01and correlations of absolute size of 0.060 or larger are statistically significant at significance levels of 0.05. Taking the strict benchmark of the 0.001 significance level implies that correlations in the first three panels are mostly significant, but not those in the last panel of Fig. 9.3.

First: The timing plays a crucial role in those relationships. Engagement indicators referring to learning in the first phase are all positive, indicating that higher levels of engagement correspond on average with higher performance levels. However, bivariate relationships referring to the second learning phase become negative, or approximately zero, for performance categories Grade and Exam: only Quiz performance is positively related to some of the engagement indicators. That trend continues into the third learning phase: all bivariate correlations are negative and small in size.

Second: Quiz performance is more positively related to performance indicators than the other performance categories, and final Grade is more positively related to performance indicators than Exam score for mathematics.

Third: Highest correlations are found for the engagement indicator of finished Packages, much higher than the indicators based on the number of clicks (such as problem-solving Attempts started, the number of Examples studied) or Time on task.

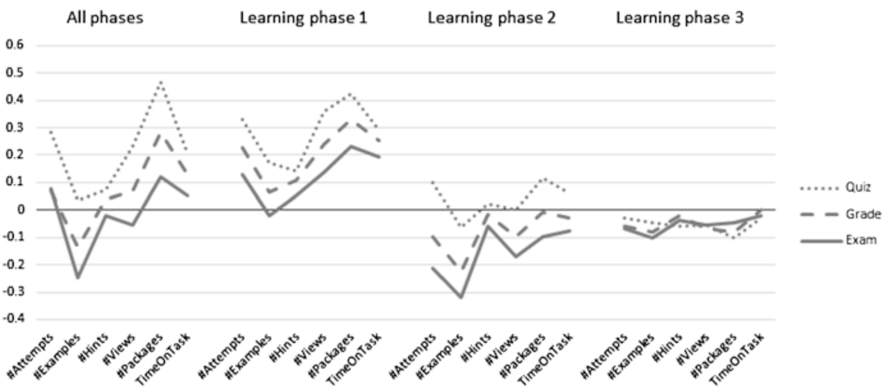

Fig. 9.3 Correlations of engagement indicators #Attempts, #Examples, #Hints, #Views, #Packages, and TimeOnTask with performance indicators Quiz, Grade, and Exam, for the full course and separate learning phases

9.3.5 Multivariate Relationships Between Engagement Indicators and Course Performance

In the multivariate relationships explaining the two course performance measures from the set of traced engagement indicators, we find strong collinearity caused by #Attempts and #Examples being collinear. To diminish collinearity and arrive at variance-inflation-factors below five for all predictor variables, #Examples is removed from all hierarchical regression relationships. What remains is weak collinearity, visible from the negative signs of several of the regression coefficients, knowing that most bivariate relationships between engagement indicators and course performance variables are positive (as discussed in the previous section). See Table 9.3 for the regressions predicting Exam score and Table 9.4 for the regressions predicting Quiz score. In Table 9.3, the only predictor variable with a consistent positive regression coefficient is the number of Packages finished by the student. The higher the number of finished packages, the higher the expected exam scores. The other main predictor is the number of Attempts, always with a negative beta.

Negative betas are caused by collinearity of #Attempts and #Packages and need to be interpreted as: for a given number of finished packages, students who need more attempts to finish those packages are expected to score less well in exam, on average. A similar relationship regards the number of Views: students who use more views to finish a certain number of packages are expected to score less well in the exam, on average.

The pattern of Table 9.3 is repeated in Table 9.4. Again, the number of Packages students finish is the dominant predictor in explaining Quiz score. Collinearity amongst the five log-based engagement constructs (more Attempts go with more time-on-task with more Hints and more Views and lead to more finished Packages) together with the dominant role of #Packages variable makes the other engagement variables become non-significant, or significant but with a negative beta: if you need more Attempts to reach a certain level of #Packages, it decreases the expected Quiz score.

Table 9.3 Hierarchical regression equations explaining Exam score from log-type engagement indicators, for the full sample and each of the four cluster-based profiles: betas (standardized regression coefficients) and explained variation

Regression betas exam score	Full sample	Profile inactive students	Profile exam preparation	Profile quiz preparation	Profile tutor session preparation
#Attempts	−0.537∗∗∗	−0.582∗∗∗	−0.166	−0.529∗∗∗	−0.462∗∗∗
#Hints	−0.037	−0.103	−0.007	−0.060	−0.043
#Views	−0.109∗∗	0.023	−0.014	−0.119∗∗	−0.110
#Packages	0.637∗∗∗	0.715∗∗∗	0.186	0.375∗∗∗	0.274∗∗∗
TimeOnTask	−0.002	0.038	−0.089	0.021	−0.061
R^2	0.126	0.099	0.025	0.163	0.195

Note: ∗∗∗: $p < 0.001$; ∗∗: $p < 0.01$

Table 9.4 Hierarchical regression equations explaining Quiz score from log-type engagement indicators, for the full sample and each of the four cluster-based profiles: betas (standardized regression coefficients) and explained variation

Regression betas quiz score	Full sample	Profile inactive students	Profile exam preparation	Profile quiz preparation	Profile tutor session preparation
#Attempts	−0.345***	−0.335***	0.090	−0.418***	−0.386***
#Hints	−0.015	−0.048	−0.010	−0.037	−0.035
#Views	−0.027	0.006	0.006	−0.038	0.019
#Packages	0.768***	0.701***	0.376*	0.536***	0.299***
TimeOnTask	0.015	0.070	−0.001	0.057	−0.095
R^2	0.258	0.193	0.196	0.145	0.121

Note: ***: $p < 0.001$; **: $p < 0.01$

When we compare the two tables, we find that performance in the Quiz is better predicted than performance in the Exam. Since quizzes are administered in the e-tutorials and quiz questions are similar to problems students practice with, this is no coincidence. However, there is an exception to this rule, what can be seen by comparing columns in the two tables. That exception regards the profile of students who focus on the first learning phase, preparing the tutorial sessions. In this profile, engagement indicators predict exam performance better than they do for quiz performance. The relationships in the profile of the student who focuses on exam preparation may differ from the relationships in other profiles, but the evaluation is slightly more difficult, due to the small sample size of this cluster.

In all clusters, both #Views and TimeOnTask are statistically insignificant in the prediction of exam and quiz performance. In all cases, we investigated the change in the prediction equations would the main predictor, #Packages, not be incorporated in the regression equations. Without reporting these outcomes, the pattern that emerges is that #Attempts becomes the main predictor, with positive betas in the several regressions, and that TimeOnTask is the secondary predictor with negative betas. Giving rise to the interpretation that for a given number of attempts, students who need more time-on-task to do these attempts are expected to score less well in exam and quiz.

9.3.6 Bivariate Relationships Between Survey-Based Engagement Scores and Log-Based Engagement Indicator

As a last step in the analysis, the relationships between the main log-based engagement indicator, #Packages, and the survey-based engagement scores were investigated. We express these relationships again as bivariate correlations (see Fig. 9.4).

The first observation from Fig. 9.4 is the dominant role of learning engagement factors: both the adaptive (Planning, Task Management, and Persistence) and mal-

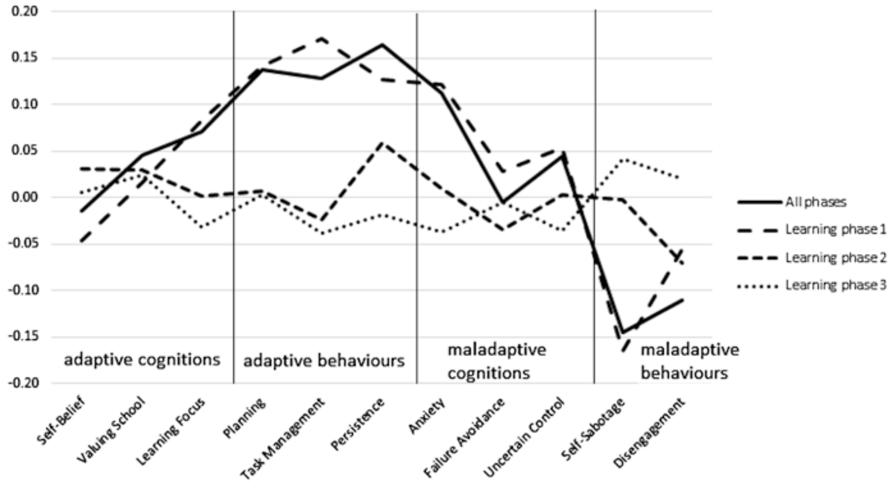

Fig. 9.4 Correlations of engagement indicator #Packages with motivation & engagement survey scores, for the full course and separate learning phases

adaptive behaviours (Self-Sabotage and Disengagement) are all statistically significant related to #Packages (all correlations larger than 0.10 in absolute size are statistically significant at 0.001 significance level), whereas the motivational variables are not, with one exception: Anxiety.

The second observation is that the maladaptive cognitions are not maladaptive in the sense that they are positively related to #Packages as a measure of learning engagement. Failure avoidance, Uncertain control and especially Anxiety, although acting as mufflers to learning in general, tend to increase learning activity in the digital learning environment.

The third observation is that the pattern of correlations is very different for the first learning phase and the second and third learning phases. In fact, measured learning activity in second and third learning phases is unrelated to any of the engagement and motivation scores (with the single exception of activity in the second learning phase being marginally significantly related to Disengagement).

9.4 Findings and Discussion

From a methodological perspective, our main finding emphasized the issue heterogeneity in engagement measures, in many different respects. There are different indicators of engagement and the story they tell tends to be different. In this study, we collected several kinds of click data, next to time on task data and engagement data rather unique to this study: the number of finished packages, or complete runs through a problem set. One of the main findings of this study is that basic measures of engagement as clicks and time are dominated in predictive power by this more complex measure of engagement. And in a multivariate context, these clicks and time-related engagement indicators get a reversed interpretation: relative to the number of packages finished by a student, taking more time, or making more attempts, has a negative impact on expected performance levels. The lesson we learned from this is that learning engagement does not have a unique and straightforward operationalization. Different contexts may demand different operationalizations and require investigations to find out what suits best.

Another source of heterogeneity is the timing of learning efforts. Profiting from the existence of three clearly demarcated learning phases, we demonstrated that the interpretation and impact of learning engagement indicators differ per learning phase. Learning activities undertaken in the first learning phase, that of preparing the tutorial session, tend to have a much stronger positive effect on course performance than learning activities undertaken in later phases. This finding has major repercussions for learning feedback and interventions. If the measurement of learning engagement has the purpose to signal inactivity in order to intervene, the question is if such intervention can ever be in time. In our context, the first moment to find out if a student fell short in the preparation of the tutorial session is at the start of the second learning phase. That in itself leaves the student ample time to catch up, unless learning activities in phases two and three appear to be consistently less effective than those in learning phase one. (Note: it is dangerous to extrapolate data from this study, since the effectivity of learning in later phases may be impacted by doing an intervention that is not in place when we collected the current data set).

Differentiating the timing of learning over these three learning phases appeared being a crucial facet of the four learning profiles: different types of learners prepare in different ways with different temporal patterns. Moreover, and of crucial importance in the context of this study, different engagement indicators are relevant to these different profiles.

Profiles are predictive for course performance, with profiles of more and more timely engagement achieving higher levels of performance. Largest effects are for quiz scores, due to the circumstance that quiz questions are generated from the same item pools students work with in the practice mode of the e-tutorials, and in line with general findings that engagement better predicts low-level tests than high-level tests (Sinatra et al., 2015). Highly engaged students who practised many problem sets have a cognitive advantage over less well-prepared students. Remarkably, the next highest effect size is found in the course grade, rather than the mathematics exam score. The course grade is a weighted mean of quiz and exam scores of both mathematics and statistics. Where engagement indicators summarizing learning activities of mathematical content will represent both cognitive and behavioural aspects, those same indicators will not signal the knowledge of statistical concepts. The effect on course grade being stronger than the effect on exam score thus indicates that the behavioural aspect is not limited to learning mathematics only but extends to the learning of other topics.

Diversity by learning phases is not restricted to the consequences of learning in different phases, as addressed above. Diversity also refers to the antecedents of learning activity in the several learning phases. All of the engagement factors from the motivation and engagement wheel framework are related to measured engagement in phase one, all along expected directions: the booster behaviours are positively related to the number of finished packages; the guzzlers or maladaptive behaviours are negatively related to the number of finished packages. However, learning in phases two and three is, with one exception, unrelated to any of the dispositional measures of engagement.

Next to heterogeneity, another crucial concept in the analysis of engagement data is collinearity. We found strong collinearity in our set of traced engagement scores and corrected for that by leaving out one of the engagement variables from multivariate modelling. The resulting data is still containing weak collinearity, visible from the differences between multivariate and bivariate relationships. In our context, we find that the number of attempts and time on task are negatively related or unrelated to performance indicators, rather than positively related.

From a theoretical perspective, our findings highlighted the relationship of behavioural trace data with the antecedents of measured engagement: the engagement dispositions. If the outcomes of predictive modelling suggest that some at-risk students would profit from becoming more engaged, it is a poor intervention to tell those students to spend more time-on-task, try more attempts or finish more packages. Such interventions are tackling the symptoms rather than the causes of low engagement. The causes of low engagement might be found in the learning dispositions students bring to class based on previous learning experiences. Examples of learning dispositions associated with engagement as measured in the learning platform are low levels of booster behaviours, such as Planning, Task Management and Persistence, and high levels of guzzlers, the maladaptive behaviours as Self-Sabotage and Disengagement. One can imagine designing learning interventions that address these dispositions. But even if these interventions turn out to be productive in changing learning behaviours in the adaptive direction, they will not be very helpful if, as in this study, learning dispositions have little effect on learning engagement in later phases than phase one.

From a practical perspective, the ultimate aim of all learning analytics applications is intervention. We collect data in order to make predictions, e.g., about which students are at risk and why. However, these predictions are not the aim in themselves. We make these predictions in order to intervene: provide learning feedback to the student at risk, hoping that the student will be able to adapt the learning, or to change the instructional context with the purpose to improve learning. But these interventions cannot be any better than the quality of the prediction models they are based on. Traditionally, many learning analytics applications apply the number of clicks and/or time on task as measures of learning engagement to predict course performance or risk of dropout. Clicks and time on task are easy to generate, and in many digital learning environments still the only types of log data available, but may not be the best predictors of course performance. It is only in a data-rich context as provided in our context, or in Ifenthaler et al. (2018a, 2018b), that one can sort out the relative importance of log-based engagement indicators and find out if some may even have a reversed effect on performance indicators. Stimulating students to try more attempts or to spend more time on task would constitute an inferior intervention when it is the number of finished packages rather than the number of problems attempted being the main predictor of course performance (this study), or when not time on task but the number of launched tasks is the dominant predictor (Ifenthaler et al. studies).

However, even in the case of a rich set of traced engagement indicators, allowing selecting the dominant predictors of course performance and estimating the multivariate relationships between course performance indicators and measured engagement factors as their antecedents, as in this study or the Ifenthaler et al. studies, there is no guarantee for arriving at adequate prediction models. The first issue at stake is that of collinearity: rich sets of measured engagement indicators demonstrate collinearity by default and very few empirical studies in the learning analytics area investigate the presence of collinearity. Collinearity expresses itself in regression coefficients taking surprising values, both in sign and size, and in large standard errors of the coefficients. Since the choice of intervention is typically based on what variables act as dominant predictors in course performance prediction equations, collinearity may be one cause of choosing a suboptimal format of intervention. In order to prevent collinearity dimension reduction can be utilized or obtain an interaction score from this variable or metrics.

The other obstacle to successful intervention investigated in this study has been labelled as heterogeneity or diversity. Having access to time-stamped engagement data in a learning context where three different learning phases can be distinguished, we were able to investigate both the consequences of learning engagement, in terms of course performance, and the antecedents of learning engagement, in terms of learning dispositions from the motivation and engagement wheel framework. In short, we concluded that learning engagement in the early phase of learning is predictive of course performance, but not learning that takes place in later phases. And we concluded that learning in that first phase is related to engagement dispositions, but not the learning in later phases. These conclusions have a major impact on the perspectives of learning interventions based on learning analytics generated feedback. Our early learning phase lasts for only 1 week; after that week, students enter the second learning phase. But it takes time to find out that a student lacks engagement in this first learning phase and to design an intervention in order to stimulate the student to become more engaged. In our context, that intervention would impact learning in the second phase, at the earliest, and learning in the third learning phase. However, the relationships between engagement and performance in later learning phases than the first one differ substantially and are in fact absent. So if the intervention is not that powerful that it also changes the relationship between engagement in later learning phases and course performance, there is little perspective in pushing students to become more engaged learners.

9.5 Conclusion

In conclusion, this study investigates how behavioural traces of engagement at three different learning phases (i.e. before tutorial, before quiz, and before exams) aligned with self-report measures and their impact on academic performance. Our findings demonstrated strong effects of early engagement pattern on dispositional measures of engagement as well as performances in formative and summative assessments. The issue of temporal heterogeneity and collinearity in behavioural measurements of engagement as well as its implications for learning analytics interventions were discussed. Looking forward, we propose that learning analytics studies combining measured engagement indicators of sufficient fine-grained type, such as time-stamped log data, with survey-based disposition data, can have a great potential to bring empirical research on student engagement to a next level. At the same time, this suggests being a necessary but not a sufficient condition to design effective educational interventions based on learning feedback generated by predictive modelling.

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Chapter 10
Stakeholder Perspectives (Staff and Students) on Institution-Wide Use of Learning Analytics to Improve Learning and Teaching Outcomes

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10.1 Introduction and Context

Over a period of 6 years (2014–2019), three separate but related projects were undertaken to ascertain the perspectives of both staff and students regarding the collection and use of learning related data, also referred to as learning analytics (West et al., 2016, 2018; West, Luzeckyj, Searle, Toohey, & Price, 2018). Each of these projects was driven by the fact that few previous studies had explored the views of stakeholders regarding how and why they would, or would not, use learning analytics resources. The projects sought to determine the views of two key stakeholder groups, those being staff and students. A key area we considered was linked to our concerns about the appropriate use of data, its security and gaining informed consent to use it. This chapter draws on work undertaken as part of these previous projects and draws the findings together to provide a comparison of the two views. This is an important and unique perspective as we were unable to find current literature addressing these points where both staff and student perspectives were sought and compared.

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As part of these previous studies, several literature reviews were undertaken, highlighting the lack of stakeholder input (West et al., 2019; West, Luzeckyj, Toohey, & Searle, 2017). In reviewing the literature for this chapter, we discovered that our previous work is complemented by few recent studies undertaken at scale with university staff or students.

To date, literature has moved beyond discussions around reducing attrition and development of small-scale localised activities to considering how to scale LA and develop greater institutional capacity (Colvin et al., 2016; Dawson et al., 2018; SHEILA Project, 2018; West et al., 2016); and regional or national capacity (Knox, 2017; Sclater, Peasgood, & Mullan, 2016; SHEILA Project, 2018; Siemens, Dawson, & Lynch, 2013). Dyckhoff (2011) conducted a meta-analysis of case-studies presented at an e-learning conference in Germany to identify teacher perceptions of using LA to evaluate technology-enhanced learning and teaching effectiveness. Two recent studies reflect on the importance of determining stakeholder views to ascertain institutional readiness in relation to LA adoption (Joksimović, Kovanović, & Dawson, 2019; West, 2019) while others argue for the need to consider teaching contexts and approaches as part of LA adoption (Arthars et al., 2019; Herodotou, Rienties, Verdin, & Boroowa, 2019; Lodge, Cooney Horvath, & Linda, 2019; West, 2019). One study explores the perspectives of university leaders and "presents and unpacks a leadership model for LA implementation to provide a more nuanced understanding of the factors impacting on organisational uptake" (Dawson et al., 2018, p. 237).

The small number of papers examining staff and student perspectives do not necessarily gather their insights into LA but discuss how it may be used in academic contexts. For example, Bakharia et al. (2016) explored "the pedagogical concerns and needs faced by teachers in their local contexts and how learning analytics may usefully provide actionable evidence that allows them to respond to those concerns or needs" (p. 330). Others considered how students responded to dashboards (Lim, Dawson, Joksimovic, & Gašević, 2019) or involved students in the design of dashboards (de Quincey, Briggs, Kyriacou, & Waller, 2019). Only a few studies have actually asked students about the use of dashboards and their views on them (Brooker, Corrin, Fisher, & Mirriahi, 2017; Schumacher & Ifenthaler, 2018; Roberts, Chang & Gibson, 2017). According to an exploration of trends and issues in student-facing learning analytics reporting systems conducted by Bodily and Verbert (2017), dashboards are a common feature in learning analytics literature as they inform users regarding what has occurred as well as the context. Dashboards are therefore a key method for using data and translating it into usable forms for both academic staff and students.

We only found one study which explored students' actual perceptions in relation to the collection and use of their data. This 2018 study surveyed entry-level students studying through the open university in the UK with the intention of identifying "a better understanding of students' awareness of the collection, analysis and use of their digital data in relation both to how deeply they use online services and media and to their own practices of privacy self-management" (Slade, Prinsloo, & Khalil, 2019, p. 2). This study considered how individuals may think about the exchange of aspects of their privacy (as data is collected) for personal benefits. Slade et al. (2019) determined that students are willing to entrust their data to others if they receive personalised benefits; they wish to control how data is collected and used. The contexts in which data is collected and used make a difference to students, who can be naïve and/or inexperienced in collecting or interpreting data, so they need to trust the service provider collecting their data.

10.2 Approach

Uniquely, this chapter draws on three studies undertaken with university staff and students to reflect and compare the perceptions of both stakeholder groups. The first project, funded by the Australian Government, involved surveying staff across 25 Australian institutions about their perceptions of LA (West et al., 2016). The second project was funded and endorsed by the Australian Innovative Research Universities (IRU) which is a network comprising 'seven comprehensive universities committed to inclusive excellence in teaching, learning and research in Australia' (Innovative Research Universities, 2019). This project involved conducting focus group workshops with staff from three of the IRU institutions (West, Luzeckyj, et al., 2018) and aimed to gain further insight into teaching staff perspectives on the use of learning analytics to enhance improvements in teaching practice and was based on the interrogation of the survey responses from the previous study.

The IRU also funded and endorsed the third project, which considered learner-facing analytics and analysed student perspectives (West et al., 2019). It broadly aimed to gain insight into how students understood LA, their concerns in relation to LA; the LA tools they believed would support them to succeed in their studies and how these might best be implemented (what sort of policies, information and training students thought might be useful).

Survey data from the projects was processed using SPSS version 25 and Microsoft Excel. Further details regarding the quantitative analysis are provided in the context within the sections below. The focus groups were audio-recorded and then transcribed with participants de-identified. A broad mix of views and insights into academic challenges and teaching approaches was garnered through this approach. The focus groups enabled researchers to further explore areas where survey respondents had indicated concerns or responses either broadly agreed or disagreed. They also provided the opportunity to determine potential explanations for responses and delve more deeply into areas of interest or complexity identified in the survey results.

All focus group transcripts were read and coded by two of the researchers who analysed them using thematic analysis (TA). TA is a qualitative research method where data is explored to allow themes to emerge (Fereday & Muir-Cochrane, 2006). Braun and Clarke (2006) define themes as important elements in the data and suggest themes demonstrate where "some level of patterned response or meaning within the data set" occurs (p. 82).

These staff and student projects differed in a number of ways. In the student project, several activities, (focus groups and a survey followed by a second round of focus group exploration) were brought together as one piece of student-related research. The survey and interview questions across the two rounds of focus groups and the survey included different questions.

This chapter focuses on reporting and comparing results from these three Australian studies. It discusses the approach and results from the staff studies before discussing the exploration into student perceptions. A comparison of findings from cohorts is then undertaken before we identify recommendations and draw conclusions. The comparison of these two important stakeholders provides unique insights and allows roadblocks to be identified so they may be addressed. It also informs institutional practice in LA development so it may move beyond smaller local projects.

10.3 Staff Perspectives on LA

The first two projects explored academics' attitudes to and experiences of LA, in particular, their involvement with LA. The first project involved an online survey of Australian academics. The second had several phases, which included a series of focus groups and interviews.

The survey conducted during September and November 2014 involved a design specific to this study and, as discussed in West et al. (2016), set out to explore a broad set of research questions:

- In which LA-related activities have teaching staff been involved?
- In which retention applications of learning analytics are participants most interested?
- How are institutions supporting learning analytics use amongst teaching staff?

The survey employed a purposive, snowball sampling strategy to recruit self-selecting individuals. The invitation to participate in the survey was sent to staff in at least 25 institutions with 401 individuals viewing the first question. Of those, 48 (12%) either answered no or only answered the demographic questions and were excluded. Of the remaining 353 participants, 276 indicated they were directly involved in teaching and were included in the study. These respondents were from 21 distinct institutions. Sixty-seven percentage of respondents reported a primary work role of "teaching students", with the balance in other teaching related roles such as "learning support", "academic development" and "student support". Seventy-one percentage of respondents were at lecturer or senior lecturer level, and 70% had been employed at their current institution for 5 or more years.

The survey included the following definition of LA: "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", and participants demonstrated a high level of interest in LA with 60% of the

Table 10.1 Frequency distribution of involvement in selected learning analytics activities ($n = 276$)

Learning activity	% of respondents who indicated an interest (multiple responses allowed)
None of the listed below	40
Reading about LA for my own professional development	37
Using LA to help with analysis and decision-making	37
Advocating for the use of LA to colleagues	26
Attending conferences/presentations/training specifically to learn about LA	21
Conducting formal research and/or publishing work on the topic of LA	10
Being part of the group that is leading LA at my institution	9
Delivering training on the use of LA	3

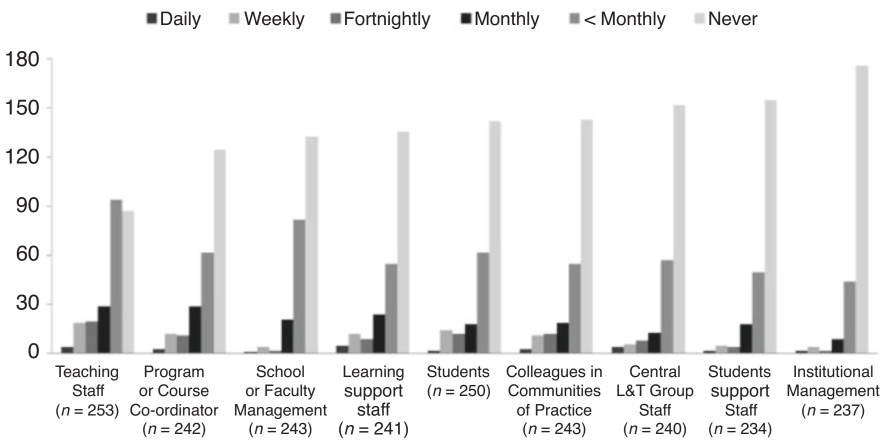

Fig. 10.1 Frequency of learning analytics discussion with select groups of colleagues

respondents having been involved in LA in some way. Thirty-seven percentage of respondents reported they had been reading about LA as part of their professional development or using it to help with analysis and decision-making (Table 10.1).

Staff interest in LA is also demonstrated by how often the respondents discussed LA with colleagues in a range of roles as shown in Fig. 10.1 where it can be seen that discussions are held more often with teaching staff and program or course coordinators.

The exploration of participants' interest in the use of a range of LA applications (Fig. 10.2) suggested their focus mainly related to identification of "at-risk" students and how that could trigger or inform their response to those students. Other applications that showed a high level of interest included the use of LA applications

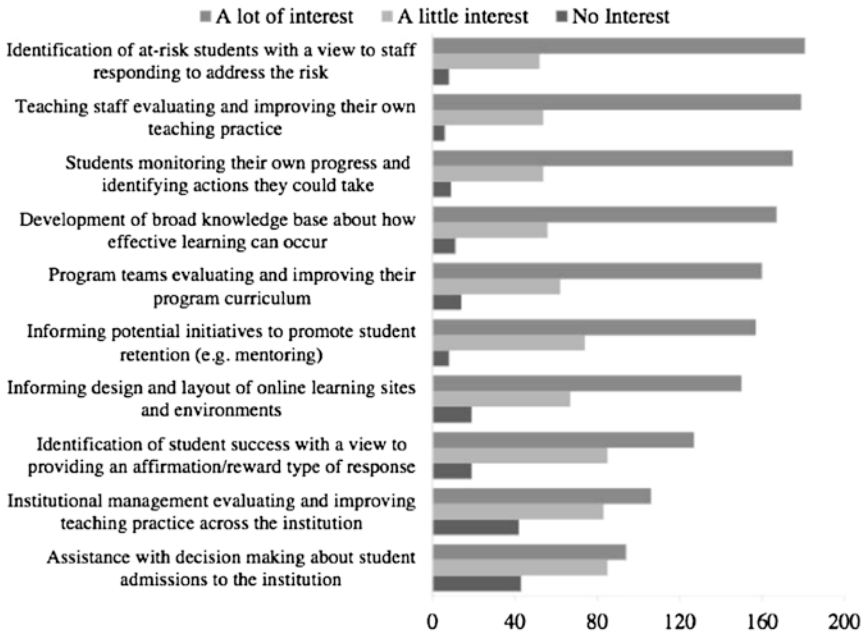

Fig. 10.2 Participant levels of interest in selected potential applications of learning analytics

by teachers who wished to evaluate and improve their own teaching practices, and how students could use LA to monitor their own progress and identify actions they could take. In both scenarios the responses may either reflect a limited understanding of the value of LA or the respondents' specific interest in how to use it.

However, the perceptions of the teaching staff with regard to the institutional capacity to support their use and interest in LA was rated as poor or very poor (Fig. 10.3); in particular respondents were concerned about the universities' provision of information on its use and its potential impacts.

Following reflection on the original survey data, a second study was undertaken. This involved a series of focus groups, held at several of the IRU institutions. These discussions further explored areas of interest raised in the surveys.

Each session lasted 90 minutes and was facilitated by the project team at the institution. They were all structured in two parts with a predetermined set of questions and activities. A similar process was followed across each site to ensure a level of consistency was achieved. In part one participants were asked to:

1. Individually record (on post-it notes) the LA (data related) questions they would like answered or have insight into in relation to teaching/learning in their classes
2. Discuss their questions and ideas and consider the types of data that might be required to answer those questions

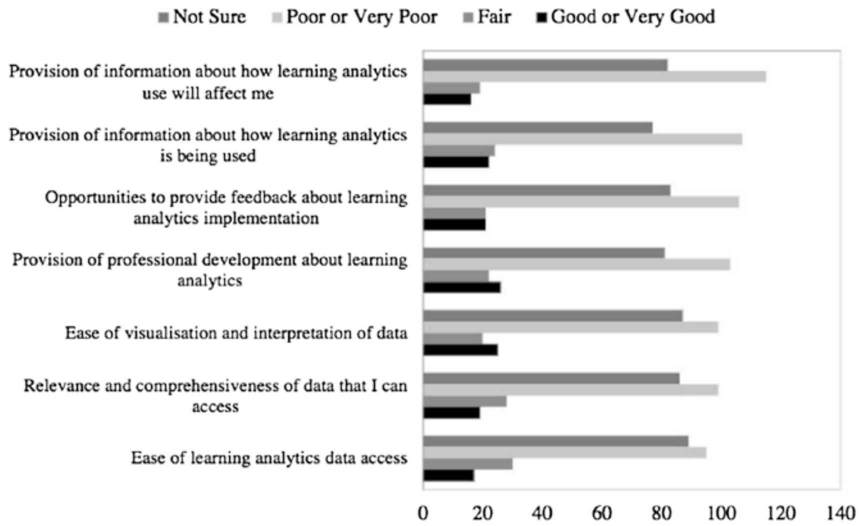

Fig. 10.3 Rating of institution at meeting participant needs and expectations in selected areas

Table 10.2 Categorised comments collected on post-it notes

Category	% of total comments
See or track students' activities	48
Demographics	18
Reflection on teaching	11
Students at risk of failing	8
Student dashboards	5
Course/program level	5
Support services	4
Ethical and operational issues	2
Total comments collected on post-it notes	**128**
Total participants	**46**

As shown in Table 10.2, the most common questions included on the "post-it" note responses related to data allowing teachers to see or to track student activity. Questions related to ethical or operational issues were the least common.

The types of questions participants indicated they would like answered relating to students' activities included students' interactions with the LMS, for example, how often and for what duration they logged in; the time spent on individual tasks; and the use of particular learning resources.

The recorded discussions mirrored these themes but included additional detail; for example, participants saw wishing to have a better idea of what students were actually doing and how they were moving through their units as being of particular importance. Participants also discussed their interest in identifying how much time students were spending on tasks and questioned LA's capacity to realistically measure and reflect student engagement at any more than a very superficial level. Staff comments also indicated they were interested in finding more sophisticated data which provided insights into how students use the resources made available to them and how they move through a topic and develop skills, for example:

> I'd really like to be able to get my hands on what they're doing, particularly for the second lot of exercises where they're starting to do the skill development, and just to measure engagement to start with would be really good. (Participant in teaching staff focus group at Institution 3)

It is interesting to note that at each of the institutions, questions concerning student preparedness for higher education study (e.g. background, how prepared they were for the unit, what kind of experience they had in relation to the discipline) were raised, particularly with regard to levels of English and mathematics proficiency. Very few questions were raised with regard to the teachers' own learning and teaching proficiency, learning and teaching practice, or the curriculum. This may be due to teachers' concerns regarding students' lack of preparedness for university, or a failure to appreciate LA can provide insights into how they may change their teaching and curriculum practices.

Part two of the focus group research required the same participants to respond to seven pre-determined LA reports/visualisations (hereafter referred to as reports) by:

1. Grading the potential usefulness of report(s) on a scale of 1 to 5
2. Describing the perceived value of report(s) and any enhancements the participant would like to see included in them by writing comments on the reports
3. Discussing each report's potential usefulness to the participant's own teaching contexts

The reports selected for this exercise were in use or about to be introduced by at least one of the universities involved in the project. When presented to participants, each report included the title and a short explanation of its function and purpose to support focus group participants' understanding. Table 10.3 provides each report's title and a brief description of it.

Participants' perceptions of the usefulness of the reports varied according to several factors, including the pedagogical approach, their role in relation to the purpose of the report and broader institutional contexts. The relationship between the underlying data in the report and the pedagogical approach the teacher uses also influence the perceptions of the usefulness of the reports. Participants suggested LA reports needed to fit their pedagogical approach and be easy to use as well as time saving.

Staff used the opportunity of attending the focus group to highlight other concerns they had about LA. Time pressure, in terms of the time needed to learn about the reports and their uses, and time required to then engage with the data were raised in a number of discussions, as this was perceived as adding to staff workload. These concerns indicate two important considerations related to the development of reports and LA more generally. Reports and other LA outputs need to be as simple

Table 10.3 Report descriptions

Report	Description
Early intervention clustering tool	Automatically identifies students who may benefit from an early intervention strategy. The tool calculates a performance metric for each student which is the average of the results obtained from three quizzes performed in the first 3 weeks of the year. An engagement metric is formed using the total number of LMS clicks made in the unit over the same three-week period. The tool places students into one of four clusters depending on their levels of performance and engagement.
Personalised learning designer	Allows the setup of rules based on a series of trigger points to customise the student experience as they work within the learning management system (LMS). Some use cases include sending the student an email welcoming them to the topic once they have posted to the Introduce yourself forum or providing a student who does not do well in a certain quiz/assessment with additional reading.
Active user block	Allows students who have not logged in to a unit or participated in a specific activity based on set parameters to be sent a message relating to the actions they might be required to take. It is possible to view a report of the students who have been contacted.
Unit at a glance	Provides summary information about a unit, and comparative information against a group of other units in the same school. The report can help analyse how a unit is designed, how the unit compares to the average of others and how the students in the unit are using and performing in the unit site compared to the average of all students enrolled in the unit site.
Student at a glance	Provides summary information about a student compared to the other students enrolled in the unit. This report can help identify how much the student is using the unit site compared to their class.
Heat map	Provides the teaching staff with a quick overview of which objects/activities are being viewed/completed by the students; the darker the colour, the more times the object has been accessed. The number of views and the number of unique users are shown for each object.
Progress bar	Is used to view when a particular student last logged in to the LMS, and which objects/activities have been viewed/completed. Each row represents one student's progress, and each of the coloured boxes an object or activity.

as possible, and they need to be easily accessible with a very clear purpose. It was also clear that staff wanted to ensure LA reports present a clear value proposition for the teacher in terms of either saving them time or assisting with something this is a key part of their role.

10.4 Students' Perspectives on LA

Given the success of the research with academic staff, a similar approach was taken with students from six of the seven IRU institutions. Through this project we explored students' attitudes to and experiences of LA through a survey and focus groups conducted at each member university. The aims of this work were to explore students' understandings of and opinions regarding:

Table 10.4 Demographic distribution of respondents

		% of respondents	% IRU universities combined[a]
Gender	Male	29	40
	Female	70	60
	Other	1	–
Origin	Domestic	83	79
	International	17	21
Level of study	Undergraduate	76	78
	Postgraduate	24	22
Study load	Full-time	79	72
	Part-time	20	28

[a]based on data from the last available national data (Department of Education and Training, 2017)

- Their understanding of data the university collects about them
- Their level of comfort concerning the use of data to help support their learning
- How useful they believe a range of LA-driven 'interventions' will be to their learning experience
- Levels of concern regarding the data collected about them
- When they would like to be reminded about university data policies and practice

This research was conducted during 2018 with the initial survey distributed via email in Semester 1 to all undergraduate and postgraduate on-shore coursework students in the six IRU universities who chose to participate (approximately 158,000 students). A total of 2017 valid responses were obtained from the survey (1% of total university population) that makes this data set one of the largest of its kind exploring student perceptions. The participant population was considered representative of the general university cohort in that survey respondents were more likely to be domestic (83%), undergraduate (76%) students studying full-time (79%). It is important to note however that a greater proportion of the respondents were female (70% vs 60% of total university population (Table 10.4).

To explore student awareness of the range of data that the university collects about them and their learning experiences, the survey provided a list of 23 different options (see Table 10.5). Students were generally aware and accepting of the data that their universities were collecting about their learning experiences. It was practically taken as a given that data was being collected relating to their engagement with the learning management system (95% of respondents), and submissions within the system including assignments (99%), quizzes (98%), grades (95%) and participation on discussion boards (91%). Awareness of their university's capacity to collect more detailed data about behaviour within the LMS was less widespread; 85% aware that the university could track their participation in online lectures, tutorial or web conferencing, 78% aware that access to Lecture Capture recordings was collected and 75% aware that their access to video and audio learning materials was recorded. Outside of the learning environment, students indicated a reduced aware-

Table 10.5 Student awareness of data collected by the university and comfort level associated with each data item

Type of data collected	% of respondents	Level of comfort (/5)
Submission of assignments	99	4.25
Completion of quizzes	98	4.18
Use of text matching/originality software (e.g. Turnitin or SafeAssign)	95	4.08
Grades from the subjects you have taken	95	3.85
When you accessed the LMS	95	4.10
Access to particular content in the LMS	93	3.99
Activity on discussion boards	91	3.91
Demographic information (e.g. age; gender; address)	90	3.47
Academic background (previous study, credit applications)	90	3.68
Looking at your grades for assignments and quizzes	88	3.96
Participation in online lectures, tutorials or web conferencing	85	3.88
How long you spend in the LMS	84	3.95
Accessing feedback from assignments	84	3.98
Access to library borrowing services	84	3.83
Wireless network device usage (University WiFi, Eduroam, etc.)	82	3.14
Access to lecture capture recordings	78	3.86
Use of video and audio learning materials	75	3.84
Use of academic skills services	75	3.74
Access to library support workshops and training	74	3.80
University mobile app usage	66	3.06
Access to employment services	63	3.47
University social media groups	49	2.82
Location data from your mobile phone	37	2.27

ness of data that was collected by support services such as academic skills services (75%), employment services 63% and library support workshops and training (74%).

Students' general awareness of university data collection related to core learning and student support; however, it also appeared to apply to monitoring of their wider engagement with a university's wireless network (82% of students assuming that the university was monitoring usage). Significantly fewer students thought that location data from mobile phones (37%), social media (49%) or university mobile app usage (65%) was collected.

The survey also permitted the research team to explore the level of comfort that students felt when considering each of the 23 potential data sources on a 5-point Likert scale, with *Very Comfortable* scoring 5 and *Very Uncomfortable* scoring 1. A summary variable, *Comfort Level*, was calculated as the mean score of the responses (Table 10.5). In a pattern similar to that of awareness, students were most comfortable with the collection of data when it was directly related to the engagement in key learning systems with the highest comfort associated with access to the LMS (4.10/5) and the use of video resources and audio learning materials the lowest at 3.84 and learning outputs (grades, assignments and quizzes, range 3.85–4.25/5). They reported a lower level of comfort when data collection involved their submission of personal information (demographic and previous academic information, range 3.68–3.47/5). However, the items where students reported the lowest levels of comfort were those not directly related to learning and included location data from their mobile phone (2.27/5), data about university social media groups (2.82/5) and university mobile app usage (3.06/5). These data points may help analysts determine whether technical connectivity/access to networks, etc. is causing an issue, identify areas for campus improvement and illustrate cultural or behavioural issues around propensity to share and post in electronic environments. Some staff believe this data can provide insights into student behaviour (attendance, focus in class, etc.) that may help understand them better.

Conducting focus groups allowed further contextualization of the two main areas identified as points of concern for students in the survey. These related to the degree of comfort students felt about universities using various types of data to help support their learning and how the data was used by institutions. Students were particularly concerned that demographic information may be utilised to categorise or profile them. The following statements reflect these sentiments: "you're putting them in a category they might not want to be in" (FG 4); "that you're specifically identified as an accounting student from the [campus X] with an international background. So, you specially represent a certain group" (FG 2).

Students reflected a desire to understand the reasons why the university would be interested in these kinds of information and were seeking confirmation of the relevance of the data. Specifically, they questioned the collection of their location data, the use of social media, wireless network devices and mobile apps. All of these concepts aligned strongly with items that scored low on comfort. Students frequently considered the collection of this information "creepy" (FG 4) and in particular associated this with "being watched" (FG 2).

To further explore the student perception of the usefulness of data, the survey asked students to provide their perspectives of a number of practices (see Table 10.6). Students were highly supportive of data collection that might potentially lead to the provision of additional materials or services to support their learning. They were far more comfortable about being contacted about their learning than other issues (such as health or wellbeing) but preferred to be contacted by an academic staff member that they knew. One participant from FG 2 explained why they thought the academic was the best point of contact:

> … you have the trust with the teacher, you go first, or your teacher first comes to you like what's going on. And if you do have mental health issues or you're actually struggling with understanding the subject, the teacher can guide you and same with here, with the lecturer. Comes to that bond or that trust between you and your lecturers.

Students were less positive receiving information that compared their performance and engagement with those of other students in the class (range 61–72%),

Table 10.6 Degree of usefulness of specific practices (higher percentages illustrate more positive responses)

Usefulness of practice in relation to learning experience	% positive responses
You are given information about additional materials (readings; resources) you might like to access based on an assessment you have coming up	96
You can see your progression through subject material	96
You are given information about additional services at the university (e.g. academic writing support; library) you might like to access based on an assessment you have coming up	96
You are given information about additional materials (readings; resources) you might like to access based on ANY grade received on an assignment/quiz	94
You are given information about additional services at the university (e.g. academic writing support; library) that you might like to access based on ANY grade received on an assignment/quiz	94
You are given information about additional materials (readings; resources) you might like to access based on a LOW grade received on an assignment/quiz	91
You are given information about additional services at the university (e.g. academic writing support; library) that you might like to access based on a LOW grade received on an assignment/quiz.	91
You are given a projection of your likely final grade.	86
You are given information that suggests that you will need to change your study behaviours in order to achieve a passing grade.	84
You are given information that suggests that you will need to change your study behaviours in order to achieve a higher grade	82
You can see how much you are accessing the LMS	81
You can see your grades compared to others in class	72
How your access to the LMS compares to others in your class	61
The number of times you accessed the LMS compared to others in class	61

though they were more positive about data leading to a potential prediction of their grades (86%), and indications of areas in which they could change their behaviour to improve their grades (82%) or pass the subject (84%).

Reflecting holistically, students were concerned about the security of their data and the relevance of such data to their study or experience. A clear majority (90%) indicated concerns about third parties receiving their data. This finding is not surprising in the context of broader public concerns with regard to data security. It is also important to note that this question will have included substantial variation in the scope of both potential information shared and end users, including that which is required for the operation of third-party teaching arrangements and reporting to government versus external organisations for which it is illegal for the university to share student data. Interestingly, fewer than 50% of the respondents expressed concern about options that involved their data being used by the university to tailor student support or to improve learning and teaching or services (Table 10.7).

This increased desire for transparency, and consent to data collection was further explored in the survey (see Table 10.8). Students clearly wish to be given the oppor-

Table 10.7 How concerned respondents feel about how their data is managed and used (the higher percentage indicates greater concern)

	% concerned responses
Third parties receiving your data	90
Your data being kept safe and secure within the university	69
Your data being used to trigger support services to contact you	63
Your data being used to trigger academic staff to contact you	63
Your data being used by the university for research	54
Your data being used to provide support to you	49
Your data being used by academics for research into learning and teaching	49
Your data being used by academics to improve their teaching	44
Your data being used by the university to improve services	42
Your data being used by the university to improve learning materials	41

Table 10.8 Preferred timing of notification of university data policies and procedures

Timing of notification	% of responses
When you first enrol at the university	23
At the beginning of each academic year	31
At the beginning of each semester	32
When you enrol in each subject	13

tunity to provide consent to access their data more often than on enrolment, with more than 60% of respondents indicating that they would prefer to be notified either annually or at the commencement of each semester.

The issue of compulsory or non-compulsory provision of dashboards was also explored. Students were asked to indicate the options they would prefer if dashboards were available. As shown in Fig. 10.4, only 23% of respondents agreed with the idea of a compulsory dashboard to display their information, while the majority 73% were not in favour of this. The response to options with the ability to either opt-out of the dashboard (63%) or turn it on and off (79%) were viewed favourably indicating that participants clearly wanted a choice.

Students are generally in support of initiatives that have the potential to support and provide feedback on their performance, particularly if there is perceived to be a short-term or quick fix correction that might help them achieve their goals.

Where concern exists, it is manifest in what could be termed university (administrative) over-reach, where support either monitors or acts on data coming from sources that students consider to be their own and distinct from dedicated academic platforms.

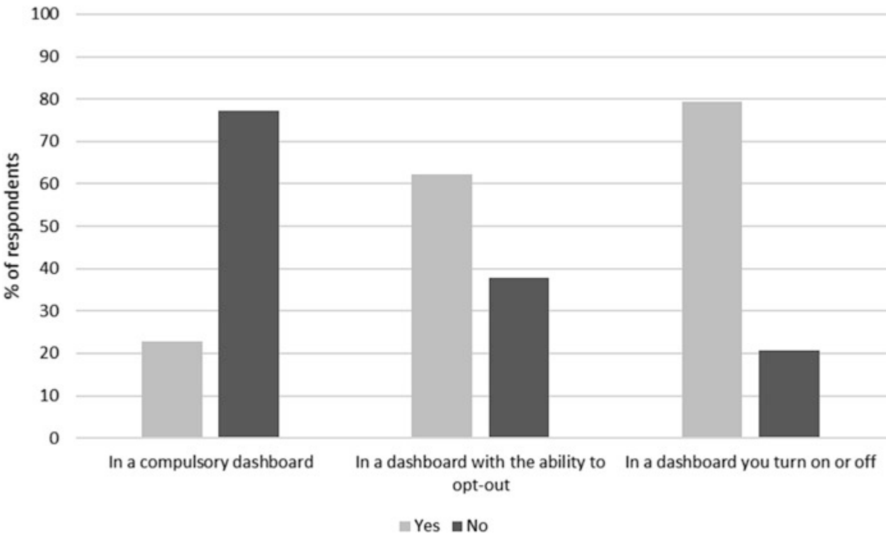

Fig. 10.4 Responses regarding dashboard availability

10.5 Comparing Responses from Staff and Students – the 'Standout' Messages

The two projects bring insights from different points of view: that of the learner and that of the university teacher around some key areas: 1. awareness and knowledge of learning analytics; 2. concerns and 3. how data might be used to support learning. This provides a unique opportunity to explore differences and commonalities from two critical stakeholder perspectives which translate into practical actions for more effective use of LA by Higher education institutions (HEIs). These include a need to ensure appropriate governance of data collection through the development of strategies and frameworks; improved services provided by IT and other departments and teams who collect and manage data and the creation of timely, coherent training, delivery and communications strategies.

10.5.1 Awareness of Learning Analytics and Data Collection

The teacher survey included several questions which broadly translate to the concept of awareness and knowledge of learning analytics. Specifically, teachers were asked about the frequency of their involvement in discussions related to learning analytics and with whom and their involvement in learning analytics–related activity. The scale used included daily, weekly, fortnightly, monthly, less than monthly and never. In this construct awareness and knowledge would presumably be higher if engagement in either discussion or related activity was taking place on a regular basis compared to never. As such, this can be seen to operate on a continuum from broad awareness through to a high level of awareness.

Figure 10.1 (above) provides a summary of the key areas where teaching academics have engaged with others in LA discussion with at least some frequency (i.e. more than never) and on a more regular basis (i.e. at least monthly). It shows teaching staff are talking about LA with a range of stakeholders and indicates that at least 68% of the academics surveyed had at least some awareness of LA. More regular engagement would suggest a higher level of awareness as is the case for 33% of academics who were engaged in discussions with their teaching colleagues at least monthly. It is also more likely the case that as the stakeholder group broadens, the level of awareness is likely higher. For example, those engaged in LA communities of practice (46%) are likely to have a high level of awareness and knowledge.

Teaching academics were also asked about their participation in LA activity and to identify the type of activity undertaken. Table 10.9 provides a summary of engagement where the frequency was indicated as more than never. Again, it could be assumed that those who are using LA for analysis and decision making have a higher level of awareness and knowledge of LA.

Focus groups with staff across universities indicated that they did not really understand the term "LA" but had heard it used reasonably often within their institution and the sector. This is likely reflected in the relatively high level (68%) of discussion taking place. However, taking such awareness to the level of application was far less frequent (41%) and could be seen as a lower level of knowledge about application. This suggests the need for a concerted effort to develop awareness of LA with all academic staff across institutions to ensure LA is effectively leveraged to support practice improvement.

While it is acknowledged that the two studies were some years apart, the student survey included questions regarding the kinds of data students thought the university was collecting about them (as presented in Table 10.5, above). Findings demonstrate students have an appreciation that data related to core learning and support activities is collected and that various systems are used to provide it. When this was explored further via focus groups, students indicated that they did not really understand the term "LA", which coincides with what staff had said.

Clearly there was broad awareness amongst students about the type of data that was being collected about them particularly related to assessment and general activ-

Table 10.9 Summary of frequency of activity undertaken to LA activities

Type of activity	Percent who engaged with some frequency
Reading about LA	42
Using LA for analysis and decision making	41
Advocating for the use of LA with colleagues	31
Attending LA conference(s)	25

Not mutually exclusive

ity in the LMS. However, awareness of data collection dropped as data became less obviously connected to the LMS and the online learning environment.

It is evident through both studies that there is general awareness of data collection but what data underpins learning analytics is less clear to either group. Conversely learners and university teachers in both studies offered a different focus on the use of learning analytics. Higher education institutions (HEI) therefore need to more clearly articulate what data is collected, the purposes for which it is collected and used as well as providing clear definitions of terms such as learning analytics, so both learners and teachers are more aware of what terminology means and how data is used.

10.5.2 How LA Might Be Used to Support Learning

As interest in LA has developed so too has academic interest in its application to support learning and teaching. One area staff were interested in was determining how much time students were spending on tasks; however, they questioned LA's capacity to realistically measure and reflect student engagement at anything more than a very superficial level. Some also indicated concern regarding the inclusion or evaluation of activities which do not take place in the LMS. As seen in Table 10.6 (above) students rated seeing how much they accessed the LMS reasonably highly (81% positive responses) but not as highly as many other of the aspects we questioned. The concerns raised by staff are echoed in recent studies where researchers attempted to address the issue of counting clicks to measure engagement by exploring other means to assess or validate student online engagement. Fincham et al. (2019, p. 501) used "robust empirical validation" to test a theoretical model of various forms of engagement (academic, behavioural, cognitive and affective) to determine the potential for predicting learning outcomes. In a separate study Jovanović, Gašević, Pardo, Dawson, and Whitelock-Wainwright (2019) involved students in self-reporting activities related to cognitive load and self-efficacy. They integrated trace data with academic performance and found there were associations between the two. However, these studies are not at scale, they appear complex and time consuming and they are not carried out across institutional contexts.

From our survey of university teaching staff, and as seen in Fig. 10.2 (above) academics indicated that the main areas of interest for using LA (where more than 50% of staff indicated interest) were most specifically related to:

- Identifying at-risk students with a view to staff responding to address the risk
- Teaching staff evaluating and improving their own teaching practice
- Students monitoring their own progress and identifying actions that they can take
- Development of the broad knowledge based about how effective learning can occur
- Informing potential initiatives to promote student retention (e.g. mentoring, student support)

- Informing design and layout of online learning sites and environment.

These areas of activity suggest staff wish to see LA being applied to the improvement of teaching practice and what they perceive they have control over rather than the broader institutional concerns. It is important however to note that the findings from this research identified a link between the institutional context and leadership and the development and advancement in thinking about the use of LA.

Discussion in the student focus groups also reflected the importance of context and leadership. Students indicated that they were unsure of how data was being used or if it could be used to support their learning. However, with more discussion about the context and potential applications, they started to identify how it could be useful to them. The literature related to leadership in LA includes a paper by Dawson et al. (2018) who suggest that as a result of different approaches to research and implementation in LA, coupled with the complexity of the field of education, there is a need for leadership in LA to be both transformational and shared across the institution, though there was no discussion of including students in the mix of leaders.

In the survey, students were given a range of LA applications and asked to indicate which ones they thought would be useful to their learning. In considering this data, it was apparent that some of the items aligned with what academics had indicated more broadly. Table 10.10 aligns student responses (from Table 10.6) with the LA applications identified by staff (as indicated in Fig. 10.2).

Student responses reflected a very pragmatic approach to LA as they were highly interested in things that could be done to support their learning and being prompted to take some action. This included prompts about additional learning materials and the provision of additional services. As indicated in Table 10.9, the top 7 (excluding progress) related to student self-monitoring and taking action. These all rated over 90% by students but staff only identified them in 64% of cases (see Fig. 10.2 above). The survey also highlighted that while some applications were seen as useful, students held a level of concern around their use.

10.5.3 Concerns

Both groups were asked about their concern around the use of data for learning analytics although the questions were presented in slightly different ways. Students were asked about their level of concern with data being used in various ways while for academic staff the question was framed around ethical concerns.

Academics were asked to indicate their level of concern on a scale of high/some/low or no concern related to a range of data issues and applications. Table 10.11 highlights those issues where academics had higher levels (some or high) level of concern and which are of relevance to students:

Other items where academics indicated levels of concern are not relevant to this comparison but included items related to workload changes, engagement in training and professional development and accreditation related issues.

Table 10.10 Comparison of staff areas of interest and areas of usefulness identified by students

Staff area of interest in activity	Student-valued activity	Percent
Monitoring own progression and taking action (See or track students' activities – 48% Students at risk of failing – 8%)	You can see your progression through subject material	96
	You are given a projection of your likely final grade	86
	You are given information that suggests that you will need to change your study behaviours in order to achieve a passing grade	84
	You are given information that suggests that you will need to change your study behaviours in order to achieve a higher grade	82
	You can see how much you are accessing the LMS	81
	You can see your grades compared to others in class	72
	How your access to the LMS compares to others in your class	61
	The number of times you accessed the LMS compared to others in class	61
Provision of information about additional learning materials (Reflection on teaching – 11%)	You are given information about additional materials (reading; resources) you might like to access based on an assessment you have coming up	96
	You are given information about additional materials (readings; resources) you might like to access based on ANY grade received on an assignment/quiz	94
	You are given information about additional materials (readings; resources) you might like to access based on a LOW grade received on an assignment/quiz	91
Provision of information about services (Support services – 4%)	You are given information about additional services at the university (e.g. academic writing support; library) you might like to access based on an assessment you have coming up	96
	You are given information about additional services at the university (e.g. academic writing support; library) that you might like to access based on ANY grade received on an assignment/quiz	94
	You are given information about additional services at the university (e.g. academic writing support; library) that you might like to access based on a LOW grade received on an assignment/quiz	91

Table 10.11 Areas of concern (higher percentages indicate higher levels of concern)

Issue of concern	Percent indicating some level of concern
Transparency about how and why LA are being used	82
Profiling of students	81
Consent to access data	78
Data security	80
Data ownership	72

Not mutually exclusive

Students were also presented with a range of data issues and applications and were asked to indicate their level of concern on a scale from not at all concerned to very concerned. Table 10.7 summarises areas related to data collection and use where students indicated any level of concern beyond "not at all concerned".

It is clear from this summary that the highest level of concern academics had was around how data was being used and associated transparency. While students were not asked explicitly about this in the survey, it was part of the focus group discussions to unpack the reasons for concern around particular elements. The overall theme and very strong message that came from students was the need for the institution to be clear and transparent around what data is being collected, why it was being collected and how it was going to be used.

Despite evidence that users do not engage with Terms & Conditions of online services, HEIs should strive to be transparent. Students should know what data are collected, by whom, for what purposes, who will have access to this data downstream and how data might be combined with other datasets (and for what purposes). As such this can be seen as the primary focus for both groups and these findings coincide with those identified by Slade et al. (2019, p. 243) who suggest "a unique opportunity to create a trusted relationship between institutions and students" exists through the use of LA.

The issue of profiling was specifically raised during focus groups with students expressing strong concerns that data would be used in this way. The following statements from student focus groups reflects this sentiment:

> "You're putting them in a category they might not want to be in." (Student, FG2)
>
> "I don't know, maybe there's just a bit of stigma attached to the word profile. Don't like the idea of being profiled." (Student, FG3)

Similarly, this rated highly as a concern for staff with 81% indicating some level of concern. There is also strong alignment between academic staff and students around issues related to data security and any sharing of that data with third parties.

In looking back on the key areas of awareness, usefulness of LA data and concern, there appears to be a mismatch at least to some extent between what academics are interested in doing and students level of concern around certain applications. For example, academics are interested in utilising data to explore ways to improve their teaching and curriculum while over half of students are concerned about their data being used for research purposes. Depending on how academics proceed with investigating the improvement to teaching and curriculum this could be seen as educational research or at a minimum taking a research approach.

10.5.4 Practical Actions for More Effective Use of LA

As both students and staff were involved in these projects, many of the results have the potential to be developed into policy, strategies and actions for HEIs. Given that both staff and students indicated they did not really understand the term "LA" and it was not consistently applied, HEIs could consider developing teams across central academic development, data collection and information technology areas responsible for developing resources and training. This could help all parties build confidence and could further encourage work with staff and students so they can collaboratively gain data and digital literacies, thus improving their understanding and agency when using LA. This collegial group could also take responsibility for managing and maintaining institutional policies and governance practices and ensuring these address the various areas of staff and student concern outlined in Tables 10.10 and 10.11. This would ensure that data use is transparent, that consent to collect and use data is appropriately sought and that students are neither profiled nor given a sense that they are stalked, but instead supported and helped to improve their learning.

The explicit tools these groups develop should, as discussed, occur in collaboration with students and, as indicated in Tables 10.2 and 10.10, be based on ways of determining and tracking how students are using resources and how these support their progression. Tools, including third-party add-ons to the LMS, that help determine which students require greater support or those who need to focus on specific areas in their learning would also be helpful. The tools described in Table 10.3 provide a useful place to start, but as indicated by staff, these need to be easy to learn, simply to use and time saving.

Given our findings indicate differences in staff perceptions regarding the usefulness of different reports and students' attitudes about feeling they are being watched, it is essential that HEIs carefully consider students' sense of privacy and ownership of data. Determining methods for monitoring students' activities which occur offline, through changed assessment approaches, improved scaffolding of learning activities and opportunities for students to really identify and manage their own learning pathways in their own time and in their own ways must also be thought through. Making these changes may also require identification of different, more appropriate pedagogical approaches and concurrent academic staff support/training.

10.6 Conclusion

Our findings indicate both matches and mismatches in what students and staff understand and consider important in relation to LA. Academics tend to see the application of LA through their own interests and needs which include identifying students at risk, evaluating and improving teaching practice, supporting students to monitor their own learning and identifying actions the students might take to improve results and specific LA-related research interest.

Academic staff may place a lower priority on what students see as particularly useful to them (areas where LA can help them improve their learning) or it may be that academic staff are unsure how to address students' needs in relation to LA, given both groups seem to lack an understanding of what the term means. While there is some crossover here, the findings from our research reinforce the need to gather and include student input and balance it with staff interests. To do so would require addressing, the (as discussed earlier) limited research which considers what students say they want and need. Not taking students' perspectives into account is dangerous, as it raises the risk of our LA development missing the mark of what is useful to student success from the student's own standpoint.

The use of LA in educational contexts is challenging and requires considered leadership approaches; attention to addressing informed consent/privacy; ethical frameworks and power. Staff raised a range of concerns in relation to the use of data and transparency while students suggest they have concerns about the data that is routinely collected about them (such as demographic data used for government reporting purposes), yet there is evidence that users do not engage with Terms & Conditions of online services. However, in higher education institutions the imperative is to strive to be transparent, requiring perhaps a cultural shift to ensure permissions are acquired with informed consent and data appropriately collected and used. In addition, broader consideration needs to be given to pedagogical approaches which utilise LA and ensure students are central in their learning and embraced as co-creators of knowledge (rather than just recipients of it). Achieving these outcomes will work toward the goal of progressing LA to broader institutional and more widespread use – a goal that will only be achievable if all parties (staff, students and those in leadership positions) focus on similar outcomes which are appropriately funded. The research projects discussed in this chapter provide a beginning by bringing together the perspectives of two of these important groups with a number of recommendations on how the findings might translate into action. Collaboration of staff across various areas within institutions and with students are key to the successful implementation of LA.

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Chapter 11
How and Why Faculty Adopt Learning Analytics

Wide-Scale Learning Analytics Adoption through a 'Diffusion of Innovation' Lens

Natasha Arthars and Danny Y.-T. Liu

11.1 Introduction

While there is a broad consensus around the potential for learning analytics (LA) to positively affect education, widespread adoption of LA in higher education is lacking. LA research has produced frameworks supporting policy development; however, many of these top-down approaches focus on managing resistance to change (Macfadyen, Dawson, Pardo, & Gašević, 2014). In this chapter we present a theoretically grounded analysis of empirical evidence on the longstanding adoption and diffusion of a LA platform across an Australian university.

Our qualitative study analyses interview data collected from 34 users and 1 creator of the Student Relationship Engagement System (SRES) at the University of Sydney to identify its attributes as an *innovation* that have impacted diffusion based on teachers' perceptions and needs. Then, we evaluate the *communication channels* through which knowledge and experience of SRES have spread. Finally, we propose some ways forward regarding LA adoption through the lens of a well-established theory on innovation diffusion.

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11.2 Background

11.2.1 Learning Analytics Implementation and Adoption: Institutions

In response to the dearth of institutional examples of LA implementation and adoption, Colvin et al. (2016) interviewed 32 institutional leaders from Australian universities, exploring their perceptions of LA, institutional implementations, and strategies and challenges. The interviews revealed a number of variables, such as drivers, purpose, and vendor involvement that defined two clusters of institutions. Cluster 1 mainly consisted of institutions where LA was seen as efficiency boosting and targeting institutional concerns such as student retention, with high-level leadership sponsorship. In contrast, cluster 2 institutions focused more on the potential of LA to impact student learning, with a more considered approach to the limitations of vendor solutions. Their findings also led to the development of a flow-based model representing the system conditions for sustainable LA adoption. At its centre, this model focused on the conditions that could move teachers from 'interested' to 'implementing', citing, amongst other factors, the need for user-friendly tools that were flexibly compatible with teachers' pedagogical requirements, along with a reinforcing learning capacity in the institution for iterative improvement. Leadership and institutional context were highlighted as critical elements that impacted these factors.

Building particularly on the leadership element, Dawson et al. (2018) extended this analysis using complexity leadership theory, recognising that institutions are complex adaptive systems and enterprise LA adoption requires particular leadership approaches. Through interview analyses, they found two main classes of institutional leadership. Institutions with class 1 leadership approaches mainly had large-scale implementations but little adoption or impact amongst teachers or students. This 'top-down' approach was less consultative and while the leadership had established the infrastructure for LA, it had to break down operational barriers and silos to promote uptake and collaboration. On the other hand, institutions with class 2 leadership had "divergent and undirected" (p. 243) approaches to LA but could identify exemplary cases of LA adoption and impact. One key issue with class 2 institutions was around scaling, meaning that leadership had to focus on fostering resourcing collaborations to meet increasing demands of support and change. Tsai et al. (2019) also took a complexity leadership theory perspective to analyse the responses of senior executives at UK universities. They identified two key elements of enabling leadership that would address LA adoption challenges: (i) negotiating the reallocation of monetary, infrastructural, and human resources; and (ii) brokering connections between potentially siloed internal stakeholders. Both of these studies highlight the importance of strategic leadership in supporting LA adoption, while recognising the role of teachers.

11.2.2 Learning Analytics Implementation and Adoption: Teachers

Teachers' actions are central to the success of LA, even though there have been relatively few studies that analyse their perspectives in terms of LA adoption and implementation. Indeed, Dawson et al. (2018) highlighted a key challenge: "while effective adaptive leadership can rapidly progress LA, successful implementation is contingent on the practices of individuals operating within their discrete organizational structures or silos." (p. 238). Corrin, Kennedy, and Mulder (2013) interviewed teachers at an Australian university about potential uses of LA, finding that optimising student performance and engagement, supporting administrative functions, and better understanding students' learning experiences were key. They also identified that teachers' "needs were not met by the data representations that were currently available" (p. 203), in perhaps a similar rebuff to the class 1 approaches of Dawson et al. (2018). The theme of usefulness was continued by Herodotou, Rienties, Verdin, and Boroowa (2019), who conducted interviews with teachers who had used the Open University's LA platform and found that compatibility of LA tools with their current pedagogical practices and needs was a key factor in teacher acceptance. While these studies provide valuable insight into the perspectives and pragmatics of teachers when taking up LA, a more theoretical approach may help to elucidate underlying elements of LA adoption by these discrete individuals.

There are two key theoretical frameworks that have been used to understand LA adoption from the level of individual adopters: the Technology Acceptance Model (TAM) and diffusion of innovation theory. The TAM posits that perceptions of usefulness and ease of use are fundamental in determining whether individual users will accept a technology (Davis, 1989). As with diffusion of innovation theory, TAM says little about the technology itself and instead focuses on perceptions, meaning the usefulness and ease of use are perceived differently by different people.

Following the principles and building on TAM, Ali, Asadi, Gašević, Jovanović, and Hatala (2013) have proposed a Learning Analytics Acceptance Model (LAAM), which encapsulates teachers' perceptions around ease-of-use and usefulness of an LA tool and their intention to adopt it, along with the value of the analytics provided. Surprisingly, they found that perceptions related to usefulness and ease-of-use "were not sufficient factors for educators to show their behavioural intention for adopting a learning analytics tool for their practice" (Ali et al., 2013, p. 140). They did, however, find that prior teaching experience may have an impact on perceived usefulness, with those in instructor roles appreciating more features of the LA tool than less-experienced teachers in other roles such as teaching assistants. This may be due to instructors having a higher level of pedagogical knowledge and responsibility for the learning process. Additionally, they found that teachers valued information about student difficulties that required their attention, provisions for solutions to these problems, and intuitive interfaces (Ali et al., 2013).

However, neither TAM nor LAAM account for how individuals become aware of a technological innovation and how it spreads from being adopted by an individual to reaching a critical mass and widespread adoption across an educational institution to users in a broad range of contexts. For example, in Ali et al.'s (2013) study, the LA tool was introduced to participants as part of the study, who had predominantly computer science or information systems backgrounds.

In Macfadyen and Dawson's seminal piece on LA adoption failure (Macfadyen & Dawson, 2012), they provide a potential theoretical framework for this: diffusion of innovation theory (Rogers, 2003). Here, they briefly use diffusion of innovation to theorise teacher resistance, pointing out that LA tool complexity may dissuade uptake due to the workload associated with its learning curve, as well as teachers failing to see an advantage or reward over current practice. More broadly, diffusion of innovation theory has been used as a conceptual framework to understand the adoption of educational technology. Emin-Martinez and Ney (2013) studied the adoption of game-based learning in high school teachers, briefly outlining how this was influenced by teachers' understanding of its benefits as well as their ability to fit it in with their existing pedagogies. Diffusion of innovation was also used by Liu, Bartimote-Aufflick, Pardo, and Bridgeman (2017) to theorise a number of design principles for LA tools. In studies where tertiary teachers were surveyed on factors relating to prospective adoption of technologies, compatibility with current working practices, seeing positive results, the ability to trial the technology, and the simplicity of learning and using the technology were positively correlated with potential adoption (Tabata & Johnsrud, 2008; Ntemana & Olatokun, 2012). In common practice, the infamous adoption bell curve (showing 'innovators' and 'early adopters' to 'late majority' and 'laggards') pervades discussions of technology adoption in higher education.

There is no doubt a multifaceted relationship between tool complexity, its affordances for teachers and students, and the realities of teachers' jobs impacts their adoption of any educational technology. Aldunate and Nussbaum (2013) found that early adopters who make a significant investment of time incorporating technology into their teaching are more likely to adopt a new technology even if it is complex in nature. Conversely, teachers who do not fall into the early adoption category and make only a small investment of time incorporating technology are less likely to adopt and are also likely to abandon adoption. Glass (1999) proposed a model for teachers' adoption of new technology, plotting benefits over time, showing there is an initial learning curve in which no immediate benefits are realised – emphasising the need to minimise the effect of the learning curve. Specifically in LA, stakeholder acceptance, the affordances of LA software, and LA's impacts on student success have been identified as key issues (Mah, Yau, & Ifenthaler, 2019). Diffusion of innovation theory brings together these sociotechnical elements and examines the interaction between the affordances of innovations and the humans who use and share them.

However, diffusion of innovation theory has not been systematically applied to LA innovation and implementation despite LA being one of the most lauded transformative technologies of the past decade (Joksimovic, Kovanovic, and Dawson, 2019). Moreover, the high-level LA adoption studies outlined acknowledge the importance of teachers but focus on leadership. The complex interactions of these stakeholders was recognised very early on by Beer, Jones, and Clark (2012), who proposed that LA was situated in complex adaptive systems and that the agents best placed for impact with LA would be working at the micro-level: the teachers and students. To address these gaps, here we apply diffusion of innovation theory to systematically analyse data from the adoption and implementation of SRES by teachers and other staff involved in learning and teaching.

11.2.3 Theoretical Framework – Diffusion of Innovations

Rogers (2003) defines an innovation as “an idea, practice, or object that is perceived as new by an individual or other unit of adoption” (p. 12). What is considered to be new depends on the perception of the individual, meaning if it appears to them to be new, then it falls within Roger’s definition of an innovation. Rogers notes that there are three elements to the aspect of “newness”: knowledge, persuasion, and the decision to adopt. Importantly, Rogers notes, “the same innovation may be desirable for one adopter in one situation, but undesirable for another potential adopter whose situation differs” (2003, p. 12).

The process of adoption is explained by Rogers as moving through five stages (Fig. 11.1). At the *knowledge* stage individuals develop an awareness of the innovation; however, they do not have the goal of adoption. Knowledge can include knowing that the innovation exists, knowing how the innovation works or knowing the underlying principles of the innovation. From the initial knowledge stage, individuals move to the *persuasion* stage where they may actively seek out information about the innovation. This information is related to the perceived attributes of the innovation as outlined in Table 11.1.

For technological innovations, individuals generally seek two types of information about the innovation: software information and innovation-evaluation information. The information sought about the software relates to how and why it works,

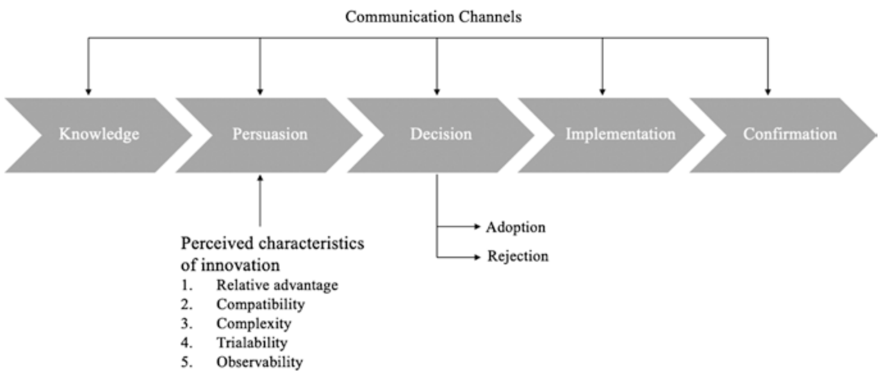

Fig. 11.1 Five stages of adoption (Rogers, 2003)

Table 11.1 Perceived attributes (Rogers, 2003)

Relative advantage	"The degree to which an innovation is perceived as better than the idea it supersedes" (Rogers, 2003, p. 15). Individual perception of relative advantage is more important than objective advantage. "The greater the perceived relative advantage of an innovation, the more rapid its adoption rate will be" (Rogers, 2003, p. 15).
Compatibility	"The degree to which an innovation is perceived as being consistent with existing values, past experiences, and needs of potential adopters" (Rogers, 2003, p. 15).
Complexity	"The degree to which an innovation is perceived as difficult to understand and use" (Rogers, 2003, p. 16).
Trialability	"The degree to which an innovation may be experimented with on a limited basis" (Rogers, 2003, p. 16).
Observability	"The degree to which the results of an innovation are visible to others" (Rogers, 2003, p. 16).

whereas the information sought in relation to innovation-evaluation is its consequences together with the advantages and disadvantages associated with the individual's situation (Rogers, 2003). Communication is particularly important during the knowledge stage. Communication is a process of creating and sharing information for the purpose of achieving mutual understanding. In the context of diffusion, communication is aimed at sharing information about a new idea. This process includes four elements: (1) the innovation; (2) an adopter *with* knowledge of the innovation; (3) one or more individuals *without* knowledge of the innovation; and (4) a communication channel. Communication channels may include mass media or interpersonal channels.

During the *decision* stage, the individual assesses the innovation in terms of its advantages and disadvantages, through activities such as analysis and testing, eventually coming to a decision about whether or not to adopt it. If the individual decides to adopt the innovation, they then proceed to the *implementation* stage where the innovation is introduced into either their own or someone else's daily practice. Engaging in implementation also leads to reflection and evaluation of the innovation in terms of both its costs and its benefits. Re-invention is also a feature of the implementation stage, where a user may modify an innovation while adopting and implementing it. The final stage is the *confirmation* stage, where the individual collects information that supports their decision of adoption or rejection of the innovation as well as information about the sustainability of their decision.

11.3 Methods

11.3.1 Research Questions

The purpose of this research is to understand the bottom-up and widespread diffusion of SRES at the University of Sydney, where it was first developed and has subsequently seen widespread adoption by teachers. We therefore sought to answer the following research questions:

1. What attributes of the SRES innovation have impacted diffusion and how?
2. What communication channels have enabled SRES knowledge and experience to spread?

11.3.2 The SRES as a LA Platform

The SRES software was borne out of the merging of two bespoke web-based applications that individually served specific but different needs of teachers of large introductory student cohorts at the University of Sydney. One of these applications was the ‘Barcoding System’, which addressed coordinators’ needs for administrative efficiency by affording teaching staff the ability to scan student cards in class with their smartphones to monitor attendance. The other application was the ‘Early Warning System’, which allowed coordinators to import spreadsheet data into a centralised, online database, and use these data to personalise emails to targeted subsets of students: in essence, an online mail-merge application. This helped to address a pressing and growing student need of more personalisation and care from their teachers. When these were merged in 2014, the platform was renamed SRES to emphasise its purpose of fostering student engagement and positive relationships with teachers.

Being a LA system SRES relies on data about students but it takes a paradigmatically different approach to prevailing LA systems where pre-prepared warehoused data is analysed and presented to users (e.g. Course Signals). Instead, SRES gives teachers an initially empty online database, which can be populated with data that they see as relevant to their unique contexts (Fig. 11.2, middle). In keeping with its roots, SRES allows teachers to enter data directly into the platform via mobile devices, from attendance or participation grades in tutorials to complex rubric-based scores and feedback such as during in-class presentations or clinical examinations (Fig. 11.2, left). This avoids double handling of student data and unreliable paper-based approaches. Teachers can also choose to synchronise data from learning management systems (LMS) (such as grades, engagement, discussion participation), as well as being able to import spreadsheet data per the original application. The development of LMS synchronisation (in 2017) was a major milestone that coincided with the implementation of a new LMS across the university, and significantly streamlined the ingress of key data such as enrolments and interim grades.

In keeping with its practical focus, a key element of SRES is action upon data (Fig. 11.2, right). At the most basic level, advanced mail-merge capability is present and allows teachers to compose, dispatch, and track engagement with tailored messages to students (Fig. 11.3). Teachers can also build similar support into ‘portals’, programmable web pages that can be embedded into the LMS so that students can receive tailored advice through that channel. Automated reports can also be configured and sent to teachers to highlight students belonging to conditions of interest, such as those with downwards-trending engagement or achievement (Fig. 11.4).

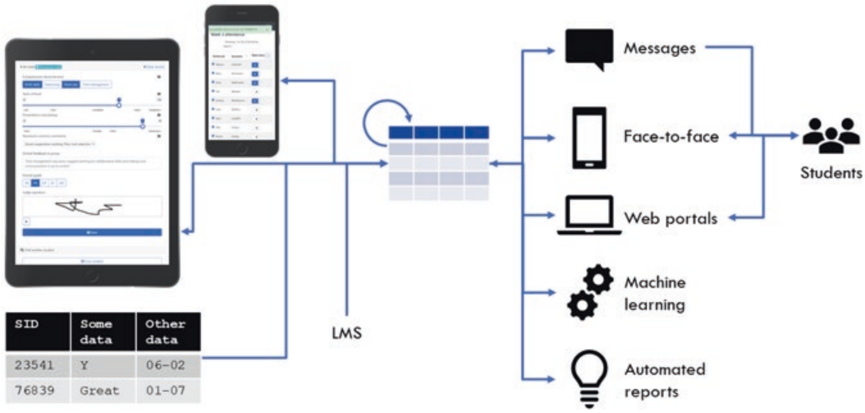

Fig. 11.2 Schematic of SRES. Data can be collected and curated from multiple sources so that educators have relevant data in one place, a cloud-based educator-designed database. Meaningful, educator-controlled actions can then be performed based on this data

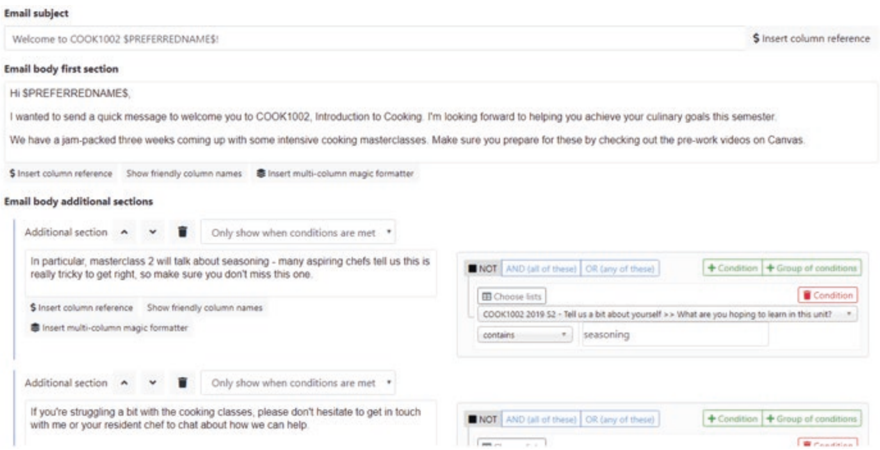

Fig. 11.3 Example of the graphical mail merge builder that allows educators to personalize feedback and support for students at scale

The diverse feature set of SRES has grown alongside increased and wider adoption, largely due to co-creation efforts between teachers and the platform developers (see Dollinger, Liu, Arthars, & Lodge, 2019). For example, some staff wanted an 'online roll call' interface. This was developed and has since expanded to not only record simple attendance information but be able to drive complex marking rubrics to save information *to* the database as well as display relevant information *from* the database. This flexibility has meant that teachers have taken this feature and used it in unforeseen ways such as a web-based student photobook (Fig. 11.5) allowing teachers to more personally interact with their students in class (images being student data that SRES can also handle). Although SRES is intended only to be visible

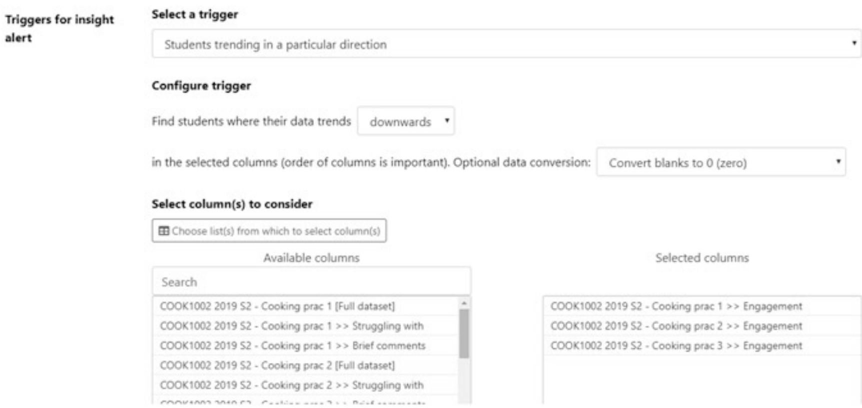

Fig. 11.4 Educator-configured automated reports

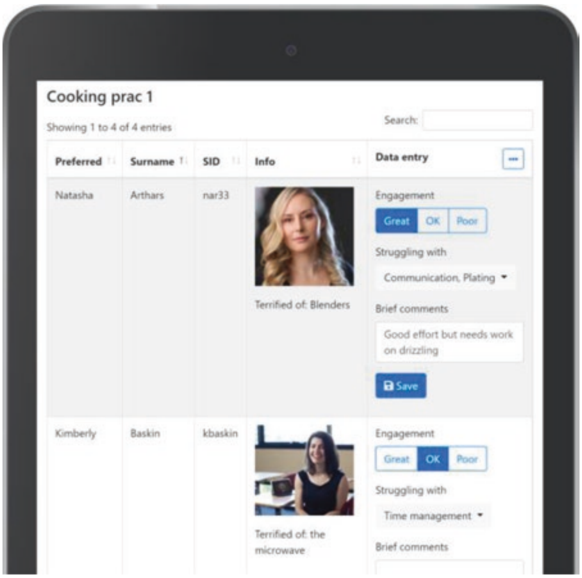

Fig. 11.5 Example of an SRES interface where teachers can simultaneously surface and record relevant data about students

to teachers, LMS integration has enabled other functionality such as allowing students to enter data for themselves and their peers directly into the database, enabling new pedagogical approaches such as peer review and self-reflection (Fig. 11.6).

From the three teachers who started building and using the two separate applications in 2012, in 2019 SRES is currently being used by over 1700 teachers, covering over 60,000 students at the University of Sydney. Adoption has increased by approximately 50% per annum, and SRES is also now being piloted at a number of other Australian institutions.

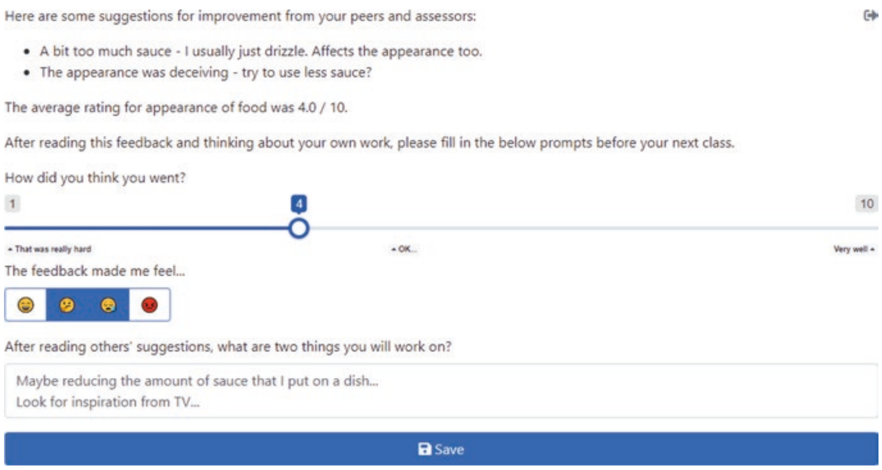

Fig. 11.6 An SRES web portal that simultaneously presents tailored data to students (e.g. derived from peer and educator marking and feedback) and invites data entry from students themselves (e.g. self-reflection upon feedback)

11.3.3 Data Collection

For this study there were two groups of participants: SRES *creators* and SRES *users*. SRES creators included staff at the University of Sydney who were involved in the creation and/or ongoing development of the platform. SRES users included all faculty and staff at the University of Sydney who had a SRES account. This included past and current users of SRES. Approval from the university's human research ethics committee was received before participant recruitment and data collection commenced (approval numbers 2017/018 and 2019/463).

SRES creators and users were invited by email to participate in semi-structured interviews. 35 participants (1 creator and 34 users) were interviewed with interviews ranging from 35 minutes to 80 minutes in length, each being audio recorded and later transcribed. Interviews were determined to be the most suitable method of data collection as they offer the opportunity to gain insight into SRES users' perceptions of the attributes of the platform, together with their communications regarding SRES. While the insights gained from interviews are richer and more detailed than those gained from questionnaires, they limited the possible sample due to their time-consuming nature. It was therefore important to ensure that interviewees were representative of the population of SRES users. Also, although students were the ultimate beneficiaries of their teachers' use of SRES, the felt effects of the platform would be pedagogical changes such as personalised feedback, tailored support portals in the LMS, or more efficient grading. Although these effects derive from the application of LA, students themselves did not adopt the LA platform and so their perception data would not assist in answering the research questions here.

User interviews were conducted with both academic and professional staff across the University of Sydney between February 2017 and October 2019. Interview par-

Table 11.2 Characteristics of interview participants: *users* (n = 34)

	Course/ Laboratory Director	Unit Coordinator	Tutor/ Lecturer	Technical Officer	Teaching Support Staff
Science	5	3	3	1	1
Medicine & health	–	2	–	–	2
Business	–	3	1	–	–
Arts & social science	–	5	1	–	–
Engineering & IT	–	1	–	–	–
Health sciences	1	1	–	–	–
Architecture	–	1	–	–	–
Other	–	1	–	–	2
Total	*6*	*17*	*5*	*1*	*5*

ticipants (users) were representative of the faculties and roles using SRES and are outlined in Table 11.2. For example, there are only a small number of instances where SRES is being used at a course or laboratory level, whereas the platform is being used primarily at a unit of study (individual subject) level by unit coordinators. Interviews explored the context in which individuals used SRES, how and from whom they heard about the platform, and factors that influenced their decision to use the platform.

Additionally, one semi-structured *creator interview* was also conducted in September 2019 with one of the creators of SRES. The interview focused on the evolution of SRES, including key drivers and context for the development, implementation and continuous improvement of the platform, together with factors that have influenced and hindered adoption of the platform at the University of Sydney.

Interview transcripts were reviewed and references to perceived attributes and communication channels were identified and coded in Nvivo. Perceived attributes were coded based on the five attributes listed in Table 11.1 above and communication channels were coded to either mass media or interpersonal channels. Following this initial round of coding, each perceived attribute and communication channel was reviewed and coded into themes, which are outlined in the findings section.

11.4 Findings

11.4.1 Perceived Attributes of the Innovation

Analysis of interview transcripts showed that all five perceived attributes (relative advantage, compatibility, complexity, trialability, and observability) played an important role in either helping or hindering the widespread adoption of SRES. We discuss each of these attributes below and explain how they have impacted diffusion at the University of Sydney.

11.4.2 Relative Advantage

Analysis of interviews revealed four key features of SRES that individuals identified as being important as they resulted in the opportunity for relative advantage. These were SRES's ability to replace paper-based systems for collecting data, personalisation and automation of communication with students, scaling personalisation across large cohorts of students, and getting to know students. We first outline each of these features in terms of the potential for change in practice, including the practice that it supersedes, and then discuss the relative advantages of these changes for adopters of SRES.

One of the largest perceived advantages of SRES stemmed from its ability to replace current systems for collecting data, which were primarily paper-based. This was in relation to class rolls that are used by many teachers to mark attendance, but also extended to paper-based systems used to record student performance, such as qualitative and quantitative feedback for oral presentations or group work. In fact, many teachers referred to SRES's ability to collect attendance data as being the reason that they initially decided to use the platform.

Another major perceived advantage of SRES was its ability to personalise communications with students. The majority of teachers had previously used LMSs, such as Blackboard and Canvas, to send mass announcements to students. As the LMSs did not have functionality that allowed them to personalise the announcement or to send it to a select group within the cohort, they were faced with the choice of either sending bulk announcements or going through the manual process of creating an Excel spreadsheet and using Outlook mail merge to send personalised emails to students. Even for those who were already using a manual mail-merge process, SRES represented a way to further scale this process.

For teachers who were used to personalising support for students and were able to do this in small classes where they got to know and interacted with all of their students, SRES represented a way to scale this approach when faced with large cohorts of students. As one teacher commented *"when we do work to a smaller scale, say in postgraduate coursework, we do this naturally. We monitor how people are showing signs of engagement, or not coming to class, and then we will send emails. This just makes it scalable for me."* The flipside of SRES's appeal of personalisation for large cohorts of students also meant that those teaching small cohorts did not necessarily perceive, or perceived much less of, a relative advantage of adopting the platform for supporting those cohorts. This is captured nicely by one teacher who mentioned *"I think by definition this is a system that helps me in my 350 student unit in a way more than it helps me with my 30 student unit in third year [*…*] I wouldn't bother using it because I don't need to because I can actually talk to each student individually*".

The fourth main perceived advantage identified through interviews was the ability to get to know students. This advantage included getting to know students at an individual level and to understand similarities or differences across students at a class and cohort level. The ability to ask students to enter personal information, whether it be about their interests, their major, or even asking them to upload a photo of themselves, into an online portal represented a way of getting to know individual students early on in the semester and personalise teaching and support accordingly. Reflecting on how this information is helpful, one teacher commented *"I've got a much richer database that I can use in class. I know Mary Jane looks like that, and Mary Jane is a marketing person. So, during these Harvard case studies, I've got a marketing thing - Mary Jane, what do you think about this?"* Even though teachers can get to know small to moderately sized classes over the course of a semester, SRES represented a way in which teachers could gather this data in a more systematic manner from all students at or before the first week of classes.

Using SRES rather than continuing to rely solely on paper-based systems presented relative advantages that were primarily for the teacher. These advantages included timeliness, visibility of data, and consistency of grading. Many of these advantages were important for teachers who coordinated large units of study rather than teachers who were responsible for individual tutorial classes. In fact, in these cases the decision to adopt SRES tended to be made by the coordinator and resulted in a requirement for tutors to change their practices accordingly.

Coordinators who relied on a group of teachers to mark weekly paper-based rolls explained that collecting these pieces of paper was not feasible on a weekly basis and as a result, by the time they had collected them it was often too late to aggregate and analyse the data and then take action while it could still make a difference. By contrast, SRES offered a way for teachers to record participation electronically into a platform where the coordinator had real-time visibility and access to data all in one location, rather than spread across pieces of paper. The potential for such timely and visible data meant that coordinators could take action. As one coordinator stated, *"we can then start addressing any issues we may need to address when we can address it, not when it's too late"*. The ability to take timely action also represented the potential to improve awareness of the importance of attendance and to retain students who may have otherwise been at risk of failing due to not meeting attendance requirements.

Moving from paper-based systems to SRES had the perceived advantage for coordinators of ensuring a more consistent approach to allocating grades across a cohort. As discussed above, issues around timeliness and visibility prevented coordinators from taking action to support students, but they also prevented them from taking action to ensure their consistency across their teaching. Consistency was identified as an issue for allocation of grades for class participation. This is reflected in the following statement from a unit coordinator in relation to marking class participation: *"So you've got one tutor who might say everyone is fantastic. Then another one says these students are terrible. The reality is actually they're probably somewhere in the middle. But we don't see that until the end. So we don't have a chance to address that until pretty much it's too late."* To address the issue of consistency, coordinators saw SRES as a viable option for real-time monitoring throughout the semester that allowed them to take corrective action, where appropriate, in a timely manner.

11.4.2.1 Compatibility

Analysis of interview transcripts showed that because SRES was designed by teachers for teachers, and because it was designed to be flexible and adaptable to individual teachers' practices and needs, it was perceived to be highly consistent with teachers' existing values and needs. For many users, these values related to understanding, caring for, and supporting students, particularly those who were at-risk of failing, and as such were important factors in teachers' decisions to adopt this innovation.

A consistent theme across interviews was the desire to engage with and show care for students; however, those managing large cohorts of students explained that this was usually not feasible due to time and technological constraints. They viewed SRES as key to being able to start engaging with students in a personalised way at scale, even if only through emails addressed to the student's preferred name instead of bulk announcements through an LMS. Teachers commented that using SRES was *"an ideal opportunity to show students that you notice"*. While many teachers were focussed on the need to support at-risk students, some did discuss the need to recognise and encourage students who were succeeding. This was emphasised by one coordinator, who commented: *"reinforcing the good [students] - there's immense value in that and we forget that group, often. We don't give them enough praise and recognition"*. Teachers also discussed the need to provide a higher level of support to first year, first semester, undergraduate students and to be able to remove some of these supports in subsequent semesters. Reflecting on their practice, one coordinator stated, *"So first semester I would support [students] in a more active and obvious way than second, and I would deliberately remove some of those supports in second semester."* The flexibility of SRES for teachers to choose which students to support and how, was therefore important in driving compatibility of the innovation with individuals' values and needs which were also different depending on which units of study they were coordinating or teaching.

11.4.2.2 Complexity

Although the flexibility of SRES positively influenced the perception that it aligned with the values and needs of many teachers, this flexibility has also influenced the perception of many that the platform is complex in terms of understanding how to use it and how it could be used. Reflecting on how difficult they initially perceived SRES to be to learn compared with how difficult it was, one coordinator said: *"I just felt that it was more effort... it would take more effort than the time that I had to do it. But I think once you have mastered the actual process, I don't think it's difficult at all."* This perception was prevalent in many of the interviews, with adopters referring to an initial learning curve that was somewhat complex but worth enduring due to the benefits that resulted from being able to use the platform. Continuous improvement of the platform has also led to a positive change in this perception, particularly since LMS integration in 2017.

While perceptions have changed over time in relation to understanding how to use SRES, the increase in features has resulted in more potential uses, consequently increasing the perception of complexity. To avoid this complexity, many adopters have started by identifying and trialling one applicable use before deciding whether or not to expand their use of SRES further.

11.4.2.3 Trialability

SRES was perceived by teachers to be open for experimentation and, perhaps most importantly in terms of adoption, teachers felt they could choose what feature within the platform they wanted to use, with what students, and could subsequently expand or contract their use as they went along without feeling that they had to continue using it. The flexibility of the platform allowed users to keep certain aspects of their practice constant, while experimenting with the platform. For example, teachers were able to continue collecting data using paper-based methods (e.g. ticking names off on a paper roll) and transfer that data into SRES, later making a decision about whether or not to move to a purely electronic means of data collection.

Although SRES was perceived to offer the greatest degree of relative advantages to teachers in large first year units of study, it also posed the greatest risks for coordinators of these units due to the potential to negatively impact large numbers of students if errors were made. However, the perception of trialability enabled coordinators of large units to adopt and initially use the platform in limited ways, such as to collect data without acting upon it, or to trial the platform in just one class and then expand use to all classes at a later stage. This enabled them to limit the risk of unintended negative consequences that could otherwise have large impacts, particularly when coordinating cohorts where more than one thousand students were enrolled.

The trialability of SRES enabled adoption to begin at either a coordinator level or at a tutor level and subsequently spread across an entire unit of study or teaching team. Some tutors who perceived relative advantages in adopting SRES were able to trial the platform in their tutorial class, provide evidence of the positive impact of the platform and subsequently convince the coordinator to implement it across the entire unit of study.

11.4.2.4 Observability

Providing observable results was important for convincing others of the benefits of SRES and often went hand-in-hand with trialability. As one tutor reported: *"When I was trialling this back in first semester last year, I presented it as an opportunity to other people, to trial. 'Oh, but it may not work. I'm going back to the paper version.' There was that if it doesn't work, and it's not proven, I'm not going to take a risk and I'm not going to trial this thing. I think it was really just around that inertia. This thing is there. It does work. Go for it."* Observable results that were important to adopters included evidence that the platform would work as intended, evidence of efficiency gains, and evidence of positive impact on students. The type of positive impact on students of course depended on the intended aim and actions of the user and ranged from reducing the number of students who failed due to failure to meet attendance requirements to improving the relationships between tutors and students.

While creating observable results of positive impacts on students was not necessarily a challenge for SRES adopters, differentiating what was attributable to the platform and what was attributable to other changes in practice proved more challenging. Early adopters of SRES were often trialling multiple innovations at once, making it difficult to distinguish the effect of one particular innovation. Many interviewees explained that while it was difficult to provide a systematic evaluation of the impact of using SRES in relation to students' learning experience, they were able to provide many anecdotal examples of how their use of the platform has helped individual students.

11.4.3 Communication Channels

Communication channels are important for spreading knowledge and experience of the innovation and these channels can be categorised as either *mass media channels* or *interpersonal communication channels*. Interviews with users indicated that while mass media channels played a key role at the knowledge stage, it has been interpersonal communication channels that were most important during the persuasion stage and it was here that what we refer to as *champions* played a critical role.

Mass communication channels played an important role in creating awareness that SRES existed and was available to teachers to use. These communication channels were both face to face and online, including media such as presentations and blogs. As one current user commented: *"I heard about it when it was first being designed, I think. It was a presentation, years, and years and years ago. [The creators] first started talking about it as a concept, and I thought it was fantastic, but I couldn't see myself ever using it. I just thought no, it's going to be too difficult."* Mass communication in itself was insufficient at driving adoption of the platform due to perceptions of complexity and uncertainty around the relative advantages it may provide in an individual's context. However, mass communication was also useful in creating awareness of continuous improvements made to the platform and the addition of new features, such as LMS synchronisation.

Many users reported in interviews that interpersonal communication was crucial in deciding to adopt SRES. This interpersonal communication was generally with a user who (1) was able to explain what relative advantages that the potential adopter may experience as a result of implementing SRES in their teaching context, (2) was able to assist or direct them to assistance that would help to overcome the perceived complexity of the platform, and (3) was able to communicate observable benefits that themselves and others had realised as a result of adopting SRES.

These interpersonal communications in which SRES was introduced were often in the form of informal conversations that centred on a problem that the individual was having. The SRES user would then suggest the platform as a means of solving that particular problem, such as having visibility over attendance. As an SRES creator remarked: *"every academic has a different problem that they start with and as long as it can solve that problem for them, they become converted so to speak."* Communication at the persuasion stage is therefore in relation to how SRES might be able to solve a particular problem, or set of problems, that a teacher has. While these informal conversations were often with peers within the same discipline, educational designers and staff from the central area of the university were also heavily involved in interpersonal communications that resulted in the decision to adopt SRES as they were also able to suggest solutions to teachers' problems based on their experience with the platform. Teachers, educational designers, and other staff acted as champions in increasing awareness and adoption of SRES through these interpersonal communications.

11.5 Discussion & Conclusions

While the flexibility of SRES has positively enhanced teachers' perceptions of relative advantages, compatibility, and trialability, it has unfortunately negatively influenced their perceptions regarding complexity. These findings are somewhat inconsistent with those of Macfadyen and Dawson (2012) as attributes have both *positively* and *negatively* influenced individual's perceptions and decisions about whether to adopt the SRES. Importantly, having champions who can work to understand both the value system and needs of individual teachers and then determine which features of SRES may align with those values and needs and subsequently communicate relative advantages to them is of critical importance. This is particularly important in the case of SRES and many other LA tools as they only have a software component, as opposed to a hardware and software component, meaning they have what Rogers refers to as a "lower degree of observability" (2003, p. 13). This would therefore emphasise the need for communication channels, in particular interpersonal channels, to overcome the issue of lower observability and perceived complexity.

There is a need to investigate the ways in which champions engage with potential adopters in order to determine how they understand potential users' values, needs, and the problems that they are facing and how they use this information to assess and communicate the potential benefits of SRES for that particular context. For example, while the act of taking attendance does not seem to make a difference to students whether it be manual or electronic, when we look at the advantages that it provides to coordinators (e.g. having timely access to accurate data) we see that this advantage is only an advantage when we consider it within the context of compatibility of the innovation with their values (e.g. to identify and support disengaging students). Understanding the underlying value system of potential adopters of an innovation is therefore of critical importance. For example, giving coordinators timely access to and visibility over attendance data will not be enough for them to consider SRES as having a relative advantage over an existing practice if they do not consider attendance to be important. It may be because of faculty level attendance policies or because coordinators perceive attendance to be critical to engagement, learning, or success within a unit of study that this feature of SRES is considered by many to be a relative advantage. Understanding the relative advantages of a tool together with potential users' needs and values, rather than focusing on each of these individually, may well be crucial to identifying how best to communicate the potential benefits of LA to potential adopters.

Adoption of SRES may, at first glance, appear to be about solving problems and creating relative advantages for teachers (particularly coordinators); however, when we look a little deeper we can see that these problems are often driven by student needs (e.g. timely feedback) or the desire to reduce administrative workload in order to spend more time supporting students. These findings align with Corrin et al.'s (2013) categories of educational problems that faculty identified as potential uses for LA, particularly student performance, student engagement, and teaching-related administrative functions.

Given the LA field's ongoing struggle to identify realised teacher and student impact, the diffusion of innovation theory as applied here may therefore provide an important framework that extends the adoption and implementation narrative beyond more straightforward models such as the LAAM. The sociotechnical nature of LA in institutions is increasingly being recognised as a key to sustainable impact (e.g. Buckingham Shum & McKay, 2018). Rogers' framework, as evidenced by its application in our study here, highlights that many elements at the human-technology interface are critical. Compatibility with existing values and modes of operation but also observable advantages over existing practices appear to be vital in the persuasion and decision stages of Rogers' adoption process for educators and LA. If teachers are particularly concerned about impacting student performance, engagement, and their own workload, then it follows an LA tool must directly address these core needs and values to persuade adopters.

It is also crucial that LA systems are flexible in accommodating for a wide variety of needs and applications, considering the diversity of learning and teaching contexts and the educators and students in them. This flexibility allows what Rogers terms 'reinvention', the "degree to which an innovation is changed or modified by a user in the process of its adoption and implementation" (Rogers, 2003 p. 206). This is important because it sees LA users not as passive recipients of the innovation, but as active participants, leading to more rapid adoption. Other authors have termed this 'emergent behaviour' (e.g. Fischer, Nakakoji, & Ye, 2009), where users of technologies adapt flexible software to their needs. We saw this in our interviews where the flexibility of SRES meant that educators could adapt the platform for diverse purposes. Rogers suggests that the amount of re-invention corresponds with the complexity and heterogeneity of the individuals and their problems; LA tools for such complex systems as higher education institutions must then surely require the flexibility to support re-invention. Moreover, it may not be sufficient for teachers to be provided a number of disparate LA tools (or worse still, siloed systems with little interoperability). Instead, as we saw in the platform mentality of SRES, giving teachers a range of functionality within *one* LA platform was not only conducive to different initial uses but also allowed their use to grow in complexity over time, afforded by the platform's flexibility.

Finally, the importance of communication channels in the sociotechnical milieu of LA adoption must not be underestimated. Understanding the value of both mass and interpersonal communication channels is critical as they play different roles, and must both be employed in order to assist with adoption of LA. While mass communication channels may play a key role in creating awareness of the innovation at the knowledge stage, interpersonal communication channels through the use of champions play a critical role in convincing individuals to adopt LA at the persuasion stage.

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Chapter 12
Supporting Faculty Adoption of Learning Analytics within the Complex World of Higher Education

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12.1 Introduction

Today's institutions of higher learning continuously accumulate vast amounts of information about students through a network of widely diverse, yet loosely coordinated operational systems. Such systems include course learning management systems, student information systems, student activities systems, card swipes at academic support centers, and more. At the same time, novel means for making sense of this "Big Data", including predictive statistical models and visualization tools, have rapidly pushed us toward becoming a data-informed culture, both in our schools and in our daily lives. Just 8 years after the Society for Learning Analytics (SOLAR) hosted the first international Learning Analytics and Knowledge conference, Lodge, Horvath, and Corrin (2019) have suggested that learning analytics has moved from an emerging trend to an established field.

As this field rapidly advances, it seems reasonable to propose that the use of Learning Analytics (LA) may prove to be one of the most promising new developments in helping students succeed during their college years. In the LA programs

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discussed in this chapter, that success is achieved when students enter college properly prepared, remain in college after their freshman year, choose an appropriate major in a timely manner, and graduate within 4–6 years. Or, as Kuh et al. (2011, pg. xii) has aptly stated, "students persist, benefit in desired ways from their college experience, are satisfied with college, and graduate." Importantly, Kuh's definition of student success considers academic achievement and persistence with further implications that students will have experienced purposeful educational activities and attained their own objectives for attending college.

We use the term LA to mean any and all data that can be analyzed and acted upon to improve student success. For this reason, Sclater's (2017) detailed description of LA accurately defines the data used in our programs. In contrast to Long and Siemens (2011) earlier definition of LA, which discriminated between LA and Academic Analytics, Sclater (2017) suggests a method of categorizing data based upon its origins. Originally formulated by the UK Information Commissioner's Office, the four categories are: (1) reported data; (2) observed data that has been automatically recorded; (3) derived data that is produced from other data and; (4) inferred data that makes correlations between data sets. Those categories can then be related to different types of data, which often include such things as demographic, academic, and learning activity data, as well as data about the educational context in which learning takes place.

For all of our collaborative work, we use the term faculty to denote any person who holds a full-time teaching appointment at our schools, regardless of rank or appointment.

12.1.1 Background

A number of external factors are compelling colleges and universities to increase student success. In the US those factors include the increasing cost of college tuition accompanied by a student debt crisis, which according to Johnson (2019) surpassed a trillion dollars in 2018, and a looming enrollment cliff (Kelderman, 2019), where US nation-wide freshman enrollment dropped 1.7% in 2019 (Spano, 2019). Factors like this are also pushing faculty to play a more instrumental role in student success both within their courses and curriculum.

In this challenging environment, the use of LA provides new professional development opportunities for faculty, many of whom care deeply about their students but have limited time to ensure that they get the most out of their educational experiences. As Oleson and Hora (2014) have posited, teaching practices and professional development for faculty can be influenced by specific types of knowledge. In today's data rich climate, new knowledge for faculty professional development now includes LA. In earlier studies we assessed the impact LA had upon faculty who used it to conduct research about their students. Our results indicated a change in their perceptions about student performance and behavior as they came to new understandings about the critical decisions students make on their pathway toward graduation (Rehrey, Groth, Shepard, & Hostetter, 2019a; Rehrey, Groth, Shepard, & Hostetter, 2019b).

Our research has also encouraged us to consider how universities have become complex systems with many interconnected but independently functioning parts. As Siemens, Dawson, and Eshleman (2018) argue, that complexity has grown over the past few decades as a 150-year-old model of higher education has been challenged by entrepreneurs who use technology to attract potential students, by a public that has placed increasing value on jobs, by a declining population of traditional-age college students, and by administrators who have stressed the importance of students as customers.

Some of the very things that have increased complexity have also offered solutions for dealing with that complexity. For instance, advances in computing power and the proliferation of connected devices have led to the collection of huge amounts of data. Organizations of all types have drawn on that data to help answer difficult questions, to position themselves in an increasingly global society, and to ask more complex questions about internal actions and external functions. At universities, budget officers, personnel directors, and enrollment managers were among the first to tap into this new trove of data, though deans, department chairs, and individual faculty have also begun to look to data for answers on matters related to teaching, learning, and curriculum.

Siemens et al. (2018) claim that Complex Adaptive Systems (CAS) involve interactions among interconnected individuals, or agents, at many levels who exchange information and feedback within a specific environment, leading to organizational evolution. They add that complexity science has largely focused on "complexity as a phenomenon, rather than as an approach to fostering organizational change (Siemens et al., 2018, p. 30)." They further argue that a better understanding of institutional structures, especially as they relate to learning, is crucial to the future of higher education.

This chapter draws on complexity theory in arguing for a new model of data-informed decision making about learning in higher education. It starts from a principle put forth by Siemens et al. (2018) that innovative change has the greatest potential when its developed from the bottom up. In this case, the innovation is taking place among individual faculty members who, acting as change agents, draw on LA to answer questions about their students and programs. Questions that were out of reach only a few years ago, such as: Who really are our students? What approaches to teaching help them learn most effectively? How can we adapt "bottleneck courses" in which a large percentage of students fail, so that more students move toward graduation? How do changes in introductory courses affect students as they move through later classes and into their majors?

Those are just a few of the many questions that faculty and administrators have asked as they have started to use LA to conduct scholarly research about student success. They have been aided by the formation of communities of inquiry, which have enabled idea-sharing, problem-solving, and sense-making across disciplines and across universities. In this chapter, we look at how five universities have approached the use of LA through partnerships at their local institutions and through a network created by members of their universities. In doing so, we show how the analysis and application of LA follows the principles of complexity science. More specifically, we show how networks of faculty members, when given autonomy over data usage and an opportunity to interact with peers, can develop innovative ideas that would never be possible under top-down models of education.

12.1.2 The Bay View Alliance

The institutions included in this study are members of the Bay View Alliance (2019) (BVA), a community of research institutions in the US and Canada with ongoing priorities to improve undergraduate education. Informed by the Networked Improvement Community (NIC) approach, the BVA supports institutional change efforts by fostering the formation of Research Action Clusters (RACs), where participants across institutions share results, and build upon individual and collective successes and failures. A NIC is a method for linking institutions to support new innovations, focus on common problems, and test hypotheses for improvement at multiple sites (Byrk, Gomez, & Grunow, 2011). NICs improve the possibility of sustained adoption of new practices and use a combination of academic and practitioner research to analyze the local context around the issue they are trying to solve. At the same time, interventions and innovations are tested within the culture of each institution, acknowledging that all change must be sensitive to local context. With origins in the healthcare industry, NICs have also been recognized as effective in US community colleges but have not yet been wholeheartedly embraced within higher education, nor are there many examples for evaluating their effectiveness in driving institutional transformations (Byrk et al., 2011).

12.1.3 The Learning Analytics Research Collaborative

Formed as a RAC within the BVA, the Learning Analytics Research Collaborative (LARC) was initiated to advance our understanding and knowledge of the use of big data, LA, and predictive modeling in post-secondary education.

The LARC has been designed and implemented with the understanding that a change in faculty perspectives about student behavior will lead to a change in the teaching and learning cultures in their respective departments. Within LARC, each institution has created its own version of a LA Fellows program similar to one that began at Indiana University Bloomington in 2014 (Rehrey, Groth, Shepard, Fiorini, & Hostetter, 2018; Rehrey, Shepard, Hostetter, Reynolds, & Groth, 2019). Drawing upon the success of Faculty Learning Communities (Cox, 2004), these LA programs allow faculty to participate in multidisciplinary communities, where they can receive feedback on their ideas, questions, and methods, while sharing the results of their projects with like-minded colleagues. The participating institutions are: Indiana University Bloomington (lead) (IUB), University of Kansas (KU), University of California Davis (UCD), University of British Columbia (UBC), and University of Saskatchewan (USask).

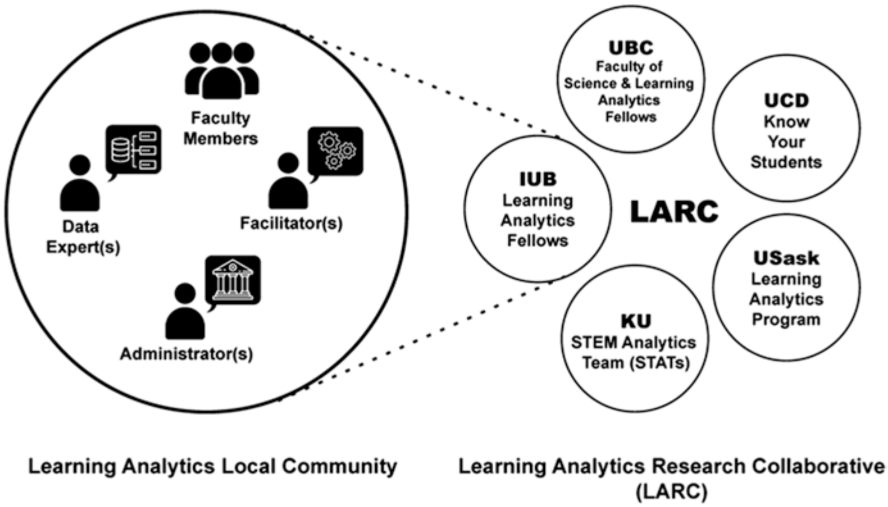

Fig. 12.1 Components of the learning analytics research collaborative

Specifically, LARC has been investigating how faculty use of institutional data can propel change and transform teaching and learning cultures in higher education in Canada and the US. LARC provides a self-organized network to support and catalyze data-powered inquiry conducted at each of our institutions. Our shared objectives are to:

- engage faculty in actionable scholarly inquiry concerning student success in courses and programs;
- propel course, departmental, and institutional change through the use of data;
- make provisioned data available to support faculty inquiry;
- provide necessary support for the work; and
- disseminate best practices and new frameworks through knowledge exchange, advancing the adaptation of LA within and across institutional communities for the improvement of student experiences, learning, persistence, and graduation.

Each participating campus has created a local LA community where faculty members are supported by one or more data experts, facilitators and administrators. Framed by NIC principles, each campus has shaped and named its local LA community appropriate to institutional context and specific program funding and outcomes (Fig. 12.1).

12.2 The Cycle of Progress for Sustainable Change

It has been widely noted that faculty engagement with innovative practices is crucial to its widespread acceptance and adoption in higher education, and often leads to changes at the department level. For example, in its five-year status report the

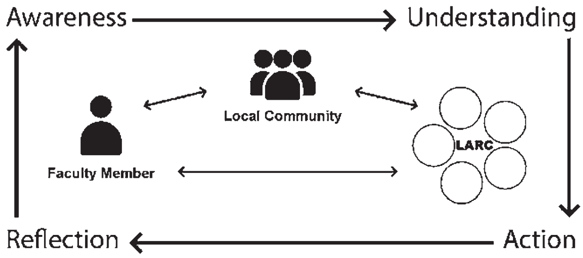

Fig. 12.2 The cycle of progress for sustainable change

Association of American Universities (2015) has proposed creating cultural change through a scaffold approach, suggesting that a change in pedagogy is at the core of institutional change in STEM departments at US institutions. Similarly, Arnold and Pistilli (2012) have discussed how the Course Signals project at Purdue University was specifically developed to engage faculty in the use of real-time feedback to their students powered by LA.

The LARC has been intentionally designed to create opportunities for faculty to become active participants and partners in student success through their purposeful engagement with LA. This engagement occurs through a Cycle of Progress for Sustainable Change (Molinaro, 2018). The cycle starts (Fig. 12.2) as faculty gain awareness of the multiple factors influencing student behaviors. From this new perspective they begin to ask deeper questions and learn from the literature and the work of their colleagues. Then they intervene with their actions, analyze the results, and reflect on the outcomes, with the possibility of repeating the cycle again with newfound awareness. All the while interacting with both their local community and LARC.

Aligned with the theory of CAS, the Cycle of Progress for Sustainable Change has been informed by other recognized change models within higher education. This includes a framework for sustained change as espoused by Corbo, Reinholz, Dancy, Deetz, and Finkelstein (2016). That framework suggests that university culture must be taken into consideration when planning and implementing effective change in higher education and identifies interactions across multiple levels of the institution as important change levers. We have also been informed by Kezar and Gehrke's (2015) study about Communities of Transformation, which analyzed the positive impact multi-institutional collaborations may have upon important initiatives, especially those within the STEM disciplines.

12.2.1 Awareness

Awareness begins once faculty are provided data in various forms, depending upon the context of their institution. This helps them shape questions that can be further investigated with obtainable types of student data found in tools and dashboards made available to them through the LA community. Often initial awareness inspires a need to understand why things are happening and what to do about it. Based on our experiences, the types of questions faculty ask at this stage can be classified into the overlapping and intersecting categories of student demographics, preparation, performance, and choice. Additionally, faculty become more aware of the impact curricular design and instructional resources, such as class size and teaching assistants, have upon their students.

12.2.2 Understanding

With the assistance of data experts, educational developers, and statisticians, faculty uncover answers to the questions provoked by their initial awareness. Usually at this stage of their projects, the data help them understand what is happening. Often these answers debunk cherished anecdotal stories about student behaviors in their courses and departments. Faculty develop a deeper understanding of the complexities influencing student success by seeking assistance from educational developers at teaching centers and other specialized units, reading the relevant existing literature on the particular issues the data has uncovered. Then they discuss the issues with their peers and may also seek input from faculty in both their local LA program or from faculty participating within the LARC.

12.2.3 Action

Faculty develop interventions to address what has been discovered about difficulties students encounter in their courses and programs. Such actions may include revising course materials, creating new classroom activities, or restructuring their programs. As faculty adopt evidence-based practices, these interventions provide new opportunities to create more interactive, learner-centered classrooms.

12.2.4 Reflection

Sometimes alone, sometimes with other faculty and professional staff, faculty analyze the impact of their interventions. Additional data are collected to determine the larger impact of the interventions and possible subsequent changes. They then share their research experience with a broader community (i.e., presentations at curricular, department, and campus-wide forums). Dissemination through presentations, publications, and scholarly works also arise. This reflection and sharing often leads to new and deeper questions that can start the cycle all over, which we have observed in several instances.

12.3 Methodolgy

We used a multiple case study approach (Merriam, 1998; Stake, 1995; Yin, 2014) to conduct research about the impact of our LA programs and LARC. Within case studies, the context matters, and because the specificity of the setting is of critical importance in case studies, this approach is frequently used in higher education research, as well as in education research in general (Merriam, 1998). The central principles underlying case study methodology are reflected in our research. We describe vignettes that focus on capturing the stories of each campus, examine questions of how or why, and draw on the research literature to examine distinctive or unique situations across campuses (Merriam, 1998; Stake, 1995; Yin, 2014). Identifying the unit of analysis and defining the case or cases is crucial for "bounding the case" (Jones et al., 2013; Yin, 2014) and articulating the parameters or boundaries of the case. For this research study, the five campuses were all connected by a shared interest and ongoing activity in exploring the use of LA to facilitate the success of students in post-secondary education.

A multiple case study allows for an analysis within each context, and then for an analysis across the cases in order to understand similarities and differences (Baxter & Jack, 2008). In this study, compelling stories were collected at five different sites. Researchers at each site shared their own stories and incorporated their campus research projects within those narratives. We then examined the five cases to compare these experiences of implementing LA in higher education institutions. Miles, Huberman, and Saldana (2014) contend that "multiple cases offer the researcher an even deeper understanding of the processes and outcomes of cases, the chance to test (not just develop) hypotheses, and a good picture of locally grounded causation (p. 30)." Miles et al. (2014) posited that multiple case sampling enhanced the confidence in the findings of the study by strengthening "the precision, validity, stability, and trustworthiness of the findings (p. 33)." Each campus's story, which Stake (1995) described as a vignette, contributed to developing an overall construction of the benefits and challenges of implementing LA approaches.

Yin (2014) noted that one strategy for analysis could be to follow the theoretical underpinnings of the study. Our study investigated the use of an international NIC that supported the implementation of LA to promote student success at individual campuses and to create a data-informed culture. As noted by Yin (2014), this theoretical proposition shaped our data collection for the study and thus yielded "analytic priorities (p. 136)" that informed the development of the themes. Each story was analyzed independently (Baxter & Jack, 2008) as we identified specific connections to the Cycle of Progress and to the CAS framework. Each vignette, with its unique context, contributed to developing our understanding of Cycles of Progress and verified the application of the CAS framework to the multiple cases.

12.4 Results

In this section we discuss the local LARC programs. By its very nature, the five programs within LARC are at various stages of maturation, a major strength of our collaborations. As we put data in the hands of faculty, we are mindful of where they fall within the Cycle of Progress for Sustainable Change.

Some of our faculty participants are currently in the awareness stage of the cycle, as they come to terms with new insights provided by LA. At this stage they gain new knowledge about who their students are, where they come from, and the choices that they make, or have made, on their pathway toward graduation. Other participants have already acquired a deeper understanding of issues raised by the data and are adopting evidence-based teaching practices to improve student success. And in a few cases, faculty have reached the final stage of the cycle, evaluating the impact of their interventions, reflecting upon the success or failure of those interventions, and asking new questions, as they move through the cycle again.

What follows are campus vignettes that describe how faculty are progressing through our Cycle of Progress and helping to achieve LARC program goals.

12.4.1 Vignettes

One of the most important aspects of the LARC is that while each institution brings their own research expertise to the table, it also gains valuable insights and support from other participating institutions. Such is the case for UBC, where their LA program is in early stages. At UBC, the Faculty of Science has been involved in numerous research and evaluation projects in teaching and learning for decades, largely facilitated by a Science-focused teaching and learning center and the Carl Wieman Science Education Initiative (Wieman, 2017; CWSEI, 2019). In the fall of 2015, initial attempts were made to identify interests in LA, when 30 faculty members representing all science departments met to address the topic.

A series of LA pilot projects were sponsored centrally at UBC beginning in 2017, but this initiative was only a beginning and could not accommodate all of the interest on campus. These discussions coincided with an invitation to join LARC, and a Science Learning Analytics committee was formed to seize this collaborative opportunity. Like other LARC members, UBC plans to model their LA program on IUB’s LA Fellows program. The Faculty of Science plans to become a more substantial, expert partner in the evolution of campus-wide efforts. This case demonstrates how NICs can be used to leverage action and advance change through collaborative research efforts. Our other institutions have already engaged faculty in research projects that require collaboration among multiple campus partners.

For example, when the USask decided to explore the effectiveness of the computer-generated student feedback system upon students enrolled in multiple sections of a first-year Biology course, a research team received funding from a newly formed Scholarship of Teaching and Learning program. The research team was facilitated by the Senior Strategist in LA and provided an opportunity for the department head of the Biology department to collaborate with a faculty member from the Education Administration Program along with a measurement and evaluation specialist from the College of Education. Together they analyzed the effectiveness of the Student Advice Recommender Agent, a personalized student feedback system designed to improve student success. Using a data matching technique to analyze data from their learning management system, they discovered that females receiving personalized feedback displayed greater feedback satisfaction, and males in the personalized group outperformed the expected grade level (Schmidt, Mousavi, Squires, & Wilson, 2018). The findings led to a second study to further explore these results. USask intends to grow participation in LA efforts across their campus in proportion to the availability of financial and faculty resources.

Similar to these two stories, we observed that other LARC campuses are at various stages of advancing the use of LA on their campuses. At UCD, the Know Your Students (KYS) program is at an advanced beta-prototype stage. Funded by the Howard Hughes Medical Institute in 2017, 30 faculty from 10 different departments are engaged in the program. While UCD strives to have all of the faculty progress through the entire cycle of change, at this time the vast majority of participants have gained awareness and some understanding, with very few going beyond to action and reflection.

At UCD, one example of a faculty member completing the entire Cycle of Progress is a professor who discovered that a substantial number of his students were multi-language learners (MLL) in his introductory biology course. Using the KYS dashboard, he uncovered a substantial grade gap between the MLL students compared to native English speakers (approximately ½ letter grade). To better understand the problem, he investigated the KYS curated teaching and learning resources in regard to how language can be a substantial barrier to MLL learners, who are not only learning the new language of biology but who are simultaneously working to improve their English comprehension.

To create an appropriate intervention, he worked with a team of undergraduates to methodically review the course online resources and study guides. Next, he removed idioms, clarified vocabulary, and minimized culturally specific references in text that the undergraduates identified as being problematic to student learning. Reflecting on his experience, he believes that the process of improving the online course materials also had the unintended consequence of improving his use of language during lectures. Furthermore, the student grade gap has been reduced with the introduction of the new refined readings. The same text is also used by other faculty members of this large-enrollment course, with the online readings propagated to several thousand students yearly. This is but one example of how a faculty member empowered with clear and usable analytical data can create ongoing positive change for students.

But working with individual faculty will not in itself create departmental change. Academic departments tend to be insular and inward-focused, especially in their curricula. They create their own complex system among faculty members who have similar interests and related goals. And though these academic departments are part of a broader university culture, their approach to teaching and learning focuses on disciplinary thinking. That is why KU created the STEM Analytics Teams (STATS) program, which was funded by the Association of American Universities and facilitated by the Center for Teaching Excellence. STATs work has led to curricular changes not only in physics, but in geography, geology, biology, civil engineering, and math. It has also helped expand interest in LA and raised faculty awareness about the importance of looking at curricula more broadly. And it has shown how a small, focused analytics program can help faculty members reach beyond disciplinary boundaries to better understand student learning.

Within the KU program a project in the physics department stands out. Two physics faculty members have been using LA to analyze a course transformation effort. In Spring 2015, one of them introduced what he called an "energy first" approach in Physics 211, a revised introductory course for engineering majors focusing on the principle of energy conservation and the use of more applied calculus. The comparable introductory class, Physics 210, maintained its traditional "force first" curriculum, which explores classical mechanics through the laws of motion and uses little applied calculus. Both classes continued their extensive use of trigonometry and vectors, but Physics 211 adopted considerable material on differentiation and integration, which Physics 210 did not have.

Controlling for previous student math scores, the they used university data to examine how students in the two introductory sections fared in a later physics course and in three engineering courses. In every grouping of math scores, students who took the revised course outperformed those in the traditional format. They also examined how students in the two sections of introductory physics performed in the next course in the department sequence, General Physics II. In this case, students who had completed the transformed course earned grades nearly a point higher in Physics II than those in the traditional course.

Finally, the faculty used university data to track student performance in three engineering courses that list introductory physics as a requirement. Again, students who took the revised course did better in engineering courses, this time by about half a grade point. Reflecting on this project, the faculty have made a compelling case that a revised approach to introductory physics improved student success in later courses. Perhaps as important, they demonstrated the value of university data in exploring questions in teaching and curricula while moving beyond departmental silos.

12.4.2 Cultural Change Indicators

In order to create sustained change at the departmental level, faculty attitudes, beliefs, and behaviors must undergo a paradigm shift as they engage in their local LA programs. LARC will have proven to be successful when participating departments:

- establish a data-informed culture for continuous improvement;
- assume a wider share of responsibility for student success;
- set expectations for faculty to be invested in student success;
- encourage evidenced-based teaching practices that have been informed by analytical research; and
- report on continuously improved student experiences, retention and graduation.

For these outcomes to be achieved, enough faculty from a given department must be engaged in LA for them to influence cultural change. A window into an emerging data-informed culture can be found in the Economics department at IUB, where faculty have sustained an interest in and continue to participate in the LA Fellows program, while recruiting their colleagues to join the program as well. The LA research being conducted by the Economics department also demonstrates a spectrum of inquiry across course, department, and campus levels.

The department involvement began when a teacher became interested in the relationship between student success in his introductory Economics course and what students ultimately decided would be their college major. Subsequently, this led him to become concerned about the effectiveness of course sequencing within his department, which he investigated by joining the LA program for a second year. His research came to the attention of the department chair, who wanted to investigate the decreases in economics majors at IUB. They decided to collaborate on a research project to better understand other issues facing their department. Meanwhile additional Economics faculty joined the LA community, investigating questions of their own. What began with one teacher using LA to better understand student behavior has grown into 10 projects being conducted by 8 Economics faculty.

As one faculty member commented about the value of the program, "I think that there is a steady cultural change going on thanks to the availability of this data and so it is definitely having an effect." Another reflected upon their participation this way, "I think that it is beginning to change my mindset a little bit even in terms of just walking into a classroom, and then the various activities or assessments we use and I have all these data points on how can I bring that all together. So, it has, I think, changed the way I approach classroom instruction (Rehrey et al., 2018)."

12.4.3 Program Support

The availability of data varies significantly across the participating campuses. At IUB, faculty are provisioned unit level student data over a 15-year window, while at KU, faculty never touch student data, but instead are working with institutional research professionals who provide targeted information. Similarly, in two other instances, faculty are provided pre-formatted dashboards that reflect known campus issues, for example, UCD has a focus on equity and inclusion. These approaches reflect differences in data provisioning policies, interpretations of governing laws and the availability of campus resources to manage data access. Despite the variation in data availability, all programs are still achieving their goals, suggesting that there are solutions to the well-documented barriers to implementing LA programs.

Administrative support and staffing at the institutions vary greatly as well. At IUB the Provost supports the work as outlined in the Strategic Plan compared to USask, where a grassroots effort, capitalized on an opportunity to engage faculty in teaching and learning activities. Most campus programs have connections to teaching and learning centers or activities on their campus, reflecting the desire for faculty participation in improving student success. Also common across campuses is the need for institutional research staff or data analysts, sometimes as members of the project team or as staff members dedicated to the fellows' work. Although there are numerous contextual differences in data access, administrative support, and staffing, all programs have persevered through various challenges, still reaping positive value from their local adaptations.

Each campus provides evidence of an emerging data-informed culture where inquiry turns into evidence which subsequently turns into institutional improvements as part of everyday life. While campuses are in various levels of development, faculty uniformly display interest in participating in this work. As indicated in the vignette, UBC is just starting their LA program but has demonstrated that there is sufficient demand for faculty willing to participate in the program. Other longer-term campuses continue to fill available project slots with repeat faculty as well as new faculty. Faculty and administrators value the use of data and have gained knowledge about the resources available as well as the factors that can improve student success.

12.5 Discussion

In this section we discuss the differences and similarities of our LA programs and the new insights that the CAS framework has provided for our efforts. We also discuss the implications of the LARC and how we plan to address the limitations of our current study in the future.

12.5.1 Commonalities and Contrasts

Common strengths and challenges, as well as contrasts that have emerged between LARC campuses, have proven to be a powerful aspect of the NIC functionality as our collaboration has developed and matured. In general, LARC campuses have experienced significant and fast growth in their LA programs and excitement from involved faculty. This indicates a strong latent demand for access to data that have long remained inaccessible. Additionally, as our programs have begun to mature, questions posed by faculty have continued to increase in sophistication. Continued faculty engagement with data analyses has prompted deeper and more meaningful engagement with campus data governance structures, setting the stage for broader accessibility with time.

Campus LA programs have also prompted the development of new or improved tools and dashboards, not only providing faculty with broader data access, but also identifying discrepancies between available datasets and the types of data faculty would like to have. Some common challenges across LARC campuses have included a steep learning curve for faculty when they first engage with LA data, which is typically a different kind of dataset than they are accustomed to. Additionally, most campuses have experienced strains on staff resources for accessing and processing data as programs have experienced increased demands.

Some interesting contrasts between campuses have also emerged. A key strength of the IUB Fellows Program has been administrative pathways put in place to support reliable data access for program participants, along with a strong institutional commitment to connect faculty with LA data. Data access has been a greater challenge at most other LARC campuses, where faculty and LA program leaders continue to advocate for greater access to data. On many campuses this challenge has been made more significant by immature data governance policies which are still being codified and tested.

A key strength of the KU program has been the extent to which teams of departmental faculty foster conversations across departmental boundaries, and how peer-to-peer collaborations have empowered departmentally situated changes in teaching practices, curricula, and student retention measures. This occurred in part because of how the program has been aligned with other ongoing curricular and teaching practice change initiatives. In contrast, while faculty at UCD have gained greater access to basic information about the students in their classrooms, and the grade inequities experienced by various student groups, this awareness has been difficult to translate to actionable changes due to time and resource constraints. This has led to some frustration from faculty who recognize a problem but feel somewhat helpless in instantiating solutions.

12.5.2 Theoretical Framework

As we consider the future of the LARC, it has been useful to view our work through the lens of Complex Adaptive Systems. In doing so, we have discovered that the 5 principles espoused by Siemens et al. (2018) have helped us develop a richer understanding of the change processes we are using both within our local programs, and our broader networked community. Those five principles are networks, emergence, self-organization, feedback sensitivity, and agility.

- Networks: We have previously discussed the value of working in a network, which continues to be a cornerstone of our efforts. The contrasts that have occurred between the LA programs have led to rich discussions about campus practices and have influenced changes in how LA programs are being shaped and implemented at each school. Through the process of openly sharing with one another our successes and challenges, we have been able to improve all of the work underway and influence campus partners.

- Emergence: Through a top-down, bottom-up model, distinct characteristics of our work have emerged that influence cultural change at our institutions. Individual faculty are acting as agents of change, helping to advance department and campus level transformations. The increasing demand to use data analysis to improve student success on the local, national, and international levels has helped us advocate for, and obtain greater levels of data access. As new tools, software vendors, and advanced statistical models continue to evolve at a rapid pace, the need for improved/codified data governance policies, staffing resources for data access and analysis, and improved tools for self-service data has increased. Our programs have been intentionally designed to leverage the heightened accountability being brought upon institutions to improve student success through multiple means.
- Self-organization & social coordination: Our collaborative community fosters knowledge creation and innovation through a culture of shared governance and self-organization. Each LARC institution has its own leadership team and has shaped its program to support faculty as change agents. We have self-organized in a manner that allows for all of our activities to be distributed across the campuses in relatively autonomous groups. Furthermore, we all embrace a model that acknowledges the importance of leadership that willing supports bottom-up (grassroots) efforts.
- Feedback sensitivity: The success of our network relies upon a listening culture that encourages continuous improvement. For the most part, feedback comes from the faculty and the results of their research projects. It also includes creating different methods for determining how best to measure the establishment of a data-guided culture that we are striving for. We are currently developing assessment tools to be shared among the institutions that will allow us to collect critical indicators of cultural change in a systematic manner.
- Agility: The LARC model is intentionally designed to be flexible. As we tackle problems that emerge from the group, we continue to embrace uncertainty while seeking new and unknown possibilities. Local variation is a strength of this networked approach, offering opportunities for understanding adaptations. As we attempt to reshape the teaching and learning culture in higher education, we are also aware of the need to address any unintended consequences of our programs, should they occur.

12.5.3 Implications and Limitations

The CAS theory has provided us with a useful roadmap for becoming effective change agents at our institutions. By looking through the CAS lens, we are able to continuously identify the appropriate intersections of people, processes and tools that must be leveraged in order to create a data-informed culture. Additionally, we have already observed three other US institutions that have adopted similar LA programs, and know of several more that plan to do so in the near future. We anticipate that as the success of these programs ripples throughout multiple academic communities and networks, the viability of both the theoretical underpinnings and practical applications of LARC will become normal practices throughout much of higher education.

Within our networked community, the LARC has influenced changes taking place on our individual campuses. However, at our current stage of network development and collaboration, the results to-date are based upon communicated exchanges of experiences, observations, and faculty reflections. While these have been carefully observed and reported, and thus exceed the bar for 'anecdotal evidence,' a clear next step is to perform a study aimed at systematically assessing measurable outcomes, which we plan to do as our work progresses.

12.5.4 Future Directions

Future assessment of the broader impact of the LARC will be accomplished through aggregation of the actions taken at each institution. An interesting question to consider, and one that we plan to investigate in a future study, is whether cross-institution teams of faculty teaching similar courses achieve better outcomes than individual LARC faculty at an individual campus, compared to faculty not involved in LARC.

To date, data sharing has been limited to 'information sharing' among administrators describing their campus processes and faculty presenting their research findings. As the LARC matures, we envision parallel analyses will emerge to determine if a research result is local to one setting or perhaps if the finding is relevant across multiple institutions. These parallel analyses require an institution to replicate a study but not share data across institutional boundaries. Sharing raw data across institutions (even if data are de-identified) has been met with great resistance. As the conversations around ethics and data governance advance, we will be prepared to contribute to the dialogue with real experiences. We can describe situations where there is value in fuller data sharing, allowing for targeted opportunities to test our data sharing models.

As we continue our work, we will be seeking more faculty and broadening the range of disciplines engaged in the work. A goal for IUB, for example, is to have at least one faculty member engaged in LA in every department. In some departments there are already more than one faculty participating, and it is important that faculty across a department recognize their colleagues engaged in this work as providing valuable insights. At KU, the goal is to fund more faculty teams and to work more closely with the Institutional Research Office in the creation and access of data dashboards that any and all faculty can use. Furthermore, the LARC's efforts will only be fully realized when faculty make applicable use of the insights LA provides, as they create meaningful innovative interventions and measure their impact. At this juncture of our programs and as indicated in the vignettes, LA informed interventions remain in the nascent stage for some, but certainly not all of our Fellows.

12.6 Conclusion

In this chapter we have discussed how the theory of CAS has shaped the work of a recently formed NIC called the Learning Analytics Research Collaborative. Each school in our collaborative has dedicated resources to the formation of a LA program intentionally designed to engage faculty in the use of LA in the pursuit of improved student success.

While the work of the LARC may be more advanced at one institution compared to others, the key power of the work is driven through reinforcement along multiple dimensions. For individual faculty, the ability to directly measure the impact of pedagogical change, targeted interventions, or course (re)design, provides evidence for continued engagement with LA. At the departmental level, insights gained from LA provides substantial support for faculty to continue their discovery efforts. Cross-campus and cross-institution interactions by groups of faculty provides for broad parallel experimentation, adoption of best practices, and more rapid advances in gaining insight from LA.

Institutions need to track the full set of outcomes in order to continue funding activities or increase funding towards efforts that have more impact. Institutional leadership is always in a position of balancing resource needs across many potential initiatives, and ultimately will choose investments leading to improved outcomes for students, especially for initiatives with positive rates on investment. Although not the sole reason to undertake the improvement of student success, positive rates can help make the argument for investing in it. One estimate calculated that increasing the retention rate by just 1% over 3 years yields approximately five million dollars of savings at large public research universities in the US (Shepard, 2016).

The search for insights through the use of LA, along with ongoing development of new tools, techniques and methods for analyzing student data, will necessarily continue, such that actions result in increased achievement of department and institutional goals. We are compelled to use LA to support all students, starting with the very first day they arrive on our campuses and continuing through the duration of their college experiences. The premise of our argument and the basis of our work is quite straightforward. The adoption of LA as a new and valuable perspective about student behavior and performance will only succeed if faculty of all disciplines and ranks are involved in its ongoing development and implementation. We must ensure that this is the case.

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Chapter 13
It's All About the Intervention: Reflections on Building Staff Capacity for Using Learning Analytics to Support Student Success

Ed Foster, Rebecca Siddle, Pete Crowson, and Pieterjan Bonne

13.1 Introduction

Universities have always had data available, such as failed assignments or non-attendance in class, to provide early warnings that students may be at risk of failing their studies. Learning analytics doesn't fundamentally transform the landscape. It adds sophistication and creates opportunities for earlier interventions than may have been previously possible. Nonetheless, we still need interventions to take place. We argue that learning analytics implementation is not the same as effective adoption. The technological implementation of learning analytics can be completed, but significant further work is required to build staff and student capacity to use the resource.

In this chapter we reflect upon ways to build staff capacity to understand, exploit and utilise data derived from learning analytics. We frame our work in the field of 'student success' (Sclater, 2017): supporting, motivating and coaching students at risk of early departure. We explore this work through the lens of one key group of frontline university staff who mentor and guide students: typically described as personal tutors (UK). We briefly discuss learning analytics and the role played by these staff members. We then consider the potential benefits and challenges associated with providing tutors with learning analytics and develop recommendations for building staff capacity to use learning analytics effectively. Our recommendations are drawn both from the literature and from our experience of working within the field: firstly, leading the implementation and delivery of a whole institution learning analytics resource at Nottingham Trent University (NTU), from 2014 to 2015

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onwards and secondly from three pan-European Erasmus+ research projects investigating the challenges of effectively implementing learning analytics to improve student success.

In this chapter, we define staff capacity to support student success in a broad manner. Capacity describes the ability for a tutor to act effectively on data provided by a learning analytics system in the context of their working environment. This capacity relies upon institutional factors such as the capacity of a learning analytics system to consistently provide accurate, meaningful data, organisational leadership and policy and the effective management needed to provide resources and time for staff to act and develop themselves. It includes the capacity for a tutor or adviser to understand systems, processes and support services. Finally, it includes the ability of the individual to effectively support a student: using a variety of skills including data literacy, communication skills, coaching and interpersonal skills.

13.2 Learning Analytics

Before considering the issue of developing staff capacity to effectively adopt learning analytics systems, we will reflect on the state of the field. At the most straightforward level, learning analytics involves collecting "… traces that learners leave behind and using those traces to improve learning" (Duval, 2012). For this chapter, we take as a starting point that for a technology to be properly considered learning analytics, there needs to be both meaningful interpretation of these traces and an integrated action step. This step could vary in complexity from simply presenting information back to the student in a codified manner to a fully developed system of escalating staff interventions. Implicit in this description is the capacity to intervene repeatedly if necessary. Therefore, we argue that a more fully formed version of learning analytics would include functions such as the capacity to record interventions, make notes and refer students to specialist support. We therefore describe learning analytics not as a technology, but as a technology-enhanced process.

The field of learning analytics is undergoing a period of maturation. Early work tested whether or not it is possible to utilise the principles of big data in an educational context and often saw developments at the scale of an individual programme or with a particular support team (Arnold & Pistilli, 2012; Campbell, DeBlois, & Oblinger, 2007). There is a growing body of evidence that suggests data can be meaningfully extracted from institutional systems and that early warning systems can be developed (Sclater & Mullan, 2017). However, whilst studies show that learning analytics-based interventions *can* work (Karkhanis & Dumbre, 2015), this is far from guaranteed (Oreopoulos & Petronijevic, 2019). Researchers are therefore becoming far more interested in the interplay between technological innovation and the managerial, cultural and educational processes required to effectively implement, evaluate and develop learning analytics (Rienties et al., 2016; West, Heath, & Huijser, 2016). For example, the author's earlier work identified six key elements that needed to be accommodated in order to successfully implement learning analytics: 'ethics and external environment', 'mission and purpose', 'project management', 'data', 'technology' and 'institutional change' (ABLE project, 2018a, 2018b). We are interested in the domain of institutional change: the process of helping staff understand and use learning analytics as they support students.

The insights from learning analytics can be used by different agents of change, for example, students or staff members. This chapter focuses on the latter. It may be useful to consider that learning analytics data can be used in broadly two ways, akin to Argyris and Schon's single and double loop cycles (1974). The first type of interventions (single loop) takes place within the current academic year, often immediately, and is designed to support individuals or groups of students. Importantly, these interventions don't usually change the boundaries or fundamental structures but provide remediation for students at risk. For interventions such as dashboards (Bennett & Folley, 2019; van Leeuwen, Rummel, & van Gog, 2019), visualisations (Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2015) or automated alerts (Foster & Siddle, 2019), the data needed to act tends to be available immediately or after overnight processing. The data for interventions such as adviser sessions (Charleer, Moere, Klerkx, Verbert, & De Laet, 2017) may be available for use immediately; however, it is typically only used at key points within the academic year (e.g. after end-of-module assessments have been marked). Nonetheless, it will be used within the year with specific students. The second type of interventions (double loop) takes place over a longer timeframe and is used to reconsider the learning environment, assessment design, etc. by looking holistically at the experience of whole cohorts, rather than individual students, and by changing some of these elements, preventing students from disengaging or failing (Rienties, Olney, Nichols, & Herodotou, 2019). These interventions are therefore preventative rather than remedial in nature. This chapter is primarily focused on the first type (single loop), specifically the way that learning analytics is used by individual tutors with individual students.

13.3 How Tutors Support Students

Any plan for implementing learning analytics needs to consider not only the capacity of the institution's IT infrastructure but also the capacity of its student support infrastructure. In this section we will discuss the role of those staff who support students at NTU: personal tutors.

Evidence of student difficulties may arise via a range of sources, for example, concerns from other students in university accommodation or encounters with the institutional disciplinary system. Most student problems are likely to be encountered within the learning and teaching context, through early signs such as poor attendance or the non-submission of coursework. However, as students in higher education tend to be taught by teams, each academic may only see one small part of the problem behaviour. Therefore, most institutions provide a range of para-academic roles to support students. The nature and origin of these roles changes due to different national and institutional contexts. They may be known as personal tutors in the UK (Lochtie, McIntosh, Stork, &

Walker, 2018; Thomas, 2006), study advisers in continental Europe (Charleer et al., 2017) or academic advisers in the USA (King & Kerr, 2005). There are many similarities between these roles: particularly the very student-centred way that they work. In the UK, tutors are typically located within students' academic programmes and therefore are often the first staff to talk to students, whereas elsewhere study advisers and academic advisers are frequently located away from the programme and therefore are more likely to be the second staff members to provide support. The recommendations for all roles are likely to be similar, but for ease of reading, please note that this chapter is written using the lens of personal tutors located within academic programmes. Tutors are expected to perform a range of roles that include coaching and encouraging students, helping them to interpret the expected norms of both the institution and the subject, enforcing institutional rules, engendering a sense of belonging, providing first-line support and referring students to professional services.

This chapter addresses the role of the tutor supporting student success: supporting students at risk of failing or underachieving. Whilst there are certain known factors that help this process including high quality staff/student relationships, effective student support services, appropriate academic challenges, etc. (Thomas, 2012; Tinto, 1993), there is no 'silver bullet', and therefore staff capabilities to diagnose problems, communicate empathetically, set goals and motivate learners are vital. To do this effectively a tutor may need to challenge their own assumptions, heuristics and biases, potentially help the student do the same and then help the student to change their own approaches to learning. Clutterbuck (1998) describes strategies to help practitioners work including a range of roles to adopt, for example, coaching, and a quadrant of behaviours to act within, between challenging/nurturing and directive/non-directive dimensions. Importantly, he argues that tutors need to tailor their approach in a continuous and timely manner to suit the needs of the learner and form a 'learning alliance' with them. A tutor's capacity to perform these roles will depend on their knowledge, experience and ability to be a reflective practitioner. Their willingness to support students is likely to depend on individual focus and priorities (Hemer, 2014).

This guiding role is, however, only one aspect of the job description for a typical academic. Huyton (2013) reported that tutors felt it was important to be 'good enough' (p. 157) at tutoring, whereas they felt expected to excel in other areas of work, particularly research. The problem of competing priorities can be exacerbated by limited training and development, lack of clarity about roles and the emotional capacity of staff to deal with the range of problems presented to them by students (McFarlane, 2016). Concerns about staff capacity have been heightened further by recent growing concerns about student mental health and increased expectations about the role of the tutor to provide support (Hughes, Panjawni, Tulcidas, & Byrom, 2018).

The tutor's role is further complicated by the nature of the students' relationship with the institution. Unlike in earlier stages of their education, students are adults, and depending on the national context, in some form of quasi-customer/provider relationship. Furthermore, there is a widespread expectation that higher education is a step along the journey to independence (Bryson, 2014; Kift, Nelson, & Clark, 2010; Mayhew, Rockenbach, Bowman, Seifert, & Wolniak, 2016), with the concomitant right to make mistakes along the way. If a student chooses not to accept support offered, tutors can find that they have relatively limited options available.

13.4 Enhancing the Tutoring/Advising Process Using Learning Analytics

The benefits and challenges of giving learning analytics to a tutor depend on the nature of learning analytics that has been implemented. As is the case for the rest of the chapter, we assume that tutors will be interacting with the current cohort of students on the basis on the outputs of learning analytics. We will start by discussing the topic generally, before reflecting on findings relating to our own specific system.

One important benefit of giving tutors access to learning analytics is that students may not possess the skills to interpret data from such systems for themselves. Millecamp, Gutiérrez, Charleer, Verbert, and De Laet (2018) report that whilst students appear to value data derived from learning analytics systems, they do not necessarily possess the strategies needed to exploit it. Jayaprakash, Moody, Lauría, Regan, and Baron (2014) found that more students withdrew from elements of their programme when risk-of-failure data was presented to them. Rather than encourage help-seeking behaviours, data appears to have driven early strategic withdrawals with some students. Furthermore, there appears to be wide variation around how students use learning analytics provided for them (Siddle & Foster, 2018), with some students using the tool extensively and others not at all. It appears that expecting all students to use learning analytics to regulate their own learning is unrealistic. We argue that there is an important role for the tutor to guide them to do so.

A second benefit is that learning analytics can be directly beneficial to tutors, providing data to help them in their work supporting students. Researchers have found that data supplied by learning analytics can help generate conversation between advisers and students (De Freitas, Morgan, & Gibson, 2015) and can trigger actionable insights (Millecamp et al., 2018). Researchers at NTU reported that 33% of tutors surveyed felt that using their learning analytics tool during a tutorial conversation had positively changed student engagement (ABLE, 2018b).

Furthermore, there are numerous examples of learning analytics systems generating early warning signals (Sclater & Mullan, 2017). If trusted, such systems can potentially enable far earlier interventions than waiting for a concrete event such as the non-submission of coursework or a failed assignment (Foster & Siddle, 2019).

Using learning analytics introduces new challenges for staff, particularly with regard to workload. For example, if learning analytics produces earlier and more frequent alerts, this may change the expectation upon tutors to respond in a more frequent, ad hoc, manner. Furthermore, once institutions begin to use learning analytics, tutors will need to acquire and maintain new skills in computing and data literacy. For example, Herodotou et al. (2017) noted that teachers' use of learning analytics was shaped by a range of factors including their confidence with the technology, their prior experiences supporting students and understanding about the nature of how they were expected to use the technology in their working practices. Ridsdale et al. (2015) define data literacy as 'the ability to collect, manage, evaluate, and apply data, in a critical manner' (p. 2). It could be argued that learning analytics dashboards reduce some of the data literacy requirements of their users by collecting, interpreting and presenting the data for their users. However, a knowledge of data collection and management is important for the later steps, particularly if tutors are using the tools in conversations with students where they may be challenged about the reliability of the data.

Learning analytics is a potentially difficult technology to operate reliably given its reliance on data from multiple sources and complex data processing (2018b; ABLE, 2018a). It may be appropriate to consider a learning analytics resource and its attendant data as a hygiene factor (Herzberg, Mausner, Snyderman, & B., 1959): most of the time staff don't notice that it's there, but when it goes wrong, it has a highly negative impact, causing mistrust and reluctance to engage. Even when working effectively, there are factors about the nature of learning analytics that may look innocuous to technologists but potentially profoundly influence the confidence of staff to use it face to face with students. The choice of data sources may be ethically challenging (Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016; Sclater, 2017). For example, using innate characteristics such as socio-economic background creates a different dynamic to using engagement data such as library use (Foster & Siddle, 2019). The data used in learning analytics tends to show proxies for learning: evidence that the student interacted with resources likely to be beneficial to learning, not necessarily evidence that they were actually learning. Furthermore, the data provided is likely to be partial, for example, a learner may take a book out of the library but may never read it, or they may already own the textbook and so the action of reading it will never register on a system. We would argue that whether, descriptive, predictive or prescriptive (van Barneveld, Arnold, & Campbell, 2012), learning analytics used for student success is essentially forward-facing and designed to be acted upon.

None of these factors invalidate the use of learning analytics, but they do serve to remind us that tutors require development in order to be confident using it. If not, there is a risk that users will fall back on resources they perceive as more reliable/ less experimental. Institutions embedding learning analytics therefore face challenges of both maintaining these new systems and developing the capabilities of their staff.

13.4.1 Methodology

The following case study and recommendations are based on the lived experience of working with staff to implement learning analytics, networking with colleagues across the sector and research with NTU staff and students. The team used findings from an annual online first year survey (the Student Transition Survey). In 2019/2020, 1401 first year students completed the survey (February/March 2019) answering questions about their experiences of studying, belonging, whether or not they have considered leaving and key aspects of their experiences of using learning analytics at NTU. The researchers conducted semi-structured interviews with 12 personal tutors (May 2019) to understand their experience of acting on alerts raised by learning analytics.

13.4.2 Case Study: Using Learning Analytics to Support Students at Nottingham Trent University

Much of the authors' previous work in analytics has been to understand the complete process of developing and implementing learning analytics (ABLE, 2018a; Siddle & Foster, 2018). However, we agree with others in the field that more focus is needed on the most effective ways of using the resources with students at risk of non-progression "… projects with no action will have little impact upon student success" (West et al., 2016, *p.43*). In the sections below we first describe the basic implementation of learning analytics at NTU before describing building staff capabilities for supporting students using our learning analytics platform.

13.4.2.1 Implementation of Learning Analytics

NTU first implemented learning analytics across the whole institution in 2014–2015 (Foster & Edwards, 2018) using a resource developed with an external vendor, known internally as the NTU Student Dashboard, or just 'Dashboard'. The tool's strategic purpose is student success, primarily measured by progression to the next year and academic attainment. The Dashboard is available to students, their personal tutors and other staff who support students. It takes data from seven institutional data systems including attendance monitoring and the virtual learning environment (learning management system) to capture an understanding of each student's academic engagement (Kuh, Kinzie, Schuh, & Whitt, 2010) with their course. The system uses an algorithm to generate an engagement rating based on these data sources (from 'high' to 'very low'), and where engagement ceases for a fortnight, a 'no-engagement' alert is sent to the student's personal tutor asking them to investigate. As might be expected, there is a strong association between engagement displayed in the Dashboard and both progression and academic attainment (Foster & Siddle, 2019).

Further to the learning analytics specific elements, the Dashboard has a number of additional features:

- Important contextual information about the student (e.g. course details, entry qualifications, attendance and coursework submissions).
- Staff members can write notes in the system. The functionality allows details about the communication (type, length) to be captured alongside free text information about the communication and action points. Reminders can be set to check actions are complete. Notes can be seen by the student and any staff member with access to their Dashboard.
- Staff members can make referrals to a variety of university support services directly through the Dashboard.
- Reports containing management information can be extracted directly from the system.

This design has helped us to overcome some of the challenges relating to personal tutoring at NTU. Personal tutors were surveyed to understand what they perceived to be the key barriers to effectively supporting students (May 2017, $n = 130$): the top barriers were 'time to conduct tutorials', 'space for meetings', 'easy referral processes' and 'information about the student' (ABLE, 2018b). Whilst learning analytics may be unable to help with space allocation, there is certainly the potential for data to help with the other three. Often tutorials are only short (15–20 minutes), and a significant proportion of time can therefore be taken up understanding the fundamentals of the student's situation. Staff described that one of the main ways they use learning analytics is preparing for tutorials by looking at the student's most recent engagement and reading any notes written on the system by themselves or other professionals. This avoids the need to re-cover this information in the meeting, leaving more time for support conversations. Tutors can directly refer students to support teams such as Student Support Services or the Library Learning and Teaching Team through the system. These two teams use the system extensively to prepare for their meetings with students. The Dashboard allows support teams to comment on the referral note or input new notes to confirm if they have successfully made contact with the student, closing the loop on the referral process. Finally, we would argue that presenting a range of information about the student alongside a record of the support provided to them enables tutors to personalise student support more effectively. This may be particularly important in situations where a tutor is responsible for multiple tutees.

13.4.2.2 Building Staff Capacity to Support Students Using Learning Analytics

The focus of our current Erasmus+ project work, Onwards from Learning Analytics (OfLA), is to build tutors capacity to use learning analytics to support students. This section discussed the capacity of staff members to act appropriately at the point where learning analytics have identified that a student is at risk. The research is framed by a three-stage model: 'trigger/prompt', 'communication' and 'intervention'. In the section below, we provide further details about the stages of this model and use it to outline a number of staff capacity requirements using examples from NTU.

13.5 Trigger/Prompt

The trigger/prompt stage is the means by which a student is identified as potentially needing support. This is a stage containing profound operational and ethical considerations. Triggers need to be actionable, balance accuracy against timeliness, generate prompts for as many students as possible and, in doing so, generate as few false alerts as possible. The rationale for the prompt needs to be comprehensible to both the staff member and student and needs to be ethical and perceived as fair by all parties.

The learning analytics resource at NTU provides tutors with two prompts that a student may be at risk: no-engagement alerts and staff-observed periods of sustained low engagement. In both cases, in order to act appropriately based on the engagement data, staff need the capacity to apply local contextual knowledge about the factors that could impact a student's activity levels (e.g. peaks associated with deadlines or troughs associated with short term placements) or personal circumstances communicated via other mechanisms (e.g. illness, family bereavement).

Interviews with NTU staff (May 2019) revealed that a small minority were inherently distrustful of the no-engagement alert data. In these cases, tutors were more likely to feel that their own observable behaviour in the classroom and their personal interactions with a student were a truer reflection of how the student was engaging with their studies than an engagement rating. This distrust was reinforced whenever there were any issues with the data or a perceived mismatch between what the data suggested and what the tutors themselves observed. One of the challenges for staff is understanding the difference between population-level and individual-level data (Illari & Russo, 2014). In our system, around 80% of students with 'partial' average engagement (the middle category) progress cleanly from the first to the second year. Nonetheless, this means that one in five students in this group doesn't progress. Even amongst students with the highest average engagement, 1 in 20 students doesn't progress. To some tutors these examples make it appear that the system is inaccurate, rather than appreciating that they are features of probability-based predictions. Building staff capacity to use their personal experiences of students alongside, rather than in opposition to, learning analytics data could improve the effectiveness of identifying students in need of further support.

Whilst tutors probably do not need to understand the minutiae of triggers generated by learning analytics, institutions do need to ensure that staff have sufficient understanding to be confident to act on them. This needs to include communication about the algorithms, ethics and choice of data but also staff development in data literacy and time to think through the implications for their own practice.

13.6 Communication

Once a trigger has been generated, the next challenge is finding ways to effectively communicate with students. Operational and ethical challenges include choosing the right media, the right sender, selecting the right time period, getting the tone right and choosing when to repeat the cycle or escalate it.

We investigated how NTU tutors act upon the no-engagement alerts. Overall, tutors felt positively about receiving them. "It's a good nudge for me as a tutor, as a supervisor, to contact them and drop them an email and basically just check if they're okay" [NTU Personal Tutor, May 2019]. Staff reported that the Dashboard data provided them with a degree of objectivity that they found useful as they were able to act as a more neutral interlocutor, rather than the initiator. "We just say, almost apologetically to students, this is flagged up" [NTU Personal Tutor, May 2019]. Tutors also reported that because the alert was raised by the Dashboard, it added significance to their communication with students "… because I had said I've received a notification, it kind of prompted [the student] to reply straightaway whereas sometimes there would be a delay. It's an extra level than me just saying, 'I haven't heard from you. Is everything all right?'" [NTU Personal Tutor, May 2019].

At NTU, we have carefully chosen the language used in alert emails and in staff guidance around communicating to potentially at-risk students based on learning analytics data. This is because of the forward-facing nature of the prompts. No-engagement alerts and staff-observed periods of low engagement are indications that there may be a problem that might adversely affect student outcomes, but this is based on probability and likely risk. These probability-based predictions are less concrete than triggers such as the non-submission of coursework or failing an assignment, and therefore communication needs to be more nuanced, and staff need to tailor their communication accordingly.

It is also important to consider the practical barriers to successful communication. A tutor must have time for both initial and follow-up communications. Moreover, they need the capacity to successfully initiate a conversation. Every tutor in the May 2019 NTU staff interviews highlighted a lack of response as the main reason for not being able to support students at risk. The reasons for a high level of unresponsiveness to tutor contact are unclear; some tutors believe that the method of communication is limiting; others believe the type of message is a factor in eliciting responses. Interestingly, in the 2019 Student Transition Survey (February–March 2019, $n = 1401$), we asked students how they would prefer to be contacted if a no-engagement alert was generated about them. Overwhelming, students reported that they would want an email to be sent to their University account in preference to text messages, emails to personal accounts, letters or phone calls. However, given the often poor response rate to institutional emails and the low likelihood of a disengaged student reading an email, this may not be practical. Institutions need to balance the preferences of adult-learners against the duty of care of the University. Often, it is the tutor who needs the capacity to ascertain when communication should be repeated or escalated to either alternative media or more senior colleagues.

13.7 Intervention

Finally, assuming a student has been successfully contacted, the last stage of the process is the intervention: the action or actions that seek to bring about change. Tutor experiences at NTU suggest that the impact of single interventions may be limited. They report that suitable support often requires not a single point of contact, but a sustained and extensive programme of interventions in order to have the impact required for behaviour change. Regardless of staff capabilities, this asks serious questions around time and resource for staff to enact change. Of course, even if the necessary time can be assigned, a change in outcomes is by no means guaranteed. One frustrated tutor noted:

> I mean, we've seen him I've lost count how many times really, with support tutorials in the last couple years or so. And he's had many opportunities to come and talk to us and just doesn't turn up. [NTU tutor, May 2019]

In this chapter, we are focusing on single loop tutor-driven remedial interventions. In this context the capabilities required for the intervention stage are perhaps the least unique to learning analytics of the three stages discussed. Whilst it can be argued that acting on warnings such as low engagement is more complicated than acting on more tangible warnings such as failed assignments, both are the visible outcomes of a series of decisions made and actions taken by students. At this point in the development of the technology, learning analytics is unlikely to be able to help tutors pinpoint the underlying causes of student behaviour. We believe that the intervention still requires human contact by someone with sufficient interpersonal and coaching skills to diagnose the problem, agree working strategies and provide ongoing support and encouragement. We argue that it is therefore important for staff to continue to build these capabilities alongside other new skills relevant to learning analytics, such as data literacy.

In the 2019 Student Transition Survey, students were asked about their relationships with their personal tutors. Students were overwhelmingly positive, reporting that tutors were accessible and approachable. Moreover, they were most comfortable with their tutors accessing their personal data about them compared with other staff within the University (e.g. student support specialists), and when asked about who should contact them in cases where they were at risk of dropping out, they most frequently wanted their tutors to be that initial point of contact.

Students were asked to provide qualitative feedback describing how tutors motivated them to engage in their studies. The responses were primarily about the quality of relationships garnered by staff, through actions such as offering encouragement and expressing interest in each student. The respondents also reported that some tutors would reveal times where they had faced challenges as students, for example, "His personal experience of uni was seemingly like mine, and to say that he stands where he does now has really motivated me to better myself …" [NTU first year student, March 2019]. In addition to expressing empathy, staff also actively fed back positive messages acknowledging good work or role modelling their own passions for their subject. Furthermore, tutors offered practical help, for instance, "[my tutor] provided me with small, achievable targets and has given me feedback on my work along the way" [NTU first year student, March 2019], or encouraged them to focus on the task at hand rather than worrying about more long-term issues. Importantly, students reported that they were motivated when tutors actively made contact because they were concerned about the student. This appeared to reinforce their belief that the tutor cared about them as individuals. It is interesting to note that student descriptions of motivators were primarily affective. No student described being motivated by more cognitive factors such as an explanation of risk.

Finally, one important capacity building consideration is the need to manage ongoing support. This could be through separate customer relations management software, but we would argue that there are benefits for integrating it within the learning analytics software itself. Tutors need to be able to add relevant notes and make referrals within the tool, to ensure involved parties have the necessary information to continue the process of support.

13.7.1 Summary for Building Staff Capacity to Support Students Using Learning Analytics

If learning analytics is to be used as part of the process of supporting students, then a combination of data literacy, technological ability and interpersonal skills is required. To the average tutor, developing and maintaining the full range of capabilities could appear a daunting task. Good design and scaffolding resources should mitigate against the additional requirements needed to use learning analytics to bring about change, but we would argue these require a concerted institutional effort and that it is important to consider resource implications for tutors.

13.8 Institutional Recommendations

In the proceeding section, the focus was on understanding individual tutor's capacity to support students at the point where learning analytics had identified that there may be a problem. This final section outlines strategic considerations for ensuring that institutional changes take place in order to support staff in this role.

Recommendation 1: Consider the Current Institutional Capacity to Support Students
Unless you work in a completely new institution, there is likely to be both an existing strategy for supporting students at risk and staff in place offering that support to students. Learning analytics is not a magic solution; it offers potential for new ways of working and for earlier, more meaningful interventions, but the intervention stage needs delivering by someone. In most instances these people will be the staff already in role. Any implementation requires an honest discussion about staff skills, barriers and limitations, the capacity of specialist referral teams, physical space and IT needed to support students. It also requires a potentially more difficult conversation about the perceived value of staff supporting students when weighed against activities such as research. There is little point of investing in learning analytics if the people who will use it are not committed to doing so.

Recommendation 2: Understand the Improvements You Are Seeking to Achieve and the Role of Learning Analytics in this Process
The second recommendation is to develop a clear vision for the use of learning analytics and an understanding of how providing learning analytics to tutors will

help the institution achieve that goal. This chapter has explored some of the benefits and challenges from providing staff with such a resource to help support student success. It is perhaps worth reiterating that in our experience the benefits from learning analytics systems are not just derived from the algorithms and large-scale data processing. There are also significant gains from adding functionality such as notes, actions and referrals to help staff support individual students.

We would suggest that this change requires investment from institutional leadership but equally consultation and communication with the end users themselves. As we have written elsewhere, successfully implementing learning analytics can be difficult (ABLE, 2018a; Siddle & Foster, 2018). The importance of the system working reliably cannot be overstated. Institutional expectations, limitations, student rights and also staff rights will need codifying into policy. It also requires consideration about how adding learning analytics will change the working practices and experiences of staff. For example, how will the institution strike the balance between reducing the risk of early departure and reasonable staff workloads? Ultimately, the resource is only valuable if it is used.

Recommendation 3: Assess the Additional Capabilities Tutors/Advisers Need in Order to Effectively Use Learning Analytics
In addition to the existing skills needed to be an effective tutor (interpersonal effectiveness, coaching and advising, etc.), staff will increasingly need data literacy and to be competent with new IT systems. Whilst good design ought to reduce the need for highly sophisticated data skills, there are core concepts and minimum thresholds required. Understanding data literacy means both functional numeracy and a specific understanding of the way that systems utilise and present data. Staff will also need to develop the skills for communicating the language of risk and data into their advising practices.

Recommendation 4: Implement Strategies to Build Tutor/Adviser Capacity for Using Learning Analytics
The final step of the process is to ensure that staff are developed in order to use learning analytics effectively. Staff need time and space to grow their expertise in this field. Support to do this could be provided centrally using existing structures, or serious consideration is needed as to the best way to build it through reflecting upon good practice with peers.

13.9 Conclusions

In this chapter we have discussed the role of one of the key staff users of learning analytics: the personal tutor. We have described many potential benefits arising from providing these staff members with additional student data and early warning alerts. These allow potentially earlier interventions and give staff greater contextual information and, through notes and referrals, a greater understanding of the support already in place. However, with even the best systems, considerable capacity-building is required to help tutors use learning analytics effectively. Some of this work, such as the underlying infrastructure, will be the responsibility of the institution and other aspects, the responsibility of professionals in staff development. However, the most important area of change may be required by tutors and other similar staff as they integrate new information into their practices supporting students to succeed. Significant further research and development (including our OfLA Erasmus+ work) is needed to understand how to integrate learning analytics into normal advising and tutoring processes, from the perspective of both the tutor and the students they advise.

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Chapter 14
Experiences in Scaling Up Learning Analytics in Blended Learning Scenarios

Practical approaches and lessons learned

Vlatko Lukarov and Ulrik Schroeder

14.1 Introduction

In recent years, there is a prominent claim that learning analytics (LA) is a key transformative approach that will transform education and its processes. The LA research and application field draws its roots and methods from data analysis, statistics, data mining, business intelligence, computer science, and educational research and learning. Extensive research has been done to develop tools and prototypes and analyze educational data to improve and innovate education, and this has advanced the research field of learning analytics (Lang, Siemens, Wise, & Gasevic, 2017). However, this has created a widening gap between what could the role of learning analytics be in education and what learning analytics is actually doing in education. Despite numerous and extensive advances in the research field of learning analytics, wide adoption and successful implementations of learning analytics as a service are still not present (Ferguson et al., 2016; Ferguson & Clow, 2017). The research evidence shows that the use of learning analytics to improve learning and education is still in its infancy, and there is a lack of practical examples and implementations on scale and, more importantly, lack of structured practical approaches of how to provide learning analytics services in education and put them into practice (Ferguson et al., 2016). The added value of LA tools and services for learners and educators is clearly recognized and identified, but there has been little research done to provide conclusive evidence that LA services have desirable effects on the learning processes (Scheffel, Drachsler, Stoyanov, & Specht, 2014). One of the main challenges for implementation of LA as a service in Germany is the strict data privacy laws which make it exceedingly difficult to access even anonymized log data from the learning platforms and impossible to access highly personal data (Lukarov, 2019;

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Lukarov & Schroeder, 2017). What impairs the implementation of LA services even more is the lack of institutional strategies and vision about using LA to leverage the learning processes and experiences. This exacerbates the situation even further with the fact that every stakeholder group involved in the e-learning part of the blended learning processes in higher education has its own expectations, goals, and understandings about what analytics is and how should analytics be implemented. These three major impediments (strict data privacy laws, lack of institutional strategy, and the lack of goals and requirements) contribute to the current situation of fragmented and different views about LA within the higher education institution (Arnold et al., 2014; Drachsler & Greller, 2016; Lukarov, 2019).

When looking through results for scaling up learning analytics in a higher education institution, there are two main types of outcome examples: the first type of outcomes (a much larger group of results) covers how LA should be scaled up in higher education institutions which outline the possible steps within the institution for development, the affected stakeholder groups, their interrelationships, and foreseen implications and results (Dawson et al., 2018; Dollinger, Liu, Arthars, & Lodge, 2019; Ferguson et al., 2016; Lonn, Aguilar, & Teasley, 2013; Maldonado-Mahauad et al., 2018; Tsai et al., 2018; Yanosky & Arroway, 2015); while the second type (smaller group) covers practical implementation of LA services within higher education institutions with specific goals and purposes and then reporting after-the-fact the effects from the introduction of such services, the involved stakeholder groups, the interrelationships, and the implications (Arnold et al., 2012; Huberth, Chen, Tritz, & McKay, 2015; Kurzweil & Wu, 2015; Poon, 2013; Sclater & Bailey, 2015; Tanes, Arnold, King, & Remnet, 2011). When looking at the aggregated research findings and experiences from both types of research results, the main message is that the higher education institutions need to develop strengths and practices to provide support use of learning analytics; define the contexts in which analytics should be used; and create and impose ethical standards including data and privacy protection (Arnold, Lonn, & Pistilli, 2014; Rebecca Ferguson et al., 2014; Lukarov, 2019). Analytics as a service in higher education is a complex topic which encapsulates social and cultural aspects, on one side, and technological infrastructure on the other side. The preparation of an institution for learning analytics can be divided into three parts (which could be addressed simultaneously): (1) technological infrastructure, analytics tools, and applications; (2) policies, processes, practices, and workflows; and (3) analytics skills and values (Arnold, Lonn, & Pistilli, 2014; Ferguson et al., 2014; Lukarov, 2019). These three main statements were the guiding principles for the development and provision of learning analytics for institutional adoption at RWTH Aachen University as an integral service to improve the learning processes and were used as a basis for this research work. The concrete research question around which this work is centered is *How can learning analytics services be provided on scale in blended learning scenarios?* The research work was split into several integral parts, and each part covered a different aspect of implementing learning analytics on an institutional level. The parts/sub-questions that were identified are the following:

- How to capture the needs of the stakeholders who are directly involved in the learning processes?
- What kind of practical data management strategies are required to provide analytics as a service?
- Where and how should analytics tools be provided in the learning processes?
- What kind of empirical tools and research methods are most suitable for evaluating learning analytics services?

In the context of this research project, the stakeholders for which these questions are presented and answered are the *teaching staff user group*. However, as part of this project, the complete requirements were elicited for the students, the teaching staff, the university's administration, and the IT staff responsible for running and maintaining the e-learning tools and services within blended learning scenarios in a higher education institution. Moreover, as part of this project, multiple LA prototypes for the students, the university administration, and the IT staff were also developed and evaluated with formative evaluation methods, but due to space limitation, they will not be presented. The paper continues as follows: section two provides a short summary of the applied research methodology for investigating and answering the research questions; section three provides the salient points of the conducted preparation for scaling up learning analytics in blended learning scenarios; section four provides the practical approaches and implementations of the projected sustainable infrastructure and services for learning analytics in blended learning scenarios; section five provides the design, implementation, and results of two extended evaluation case studies; and finally section six sums up the conclusions and learned lessons for scaling up LA services in a higher education institution.

14.2 Methodology

As an underlying research methodology, we chose design-based research methodology because it applies well to the research questions and tries to address important unsolved problems in unique and innovative ways and refines both theory and practice, and its value of a theory is valued by the extent to which its principles inform and improve practice (Barab & Squire, 2004; Dyckhoff, 2014; Hevner & Chatterjee, 2010a, 2010b). Design-based research is conducted with a "build-and-evaluate" loop, and each iteration results with better and improved models and artifacts. With this research methodology, the participants are co-participants in both the design and, sometimes, in the analysis. The participants need to interpret, understand, and act upon the information provided by the developed (researched) analytics tools. Therefore, these tools are dependent on user involvement, and user-centered design approaches have to be used when designing and developing such tools and artifacts (Barab & Squire, 2004; Dyckhoff, 2014; Hevner & Chatterjee, 2010b). The research presented in this chapter is situated in real-life context and setting where learning occurs and is by default complex because the learning scenarios depend on the people involved, their goals and expectations, and the available resources. Any of these variables change over time or every iteration. Therefore, it is essential to characterize the context and situation in all its complexity within the setting over a long period of time (Wang & Hannafin, 2005). Design-based research methodology affords flexible design and artifacts revision based on their success in practice. The newly acquired knowledge about the problem domain (LA) might even change the applied research methodology, thus leading to the development of knowledge that can be used in practice, and other practitioners and designers can learn from it (Barab & Squire, 2004; Dyckhoff, 2014; Hevner & Chatterjee, 2010b).

The three parts for preparing a higher education institution for LA from section 1 were divided into the following actionable steps: (i) collecting appropriate LA requirements for the stakeholders, (ii) preparing the legal and technical foundations of the higher education institution, (iii) developing and improving the learning analytics services, and (iv) continuous evaluation of the learning analytics services. These steps emerged from practical experience and expertise collected over a decade from building e-learning solutions and IT services for tens of thousands of students at the Center for Innovative Learning[1] and the Learning Technologies Research Group.[2] The identified steps were comprehensively investigated and realized at RWTH Aachen University over the period of 2 years by applying design-based research methodology which encompassed a comprehensive set of different methods from business market research and innovation management, software engineering, human-computer interaction, and the behavioral and cognitive sciences.

14.2.1 Collecting Learning Analytics Requirements

Learning analytics tools are interactive software systems whose designs are driven by different choices and requests from the users for whom these interactive systems are developed and the activities and actions these systems need to perform for the users. In relation to this research work, different requirement engineering practices were applied for the development of the requirements for learning analytics in blended learning scenarios. Overall, software requirements have three distinct levels: user requirements, business requirements, and functional requirements.

For the business requirements, results from market research and innovation technique called Outcome-Driven Innovation (ODI) (Christensen, 2010; Ulwick, 2014) were used to define the scope and to describe the user-defined metrics and the segments from the e-learning services and technical infrastructure for improvements. Outcome-Driven Innovation is a holistic innovation approach for business

[1] CiL is an e-learning service provider of RWTH Aachen University (www.cil.rwth-aachen.de).

[2] Learning Technologies Research Group conducts research in the areas of technology-enhanced learning, intelligent web and mobile learning systems, and didactics of computer science. They work on methods, infrastructures, and techniques for next generation technology-enhanced learning environments (www.learntech.rwth-aachen.de).

and market analysis which focuses on a job-to-be-done theory (Christensen, 2010). The ODI method is mainly used for development of new products and services but can be suitable for developing a strategy for digitalizing higher education because the results of this method are a transformation of fuzzy needs into measurable outcomes (Ulwick, 2011). This approach focuses on uncovering the metrics customers apply to evaluate solutions and aims to convert them into measurable items, because to evaluate a solution or a product, a set of metrics is applied to measure how effectively a product, service, or a solution can contribute to completing a job or contribute the degree of job achievement (Ulwick & Bettencourt, 2008). The ODI approach uses traditional customer-oriented research techniques such as user interviews and validation surveys (Ulwick, 2005).

For the requirements elicitations and building the user and functional requirements, the following methodologies were used: surveys (Pohl & Rupp, 2015; Preece, Sharp, & Rogers, 2015; Wiegers & Beatty, 2013), questionnaires, interviews (Pohl & Rupp, 2015; Preece et al., 2015; Wiegers & Beatty, 2013), and literature review and document analysis (Pohl & Rupp, 2015; Wiegers & Beatty, 2013). Moreover, brainstorming sessions were conducted (Dix, Finlay, Abowd, & Russel, 2004; Pohl & Rupp, 2015), and the results from these methods have defined the stakeholders in details and served as basis for the development of user personas (Adlin & Pruitt, 2010) to capture and describe their goals and requirements. Based on the user personas and the elicited requirements, suitable use cases (Pohl & Rupp, 2015; Wiegers & Beatty, 2013) for understanding the users' requirements concerning implementing learning analytics were also created. Finally, the validation of the business and user requirements was done with applying exploratory data analysis (EDA) (C. Chatfield, 1985; Chris Chatfield, 1986) to discover the validity and correctness of the collected requirements.

14.2.2 Evaluation Strategies

The entire learning analytics framework with the resulting learning analytics prototypes has to be evaluated within real-world scenarios which include many participants within many courses to achieve the goals of this research work. We chose to use case studies for evaluating the learning analytics infrastructure and the prototypes because the evaluation methods have to continuously observe the usage of the learning analytics in real learning and teaching scenarios and should collect feedback about the integration and correlation of analytics usage and other teaching and learning activities. In essence, a case study is a detailed examination of one or more specific situations within a specific real-life context and can be described by the following four key aspects: (1) in-depth investigation of a small number of cases, (2) examination in context, (3) multiple data sources, and (4) emphasis on qualitative data and analysis (Lazar, Feng, & Hochheiser, 2017).

14.3 Scaling Up Learning Analytics

We separated the process for scaling up learning analytics into four main steps: collecting learning analytics requirements, institutional preparation, technical implementation of the LA infrastructure, and evaluation of the implementation. Collecting learning analytics requirements covers the identification of stakeholder groups and by using different techniques borrowed from software engineering and business market analysis. The institutional preparation covers the legal and practical preparations of the higher education institution for LA services. The technical implementation outlines the preparation for development of the data management and warehouse techniques, the outlining, and the application and development of the analytics engine and algorithms. The results of these preparations and process are used as the basis for the subsequent implementation.

14.3.1 Building the Requirements

The idea behind blended learning is to get the strengths of two worlds, i.e., face-to-face oral communication and technology-enhanced learning, to combine them in an optimal way to provide a learning experience which is compatible to the learning context and educational goals (Garrison & Vaughan, 2012; Oliver & Trigwell, 2005). Blended learning practice in itself is a mixture of different pedagogical approaches which combine the effective socialization of students and teacher within the classroom and different technological benefits of technology-enhanced learning (Poon, 2013). Hence, with this project, we try to improve the blended learning scenarios by analyzing and supporting the technology part of the blended learning scenarios and extending it with LA tools. The presented results here are salient summaries of the obtained results from the methods carried out to collect the requirements. The extended set of the requirements, including the methodology, the elicitation methodologies, and the results, can be found in the referenced publications, and we strongly encourage the readers to review them to gain a more substantial insight of the results.

14.3.1.1 Outcome-Driven Innovation and Exploratory Data Analysis: Results

The ODI study was conducted in which 34 lecturers from different faculties were interviewed, while 268 lecturers took part in the ODI quantitative survey in which 43 panel statements (derived from the interviews) were evaluated (Piller, Brenk, & Nacken, 2017). The results from the ODI study with the teaching staff showed that faculties differ in their evaluation of e-learning services. Whereas teaching staff from some faculties already experiment with e-learning, the rest are reluctant to deviate from traditional face-to-face teaching approaches (Piller et al., 2017). The teaching staff wants an overview of what is happening inside their courses over the semester, expects student engagement and continuous learning, and expects that students have intrinsic motivation and are able to work by themselves through the entire semester. The results showed that teachers invest a lot of time and effort in designing and implementing their learning scenarios and creating and providing these learning resources to the students. Therefore they need to intervene when they identify that the learning resources they provide are not being reworked on a regular basis by the students (Lukarov, 2019; Piller et al., 2017). This is a clear indication that they need tools to observe the student engagement with the learning resources on the learning platform. This can be achieved by providing descriptive statistics and analytics and student engagement distribution over time on the learning resources in a course on the learning platform. The teaching staff would like to have tools and mechanisms that show the student motivation and commitment to the course materials. On the other hand, they would like to reduce the time and effort for creating and managing a course on the learning platform and reduce the time and effort when using e-learning tools and services. In the context of learning analytics, the teaching staff needs tools and analytics that can provide them overview about their course and the student engagement and use of the provided learning services over the duration of the semester (Colvin et al., 2015; Scheffel et al., 2014; West et al., 2018). However, their need for a decrease of invested time and effort for using e-learning tools and services can limit the development and deployment of new and complex e-learning tools and interfaces. Hence, the learning analytics tools should be easy to use and understand and provide insight and feedback of what is happening inside a given course while reducing the time to use and decreasing the cognitive load on the users (the teaching staff) (Lukarov, 2019).

14.3.1.2 Building the Requirements: Literature Reviews

The literature review and document analysis were conducted on publications from the relevant conferences, journals, and books whose area of research is technology-enhanced learning and learning analytics. Furthermore, technical and summary reports from government bodies and educational organizations were also collected and analyzed for existing research, initiatives, and technical implementations of learning analytics. The set of analyzed documents included the complete proceedings from the conference on Learning Analytics and Knowledge (LAK); the European Conference on Technology-Enhanced Learning (EC-TEL); the German e-learning conference; different journals about learning analytics, e-learning, and technology-enhanced learning; and reports from the European Commission and educational organizations. The relevant publications (case studies) were analyzed for the following goals:

- Collect research and experiences about applied didactical approaches to didactical goals, questions, and e-learning scenarios with relation to analytics.

- Collect practical applications and technical details about implemented learning analytics tools.
- Collect technical and implementation details concerning learning analytics indicators, their definition, description, and intended users, what kind of educational data they are using, applied analytics algorithms, and applied data privacy mechanisms.

The first objective of the literature review showed that the teaching staff already have many questions concerning the resources they provide, the students' behavior, and the correlation between them. Moreover, based on the literature, there was a strong focus on research, especially action research concerning the evaluation of their implemented learning scenarios. The complete list of questions can be found in the Appendix of Lukarov (2019).

The second goal of the literature review provided very scarce and limited results. There exist publications within the research communities that present tools and services in the domain of LA, but the level of granularity and technical information and details available within these publications is scarce, and their application experiences could not be easily reconstructed nor transferred.

The third goal of the literature review resulted in analyzing 74 learning analytics tools and research projects. The underlying work was based on previous work by Dyckhoff, Lukarov, Muslim, Chatti, & Schroeder (2013), Dyckhoff (2014). Action research and learning analytics in higher education which developed a categorization scheme for the identified tools and learning analytics indicators. For each identified learning analytics tool, we conducted additional research for literature, publications, and documentation for discovering its intended users, type of data, analysis methods, and what kind of indicators the tool contained. Overall, we collected 272 learning analytics indicators and extracted the indicators' names and descriptions from the scientific publications and technical reports at hand. Afterward, we applied the categorization scheme that mapped the indicators to their respective tools; mapped the indicators to their intended users (stakeholders); mapped the indicators to what kind of data they need for their analysis; and mapped the indicators according to the identified teachers' questions from the previous literature review objective. The goal behind these categorizations was to identify to which extent the development of the learning analytics tools was driven by the available data and whether the development of these learning analytics tools was aligned with the stakeholder needs' and the didactical aspects of the applied learning scenarios. The complete list of learning analytics indicators can be found in the Appendix of Lukarov (2019). If one compares these identified goals from the research with the ones from the validated Outcome-Driven Innovation results, the difference between them is striking. The learning analytics goals from the research community are far more reaching and ambitious, while the teaching staff is concerned with much more pragmatic objectives and goals whose context is the day-to-day teaching and learning activities within the implemented e-learning scenarios. For a large-scale introduction of learning analytics and its adoption from the stakeholders within the learning process, it is crucial to consider the actual goals and needs of the stakeholders (Lukarov, 2019; West et al., 2018).

14.3.1.3 Building the Requirements: Outcomes

The collected requirements from the aforementioned methods were used as a knowledge base for the creation of personas of the intended stakeholders. We used the Persona Core poster from the Creative Companion[3] to document the details that describe a real person like name, gender, age, occupation and main character features, and specific details concerning their personality and the context in which they are going to use the developed LA tools (Mentiu, 2018). For the teaching staff, there are two personas, a university professor and a teaching assistant. The teaching assistant persona is equally important, because they are the main group of users that organize the lecture and the exercises and are responsible for the successful implementation of the didactical approaches and the learning scenarios within a given course (Mentiu, 2018). Two composite use cases were created for each persona, and they were created to have a story-like manner when describing them and contained three main components: problem description, solution, and a result. The use cases will be used when developing the learning analytics indicators, their visualizations, and their groupings and representations within the interface for each intended user. The solutions provided with the use cases were mapped to existing indicators to identify which indicators, sets of indicators, combinations, and aggregations would provide insights, actionable intelligence, and results that help the persona in fulfilling the goals and achieving a positive result (of the use case) (Gospodinova, 2018; Mentiu, 2018). The collected indicators were analyzed, discussed with the context of the personas, and matched the indicators with the personas and the use cases. The resulting sets of many indicators were too large (in some cases more than 50 indicators per persona); therefore a prioritization and classification of them was necessary because providing sets of tens of indicators on a single interface can quickly overwhelm and overload the user's understanding and cognition (Gospodinova, 2018; Mentiu, 2018). The choice was made to have around seven to ten indicators per persona, by following the findings from research about the human capacity for processing information given a limited amount of time (Miller, 1956; Miller & Miller, 1994). The following list of indicators/analyses presents what was used as basis for development of the analyses and visualizations in the technical implementation part of our work:

- Trends in student activity based on the time spent online.
- Student reactions and interactions based on teachers' activities within a course.

[3] The Persona Core poster can be found here https://creativecompanion.wordpress.com/2011/05/05/the-persona-core-poster/.

- Quantification of the use of e-learning offerings over time: learning resources, electronic tests, assignments, types of learning resources, collaboration activities, and engagement in mobile learning.
- Correlation between use and performance in e-tests and assignments over time per course.
- Timely adoption of learning resources per course.
- Combination of time spent on the course, which resources are used, when during the day the students are studying or using the learning offerings. This should be available over a time period for a course.
- Learning path analysis, which shows how students access learning resources over time, assignments and exercises, and their correlation.
- Trends in student activities over time during the semester.
- A number of unique users per resource over time and resources that have not been used over time.
- Time-dependent distribution of students in discussions and their connection to lectures and assignments.
- The grade distribution for students in lectures and assignments.
- Most popular resources and time spent on them.

Many of the identified indicators were combined to form one or more insightful indicators; some of the indicators were removed or marked as not important considering the limited design space and time for indicators, and initial finalized lists of indicators per persona were identified. These indicators are not complete, nor a comprehensive list that covers all possible indicators or learning scenarios available but covers the most suitable indicators per given persona (Gospodinova, 2018; Mentiu, 2018).

14.3.2 Institutional Regulation Preparation

Data privacy in learning analytics is a relevant issue and is an integral part of the nonfunctional requirements because it covers the aspect of collecting, storing, and analyzing personal and sensitive data that affects the privacy of the users of these systems. However, the users' privacy must be taken into consideration and protected as part of all technical solutions and technology that are employed in supporting the learning and teaching processes in a higher education institution. Therefore, the legal framework must encompass all systems and services that store private and sensitive data, and the development and deployment learning analytics tools and services are just one part of those services and must be covered by it. In reality, learning analytics implementations are just one tier of the different available e-learning services in a given higher education institution (Lukarov, 2019), and its provision and existence must be regulated by a central service provider and contained within regulations which encompass other e-learning services from which LA tools and services borrow data. The university with its internal governing bodies (the university's government, rectorate, and its senate) had to create official regulations that govern and regulate the use of technology and e-learning services within the learning processes, which includes LA services as a core component. This led to the development of the so-called eLearning Ordnung zum Schutz personenbezogener Daten bei multimedialer Nutzung von E-Learning-Verfahren an der Rheinisch-Westfälischen Technischen Hochschule Aachen or translated regulations for the protection of personal data in multimedia applications and use of e-learning methods at the RWTH Aachen University. This official document outlines the rules which apply to all e-learning services and use and process personal and sensitive data within the university for the purpose of scientific training. The legal texts and content were written by the RWTH Aachen University's legal department with technical consultations with us and the Data Privacy Officer at RWTH Aachen University to make sure that the regulations were in accordance with the state and federal data privacy laws in Germany and would be in accordance to the General Data Protection Regulation (GDPR) of the European Union. The regulations consist of 14 paragraphs which outline the scope of the regulations; define the affected persons, the basic principles, and rules in which the e-learning systems should operate; outline the responsible body and its duties towards the affected persons; and define the different types of personal data available for the e-learning services. Additionally, there is a dedicated paragraph that handles research and collection and use of personal data for the purpose of improving the learning and teaching experiences, the consent of the affected persons, and how long such data can be legally and safely stored (Lukarov, 2019).

14.3.3 Learning Analytics Services Implementation

The implementation of the interactive system that provides learning analytics as a service is based on the developed use cases from the requirements engineering results. The learning analytics infrastructure with the learning analytics prototypes was iteratively developed in several development cycles, following a rapid application prototyping and development approach. This approach benefited from the collected learning analytics requirements from multiple sources and with its intrinsic approach of minimal planning in favor of rapidly implementing working and functional prototypes of the different components of the interactive software system. The design of the software architecture followed the separation of concerns paradigm and therefore was divided into four main components which are independent and interconnected with APIs (represented in Fig. 14.1).

The basic workflow of the solution is the following: the raw data from the learning platform is imported daily in the raw data warehouse. Afterward, the analytics engine is triggered and accesses the raw data from the warehouse, transforms it, processes it with the different analytics algorithms, and then stores it in the analytics results data warehouse. The user interface or the analytics indicators read the analyt-

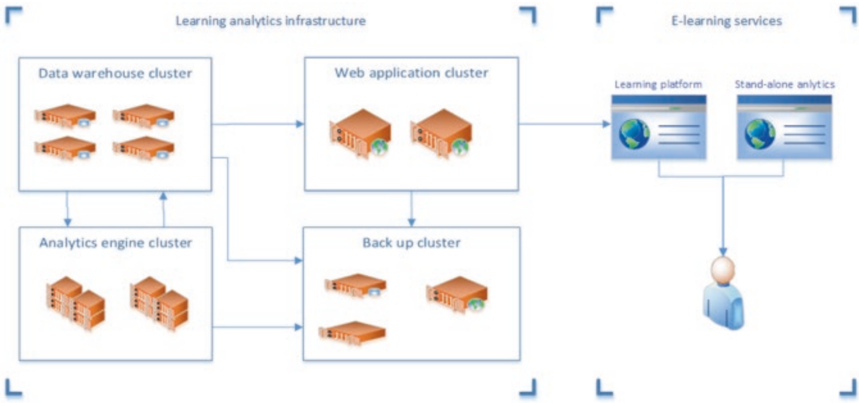

Fig. 14.1 Abstraction of the sustainable learning analytics infrastructure

ics results and deliver the data in the form of various visualizations to the users from the stakeholder groups presented at the end of section 1.

14.3.4 Data Management

The analytics data management covers the management of raw data that comes from the firewall servers in the form of URI requests towards the learning platform and its integrated modules and third-party systems and management of the resulting data that comes out of the analytics engine. One of the biggest concerns when designing the solutions for managing the data was the sheer amount of data generated by the users because the data collection methods worked on platform level. From October 1, 2017, to October 1, 2018, 322.211.812 interaction events on the learning platform were generated with the daily average of 25.916 different users. This poses a particular challenge because it calls for maintaining another large system infrastructure in parallel with the learning platform, for the sole purpose of storing and analyzing data, coupled with other hardware systems for the reason of providing analytics as a service within the learning processes. On the other side, there was a strict nonfunctional requirement about a sustainable and "low-cost" infrastructural solution which influenced the design and modeling of the data warehouse. The nature of the collected data and the organizational structure of the platform with its limited data concerning concretely and consistently identifying an individual over time meant that data models which were centered around a user or an actor were unsuitable for this purpose. This included the Experience API or xAPI, the Learning Context Data Model (LCDM), activity streams, Learning Registry Paradata data models, and Contextual Attention Metadata (CAM) (Lukarov et al., 2014; Niemann, Scheffel, & Wolpers, 2012; Suthers & Rosen, 2011). Due to the nature of the collected data, we chose to use a custom solution that simply partitioned the incoming data into temporal chunks (days) and built a data privacy conformant service that took care of the management of the raw data. The raw data was collected from the Forefront Threat Management Gateway firewall, managed and used for all IT services, and provided by the SuB department from the IT Center at RWTH Aachen University.

The data itself was provided in one big stream, and as such, it was difficult to analyze, and for this reason, we developed a data privacy conformant strategy to transfer the data to a separate data warehouse and partition it into smaller meaningful chunks. We developed and deployed a scalable database and an automated raw data import service which checked daily for new data. The service checked if there was new raw data available from the log data database, and if there was, the service split the available raw data into days (one chunk raw data = 1 day worth of log files), created a raw data table for each available day, and transferred it to the raw data warehouse for further processing and analysis. After the service partitioned and transferred the data, it was cleaned to remove all user events related to service calls to web resources that are necessary for having streamlined web experience (but are not related to learning events). The data cleanup resulted in data logs about user read/view and create/edit activities within the learning platform, and the data was ready for analysis. The raw data provided the time, the agent, the course, the module, the user action, and its result code (depicted in Fig. 14.2). We reviewed several data formats and models as potential candidates in which the analytics results could be stored and accessed. The data format should incorporate information about the learning and teaching activities on the entire learning platform of each individual faculty, the different departments within each faculty, the teaching and learning activities within individual courses, the individual modules within a course, and, potentially, the individual user actions. The data model had to be fast, scalable, and extensible while supporting many concurrent read operations during the day. Additionally, the update of data from the analytics results should not have any side effects on the existing data and results. In the end, we opted for a custom solution which stored the analytics results in a read optimized column-oriented database structure to support the large-scale and data-intensive applications that manipulated and displayed the data in the different indicators. All of the data tables that stored the analyzed data were created specifically with built-in column store indexes with an updateable non-clustered index (the course ID) which performed well on large tables and scaled well as data tables and that stored analytics results grew over time.

logtime	clientip	clientagent	processingtime	operation	uri	resultcode
2018-04-16 23...	508db40c-ffff-00...	Mozilla/5.0 (Macintosh; Intel Mac OS X 10.10; rv:59....	16	POST	http://www3.elearning.rwth-aachen.de/ss18/18ss-02027...	401
2018-04-16 23...	508db40c-ffff-00...	Mozilla/5.0 (Macintosh; Intel Mac OS X 10.10; rv:59....	16	GET	http://www3.elearning.rwth-aachen.de/ss18/18ss-02027...	200
2018-04-16 23...	508db40c-ffff-00...	Mozilla/5.0 (Macintosh; Intel Mac OS X 10.10; rv:59....	1	POST	http://www3.elearning.rwth-aachen.de/ss18/18ss-02027...	401
2018-04-16 23...	508db40c-ffff-00...	Mozilla/5.0 (Macintosh; Intel Mac OS X 10.10; rv:59....	16	POST	http://www3.elearning.rwth-aachen.de/ss18/18ss-02027...	200
2018-04-16 23...	89e206ca-ffff-00...	Mozilla/5.0 (Windows NT 6.1; WOW64)	218	GET	http://www3.elearning.rwth-aachen.de/_vti_bin/t2pservic...	404
2018-04-16 23...	89e206ca-ffff-00...	Mozilla/5.0 (Windows NT 6.1; WOW64)	234	GET	http://www3.elearning.rwth-aachen.de/_vti_bin/t2pservic...	404
2018-04-16 23...	58990701-ffff-00...	Mozilla/5.0 (Macintosh; Intel Mac OS X 10_13_3) Ap...	47	GET	http://www3.elearning.rwth-aachen.de/ss18/18ss-06862	302
2018-04-16 23...	89e2957b-ffff-00...	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleW...	15	GET	http://www3.elearning.rwth-aachen.de/SiteAssets/SitePa...	200
2018-04-16 23...	89e2957b-ffff-00...	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleW...	16	GET	http://www3.elearning.rwth-aachen.de/SiteAssets/SitePa...	200
2018-04-16 23...	89e2957b-ffff-00...	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleW...	15	GET	http://www3.elearning.rwth-aachen.de/SiteAssets/SitePa...	200
2018-04-16 23...	89e2957b-ffff-00...	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleW...	15	GET	http://www3.elearning.rwth-aachen.de/SiteAssets/SitePa...	200
2018-04-16 23...	89e2957b-ffff-00...	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleW...	16	GET	http://www3.elearning.rwth-aachen.de/SiteAssets/SitePa...	200

Fig. 14.2 Raw data excerpt

Practically, the analytic engine and the warehouse were designed in such a way, so that summaries and aggregations of all activities within each individual course on the platform were stored and analyzed. This made the activation and provision of the analytics results in every single course a straightforward task because the analytics results were already available in the warehouse.

14.3.5 Analytics Engine

The analytics engine was developed and deployed as a background service which was triggered automatically after each successful import of newly available raw data. It was developed in C# and .Net and uses the Windows Communication Foundation and Web API services for providing data and communication interfaces between the different components of the analytics infrastructure. The process itself consisted of three steps: (1) getting (loading) the raw data from the data warehouse in the main memory, (2) analyzing the data with the analytics engine, and (3) building and formatting the analytics results and saving them in the results data warehouse.

Loading Raw Data The amount of raw data and user events amounted to millions of events which posed a challenge of how to deliver (parts of) the raw data to the analytics engine and its algorithms and methods for analysis. The data delivery methods for raw data were optimized with two strategies: by using stored procedures and by using parametrized methods that delivered the same raw data set only once for multiple analytics methods and algorithms (the same strategy was used in the results database). The parametrized methods used the stored procedures to load the needed (and suitable) raw data by selecting data which was needed for each analytics method and indexed it in the main memory.

Analyzing Data: The Analytics Engine After the raw data was loaded in the memory, the analytics engine initiated its analysis. The algorithms and analysis methods were executed in parallel as a background service which used (or rather reused existing) multiple threads to analyze the raw data. This multi-threaded approach enhanced the performance and throughput of the code, thus reducing the time necessary to analyze the data. Each thread had a data loader method which loaded a chunk of raw data and provided it to another method which called upon further optimized and parametrized static methods which analyzed only this chunk of data and returned a result (either intermediary or a final result) which was later reused or saved within the results data warehouse. Whenever a thread has finished execution for the current data chunk, it picked up new data and continued analyzing the data. If, by chance, the thread failed to execute or encountered an error, the intermediate results were discarded, the error was saved, and another thread tried to reanalyze the raw data chunk. The analysis of the data was executed until all of the available raw data was analyzed. These methods were organized in modular and extensible units which made it straightforward to maintain and upgrade them accordingly without changing the overall logic and structure of the analytics engine.

Saving the Results After the analytics engine finished with analyzing the loaded data, another method organized the obtained results to prepare them for the results data warehouse. The results were formatted in the column-friendly fashion of the tables within the results data warehouse, and they were inserted as a bulk via a stored procedure.

14.3.6 Results Visualization

The user interfaces consisted of learning analytics indicators based on the indicators from section 3.1.3. The user interface was created as a single page application and was provided within the course rooms on the learning platform. The data visualization strategies were based on the work of Iliinsky and Steele (2011) and Abela (2014) which provided practical guidelines and concrete suggestions about visualization, and the visual properties of the data that needed to be encoded. Abela developed a mapping strategy that puts the charts and visualizations into four categories depending on what a specific chart should accomplish. The chart/visualization can show the *relationship* between data; the chart/visualization can show a *comparison* between different data entities; the chart can provide a *distribution* of the data over temporal or spatial properties; and lastly, the chart can show the *composition* of the data (Fig. 14.3).

The resulting analytics data in most cases had temporal characteristics, and special attention was placed on the position, the layout, and the axes. In the context of the implementation work in this research work, histograms, bar charts, line graphs,

Fig. 14.3 A screenshot of the "Insights" prototype within a course room on the learning platform

time series, pie graphs, treemaps, and heat maps were used as comparative and quantitative formats for the visualization layouts (Iliinsky & Steele, 2011). The "Insights" prototype automatically detected the role of the user and was also responsive and adapted to the screen size of the user's browser, and the number of presented indicators was dependent on the course room setup and the activated modules within the course room. This means that courses that used videos as part of their learning scenarios would receive indicator(s) concerning the lecture videos; if in the course there were assignments, indicators concerning the assignments would be provided. The indicators and their visualizations in the prototype were simple and responsive, and as such, they kept the cognitive effort upon the user low. This meant that the user could concentrate on the visualizations themselves, instead of concentrating on understanding the interface. The rapid application prototyping and implementation led to the design and development of a number of indicators; however considering their fidelity and how well they fit in with the collected and assigned indicators, the complete set was not used for the conducted evaluation.

14.4 Evaluation Strategies for LA

The evaluation consisted of two extended case studies which ran over two consecutive summer semesters at RWTH Aachen University. The underlying hypothesis of both case studies was that teachers, while doing other teaching activities within the course on the platform, would also use the analytics prototype within the same session on the platform. The additional goal of the two case studies was to answer the following questions:

- How the users (teachers) are interacting with the learning analytics tool?
- Are there any features/indicators that are meaningful to some users?
- Do the users plan to change something in their teaching activities or courses after being presented with the tool?

14.4.1 Study Setting

The first case study was on a smaller scale involving a small number of courses, and the second case study was on a larger scale involving hundreds of courses. The advantage of the case studies was in the fact that it was conducted in the field which afforded a great deal of freedom of the participants which meant that the results were closer to reality (in comparison with lab studies). However, the downside of the study setup was that there were a lot of external factors that could not be controlled, thus influencing the users and the results. For both case studies, we built three types of data collection mechanisms to collect corroborating evidence and with the help of data triangulation clarify and support the observations and results.

For this purpose, we collected anonymous log data on the usage of the analytics prototype (in seconds), collected log data on the users' activities within these courses on the learning platform (online teaching activities which included uploading learning resources, grading assignments, distributing course information), and conducted a two-part survey. The survey consisted of questions that collected qualitative feedback about the analytics prototype and a seven-point Likert scale usability questionnaire based on the ISO 9241/10 international standard (Figl, 2009; ISO, 2010).

Case Study 1 We randomly selected and contacted a wide audience of professors and teaching assistants of different faculties at RWTH Aachen University via email to offer them to participate in the case study. The case study was conducted in the summer term of 2017. Professors and teaching assistants of 53 courses agreed to take part (The course distribution is presented in Table 14.1). The number of students participating in each course varied from 20 students to 2200 students. After activating the "Insights" module in their courses, all participants received instructions via email and explanations about the module, descriptions about the visualizations, what kind of data is visualized, and guidelines about possible (valid) interpretations of the represented data within the visualizations. They also received information that the module activities would be observed by automatic logging tools, and, towards the end of the pilot phase, they would be given an online survey about their experiences with the "Insights" module.

Case Study 2 The second case study consisted of deploying an analytics prototype to a large number of courses (400 courses) on the learning platform. The case study was conducted in the summer term of 2018 from April to September. In comparison with the previous case study, the idea was to examine and evaluate the entire learning analytics infrastructure and the "Insights" prototype and inspect whether the infrastructure would scale to support a large number of courses. The context of the study was the technology aspect of the implemented blended learning scenarios in

Table 14.1 Types of courses participating in the case study of SS 2017

Case study: Summer Semester 2017	
Type of lecture	# of courses
Lectures (with exercises)	33
Labs	15
Seminars	5
Faculty distribution	
Faculty of Mathematics, Computer Science, and Natural Sciences	17
Faculty of Mechanical Engineering	6
Faculty of Electrical Engineering and Information Technology	3
Faculty of Arts and Humanities	11
School of Business and Economics	15
Faculty of Medicine	1

Table 14.2 Types of courses participating in the case study of SS 2018

Case study: Summer Semester 2018	
Type of lecture	# of courses
Lectures (with exercises)	302 (66)
Exercises	33
Labs	28
Seminars	18
Language courses	3
Faculty distribution	
Faculty of Mathematics, Computer Science, and Natural Sciences	108
Faculty of Mechanical Engineering	89
Faculty of Civil Engineering	38
School of Business and Economics	38
Faculty of Electrical Engineering and Information Technology	37
Faculty of Arts and Humanities	32
Faculty of Georesources and Materials Engineering	29
Faculty of Medicine	11
Faculty of Architecture	1
No information	18

courses on the learning platform to grasp a more realistic understanding of how analytics would be used within the learning platform in blended learning scenarios.

We developed a randomized selection process for courses which considered different factors which selected courses in which the prototype would be activated. The randomization took into consideration courses which have regular use by different (large) number of students; courses that use any form of formative assessment during the semester, such as assignments or electronic tests; and courses that use different kinds of media (videos) and literature or relied on student collaboration in their e-learning scenarios. The randomization process identified 400 courses (out of 1950 courses) which constitute around 20% of the total active courses for the summer semester in 2018, and the tool automatically activated the “Insights” module in these courses. Table 14.2 shows the distribution of the courses. According to the number of students per course, the sample size contained courses with a relatively small number of students and very big courses with more than 2500 course participants.

14.4.2 Evaluation Findings

The analysis of the results of the first case study showed that in 25 courses out of 53 courses the teaching staff used the "Insights" more than 5 times during the semester. The analysis on the session duration showed that the time spent on the "Insights" module ranged from 60 seconds to 7 minutes (all smaller sessions and accidental clicks/visits were removed from the analysis). This means that almost in half of the courses, the teaching staff explicitly used the "Insights" module on multiple occasions. The weekly distribution of courses in which "Insights" module that had been used also showed regular weekly peaks and troughs on the weekends. The aggregated analysis also showed that towards the end of the semester the number of courses in which the "Insights" module was used steadily decreased which was also expected. What was unexpected was the fact that in the weeks right after the lectures ended, the number of courses in which the "Insights" module was used started increasing. One possible explanation for this could be that the teaching staff wanted to observe and evaluate the students' behavior over the span of the entire semester within the course room on the learning platform.

The results of the analysis also showed that the teaching staff in 36 courses have performed various teaching activities while using the "Insights" module within the same session on the learning platform. In 24 courses, the teaching staff had performed activities that provide various learning resources (materials, slides, media, and hyperlinks) to their students. In 26 courses, the teaching staff had performed activities that distributed various course information to their students, and in seven courses, they corrected assignments or provided new ones within the same session. This is a strong indicator that the teaching staff used the "Insights" module as part of their teaching activities and confirms the second part of the goal of the case study and confirms its underlying hypothesis. Considering the results that confirmed the goal and the hypothesis of the study, it is safe to conclude that the correct place for providing learning analytics solutions and visualizations in blended learning scenarios is the course room on the learning platform. Nonetheless, this corroborated outcome does not provide evidence of whether the teaching staff understood, observed, or even acted upon of the visualizations and analytics results while using the "Insights" module. These findings show only that the teaching staff used the "Insights" module on regular basis.

The results of the second case study showed that in almost 20% of the courses in which "Insights" module was activated, the teaching staff used the "Insights" module on multiple occasions. The analysis on the session duration showed that the time spent on the "Insights" module ranged from 45 seconds to 9 minutes (all smaller sessions and accidental clicks/visits were removed from the analysis). This statement is corroborated with the upper quartile of the number of usages per course ($Q_3 = 7$), meaning that at least in one fourth of the courses in which the "Insights" module was activated and used (75 courses), the teaching staff has used the "Insights" module on seven or more occasions. The analysis also showed that towards the end of the semester, the number of courses in which the "Insights" module was used steadily decreased. What was unexpected was the fact that before and after the excursion week (last week of May), the usage of the "Insights" module spiked on both occasions. One possible explanation for this could be that the teaching staff wanted to observe and evaluate the students' behavior over the span of a couple of weeks of no lectures within the course room. The analysis indicated that there was a possibility that within the weekly usage peaks, there could have been many courses with incidental usage (although such requests and usage were filtered out from the raw data). However, the usage of data analysis and the correlation of a number of courses and usages per day showed that the "Insights" module was used intentionally especially whenever there were peaks in the number of different courses. This finding associates well with one of the goals of this case study, namely, that the teaching staff would use analytics tool on a regular basis within their course on the learning platform.

The results of the analysis also showed that the teaching staff in 190 courses have performed various teaching activities while using the "Insights" module within the same session. In 140 courses, the teaching staff had performed activities that provide various learning resources (materials, slides, media, etc.) to their students. In 112 courses, the teaching staff had performed activities that distributed various course information to their students, and in 31 courses, they corrected assignments or provided new ones within the same session. This is a strong indicator that the teaching staff used the "Insights" module as part of their teaching activities and confirms the second part of the first goal of the case study and its hypothesis. Considering the results that confirmed the first goal and the hypothesis of the study, it is safe to conclude again that the correct place for providing learning analytics solutions and visualizations in blended learning scenarios is the course room on the learning platform. The teaching staff would use learning analytics tools and results in their teaching activities while conducting their learning scenarios. Nonetheless, this corroborated outcome does not provide evidence of whether the teaching staff understood, observed, or even acted upon of the visualizations and analytics results while using the "Insights" module. These findings show only that the teaching staff used the "Insights" module on a regular basis. The evidence about understanding was extracted from the anonymous two-part survey.

The responses from the qualitative feedback showed that the teaching staff mostly used the visualizations and analytics to get an overview about how the learning resources were used and be more aware of the student behavior in the different modules of the course room on the learning platform. The teaching staff used the analytics module to learn more about the student behavior in the course rooms and comprehend what kind of behavior the students had with the learning resources, whether they used it regularly, or at which points in time they accessed which type of information in relation to the learning resources. Moreover, the teaching staff used the learning analytics module to evaluate how were their learning resources appreciated by the students which helped them to predict how many students were actually present in the course room. The analytics module also facilitated them to foresee whether the students really had prepared themselves for the lectures and, ultimately, whether the students actually were engaging in continuous learning. The most prominent findings were the discoveries about the students' learning behavior in the course room and their interactions with the provided learning resources. These findings helped the teaching staff to observe whether the students prepare for their lecture; to predict how many students were continuously involved in the course; to identify whether their teaching activities have effects on the students' behavior; and to know how the students exactly use the learning resources as part of their learning. What was an unexpected discovery in the feedback was that the teaching staff had not discovered anything new nor learned something new because they expected the observed behavior from their students.

The survey feedback also included evidence about (albeit unexpected in some ways) change in teaching activities, behavior, and improvement of the learning resources. In this regard, although many participants acknowledged interesting findings and new knowledge about student behavior and their learning resources, they would not immediately change their learning resources or their teaching activities. The notion that the module was "too new" and that it could not be completely trusted with the results was a reason the teaching staff would not change anything in their lecture. If the module were available for prolonged periods of time (multiple semesters), they would consider the presented analytics results and then maybe act upon them. However, there were clear results that the teaching staff would like to consider the new findings and analytics results more carefully and afterward would instigate changes in their learning resources and teaching activities. Another discovery was the fact that the findings from the module did initiate or helped in the course review processes after the end of the lectures. In these review processes, they would use the results to review and improve the teaching activities, the course structure, and the organization and revise and improve the learning resources for future iterations of their courses. This was a bit surprising because the future iterations of the courses would potentially benefit from the learning analytics results.

14.5 Lessons Learned and Conclusions

Overall, the important principles for scaling up learning analytics in blended learning scenarios in higher education should focus on four aspects: collecting the correct requirements, preparing the legal and technical foundations on an institutional level, continuously developing and improving the learning analytics services, and continuously evaluating the learning analytics services. One question that is strikingly omitted in the publications in the research field and community is where and how should learning analytics dashboards, tools, and services be provided to the users. The developers work vigorously on the design and development of research prototypes, learning analytics dashboards, and tools and conduct studies and research with them, but there is rarely a focus where to provide them as a service. Hence, so little practical experiences from technical perspective are present in the research literature. Most of the learning analytics prototypes are usually stand-alone applications, and, theoretically, they should be provided to the end users as another application or service. However, the simple existence of another online system or platform does not warrant success.

The dashboards that hold the indicators need to be simple, consistent, and pleasant to use. They need to engage the user, have her understand what is being shown, and guide her through the reflection processes with suitable help mechanisms. One of the biggest challenges of building learning analytics services (infrastructure) is deciding precisely what to build, which means that a comprehensive set of requirements has to be specified. First of all, the LA indicators must cover the needs and goals of the stakeholders, and they should always have a say in the end results What the stakeholders need and what the researchers think that the stakeholders need from the tools can be (and in this case are) two different things. Hence, it is crucial to use multiple and different requirements elicitation methodologies and preferably in several iterations, and it is strongly advisable that an innovation technique from the business market research field is applied to identify and leverage the possible stakeholder needs. Doing literature reviews or doing surveys within the confines of LA research do not provide the perspectives nor the actual needs and directions in which learning analytics services should be developed. The final requirements have to be a result of several incremental reviewed iterations and have a pre-defined software requirements specification (SRS) structure to ease the technical implementation.

Our implementation was deployed as a service to hundreds of courses and had to comply with the existing institutional, state, federal, and EU rules and laws concerning data privacy. The storage, management, and processing of personal data is a requirement not just for learning analytics tools and services but for all the provisioned e-learning services (specifically the learning platform and the campus management system). This means that a higher education institution must create institution-wide official rules and regulations that sanction the use of technology and e-learning services including LA as an integral service. The data collection mechanisms should not be built to collect all the available learning data but only the necessary learning data following the concept of data minimalism. The identification of the necessary learning data can only be done by analyzing the blended learning scenarios and identifying which parts of these scenarios can be enhanced with LA.

Evaluation of learning analytics tools covers the evaluation of the (1) interface design, the usefulness, and the utility of the tool and most importantly (2) effectiveness and impact. In the course of this research, these evaluation goals were attained by applying various evaluation techniques from the human-computer interaction (HCI) research field and the behavioral sciences. The first one was fulfilled in an iterative way through the applied formative evaluations during the incremental development of the infrastructure and the development of the user interfaces of the prototypes. This evaluation identified many practical problems with the interfaces and showed that the average user had problems with understanding complex visualizations. The users really appreciated the simple language and labeling of the data points and having guidance and help through the indicators. This can be achieved via stepwise introduction of LA interfaces, so that the users are not overwhelmed by the visualizations and the indicators.

The second evaluation goal is quite challenging to achieve. Previous experiences, including this work, showed that this process took a lot of time and repetition trials. We chose case studies because they provided greater freedom for conducting them, afforded data triangulation and collection of multiple data sources for corroboration, and thus allowed for in-depth investigation of the cases. The results of the two case studies showed that the "Insights" module did help teachers to be more aware of their students' online behavior, and it clearly initiated a reflection process partly towards their teaching activities and learning resources. The evaluation also showed that the "Insights" module inspired an initiation towards activities and interventions within the course structure or the learning resources. One can be safe to assume that if LA tools strive to have an impact to the users, they need to establish themselves and be present for prolonged periods of time (preferably years) to provide an actionable and measurable impact on the teaching and learning processes. An impact cannot simply be achieved by having access to a LA service for short periods of time and several discrete events of usage. LA tools have to run over the course of a long period of times and have to be coupled with multiple feedback sources (qualitative and quantitative) and telemetry data to provide conclusive and empirical evidence about the impact LA tools have on the users.

As a concluding remark, the institution has to create and support a team which can build a knowledge base (technical and people-oriented) and coach the team members to become experts for learning analytics. Moreover, the institution needs to build explicit strategies concerning data protection and provide an explicit framework and conditions which foster the team and the knowledge growth and experiences which are crucial for the provision of learning analytics. This work was built on top of experiences collected in a decade of building and running two learning platforms at RWTH Aachen University, and the collected intricate knowledge and experiences have shaped the conception and technical implementation and the deployment of this project. The strategies that were applied in this project were the same ones applied with success for the development of the learning platform and reused as guiding principles for this product-oriented research project. They are field-tested and can be reused from another e-learning/LA team to develop their service.

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Part III
Cases of Learning Analytics Adoption

Chapter 15
Building Confidence in Learning Analytics Solutions: Two Complementary Pilot Studies

Armelle Brun, Benjamin Gras, and Agathe Merceron

15.1 Introduction

The aim of learning analytics (LA) is "understanding and optimizing learning and the environments in which it occurs," as defined in the First International Conference on Learning Analytics and Knowledge (LAK, 2011). A needed optimization is to reduce the number of students who drop out as stated in the main report of the European Commission (Vossensteyn et al., 2015). One definition of a student who drops out is an individual who was but is no longer enrolled in the institution anymore and did not complete any degree. A second definition is restricted to a degree program: a student who is no longer enrolled in a study program without obtaining its degree; this is the definition used in the first pilot study. A third definition is restricted to a course: a student who quits a course without passing it.

However, while reducing dropout rates is needed, evidence of how to reach this goal is still missing. Arnold and Pistilli (2012) announced a reduction of students who drop out in courses backed up by a learning management system (LMS) with an early warning system "signals" that relied on LA. However, Ferguson and Clow (2017) argue that clear evidence between using "signals" and the reduction of students dropping out has not been fully established yet. It should be noted that this kind of work poses privacy concerns as numerous students' interactions in the courses are stored and analyzed. Schumacher and Ifenthaler (2017) and Slade, Prinsloo, and Khalil (2019) show that students are in favor of such systems if they are convinced that the LA solution can bring them benefits. One expected consequence of the adoption of the European General Data Protection Regulation (GDPR)

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in LA projects is that all stakeholders, including students, should feel confident with the way LA is implemented in their institution.

In this chapter, we present two preliminary and complementary pilot studies developed in two higher education institutions operating in different European countries. These studies aim at reducing dropout rates through the use of learning analytics. The first pilot study is part of a university-wide project in Germany, while the second pilot study is part of a national project in France. In the first pilot study, historical academic data of a selected degree program are analyzed, visualized, and mined to (1) better understand how students who complete and students who drop out differ in the way they study and (2) investigate whether subgroups of students emerge. Heads of programs and students' advisors are the targeted stakeholders. In this study, only data at the degree level stored in the information system of the university, such as marks or enrollments, are analyzed. These data do not provide insight into the behaviors of students while taking a single course. The second pilot study complements the first one in terms of the data used and the targeted stakeholders, who are the students themselves. It exploits the students' activity in the learning management system. Early and continuous feedback is given to students in dashboards to support their self-regulated skills, as described by Butler and Winne (1995). In this latter study, data at the course level stored in the learning management system of the university are analyzed, such as access to resources or marks to quizzes. No information about academic data is used.

These studies are complementary both in the data they analyze – information system-based versus learning management system-based – in the insights they can provide and in the stakeholders they target, which will allow us to draw conclusions about how to support students in developing abilities to persevere in studying. Both pilot studies follow an iterative and incremental approach and consider privacy issues in accordance with the European General Data Protection Regulation (GDPR).

The conclusions drawn in both studies will enable all stakeholders to better understand the benefits of both solutions, to build confidence at all levels, and in parallel to design solutions to limit dropout. Further, it will help to understand the implications that their deployment at the institutional level will have on the whole organization and its stakeholders. The two institutions will share the lessons that each of them has learned. This will allow for a cross-adoption of solutions that, later, other higher education institutions could also adopt.

15.2 Related Works

Reducing dropout rates is a key aim of the European Community to have "at least 40% of 30–34-year-olds complete higher education," as stated in the report (Vossensteyn et al., 2015). Actions need to be taken at the European, national, and institutional levels. In this chapter, we focus on actions at the level of higher education institutions.

Universities have long taken various measures to help reduce dropout rates as stated in (Falk, Tretter, & Vrdoljak, 2018). We review here some of these measures and begin with those that target prospective students.

One of the most widespread measures is an open day so that prospective students can get to know the university and the programs it offers in a more personal way, as they can meet staff and current students. Some universities extend this offer by allowing prospective students to attend regular classes or by designing summer courses especially for them. Another way is to require students to pass an aptitude test. This practice is mandatory in selective higher education institutions that usually have a low intake. This practice, however, goes against the principle that anybody with a high school certificate or equivalent is entitled to study. Some universities have optional aptitude tests freely accessible online and leave it to the students themselves to reflect on their abilities and decide whether or not to begin their studies. In Germany, some universities offer so-called optional "Brückenkurse[1]" especially in areas such as Mathematics or Physics so that future students can refresh their high school knowledge before starting their first university semester. Students attending those courses report that they find them useful. However, as for the other approaches discussed here, their impact on student success has not been widely investigated so far. It is also not known whether students with little prior knowledge and who could benefit from them attend them.

Regarding enrolled students, almost all universities have dedicated information / immersion activities available to new students during their first days of study. Some universities have created mentoring programs that can take various forms; in some cases, a staff member mentors a whole group of students, and, in other cases, a senior student mentors a single freshman student. Some universities introduce further information/counseling sessions later in the studies. Students with difficulties in some courses can attend tutorials, which are extra classes that are not part of the curriculum. Experience shows that not all students with difficulties attend them. As mentioned in (Karumbaiah, Ocumpaugh, & Baker, 2019), multiple factors influence whether a student seeks help or not. If visiting a tutorial is associated with a negative emotion of not being good enough, a student might not attend it.

A study by Falk et al. (2018) in the German context concludes that the best practice is to combine several measures and introduce some monitoring as well. This conclusion is close to the approach adopted at Georgia Tech University that uses the findings of LA to develop a set of interventions such as undergraduates working as tutors, pedagogy changed to flipped classroom in many introductory courses or changing some academic rules. These interventions led to the reduction of both dropout rate and time until graduation (McMurtrie, 2018).

In line with these works, the first pilot study presented in this chapter focuses on LA at the academic level and investigates key figures about students who drop out, as well as about students who complete a degree program. It is meant to guide

[1] Literally "bridge-course" between high school and university; a course to recapitulate the essential topics learned in high school

advisors and heads of programs into designing interventions to help reduce dropout numbers.

Dashboards are another solution proposed to inform and help students and have been the focus of many works in the literature, especially when they rely on learning analytics at the course level. As proposed in (Park & Jo, 2015), learning analytics dashboards (LAD) can be divided into three types according to their target audience: dashboards for teachers, dashboards for students, and in some cases dashboards for both of them (Millecamp, Gutierrez, Charleer, Verbert, & De Laet, 2018). Let us notice that most of the dashboards were developed to support teachers (Fu, Shimada, Ogata, & Suehiro, 2017) (Guo, Huang, & Wang, 2017); few of them were specifically developed to support learners. LAD can obviously be very different depending on their target audience and can even be different within a target audience.

A teacher LAD seeks to increase the information available to teachers about their students to improve the quality of their teaching (class management, learning assistance, evaluation, etc.). For example, LOCO analysis (Ali, Hatala, Gašević, & Jovanović, 2012) is a LAD that contains automatically generated information for teachers so that they can modulate their teaching. The Students Success System (Essa & Ayad, 2012) identifies at-risk students so that the teacher can provide them with additional help.

Students LADs may display learning patterns, to help students modify their learning strategies. Some dashboards like SAM (Govaerts, Verbert, Duval, & Pardo, 2012) and StepUp! (Odriozola, Luis, Verbert, & Duval, 2012) aim at stimulating students' self-regulation. Others, such as Narcissus (Upton & Kay, 2009) and SNAPP (Bakharia & Dawson, 2011), support social interactions, which have been identified as a key factor of student success.

The common goal of all student LADs is the increase of students' learning, therefore the improvement of their performance outcomes, which should lead to reducing dropout rates. The second pilot study presented in this paper focuses on the design of a student dashboard.

15.3 1st Pilot Study: Mining Academic Data

The data from 2276 students in a six-semester bachelor study program at a German University have been analyzed from fall 2005 (creation of the program) until fall 2018. The data for each student contain (1) enrollment date in the degree, (2) high school certificate mark (when present), (3) every single course the student enrolled in, with the enrollment semester and the mark earned, (4) as well as the graduation date for completing students. Since its introduction in 2005, the curriculum of the degree has been revised three times. Each revision caused changes in subjects; these changes were represented by equivalence tables to map courses from the old curriculum to courses in the new curriculum. In this study, we make use of these tables to map all courses to the present curriculum.

15.3.1 Context and Goals

To earn a degree, a student has to successfully pass every single course and has three attempts to do so. To attempt an exam, a student must be enrolled in the course. Recently, the university has put a limit of four enrollments per student for a course. Students who do not pass within four enrollments are not allowed to pursue the degree. This is one, but not the main reason for dropping out. Enrollment data show that many students abandon the study program during the first semester. However, the number of students who drop out after two or more semesters has not been investigated in detail yet.

There are 11 grades to mark an exam (1.0, 1.3, 1.7, 2.0, 2.3, 2.7, 3.0, 3.3, 3.7, 4.0, 5.0), with 1.0 being the best and 5.0 the worst. Grade 5.0 means failed, and students are required to repeat the exam if it was not their final attempt. For all other grades, the course is passed. In this study, we propose to aggregate the grades for better anonymization. We do this as follows: the values 1.0 and 1.3 are both mapped onto 1.3 (very good with distinction); 1.7 remains (very good); 2.0, 2.3, and 2.7 are all mapped onto 2.3 (good); 3.0, 3.3, and 3.7 are all mapped onto 3.3 (satisfactory); both 4.0 (pass) and 5.0 (fail) remain. It is possible for a student to enroll in a course and not take part in the exam; this is coded as NT in the data.

Each degree program has a study plan which describes all courses and the semester to which they belong. However, there is no obligation to adhere to this plan. There are two different types of courses: mandatory and elective. Mandatory courses form the basis of the study. Elective courses serve as a specialization and can be chosen from a pool of offers. If an elective course is not passed, another one can be chosen as an alternative.

Students are quite free in their studies: they do not have to complete the degree in six semesters and get no penalty if they take longer; they simply receive a warning and an invitation for special advice when they are in their third semester and have completed less than 30% of the foreseen credits. They might take semesters off, i.e., not enrolling in any course at all but still being registered and re-enroll afterward. In most German universities, there are no tuition fees, only some modest administration fees covering health insurance and public transport in the city. Some students take advantage of these benefits by remaining registered although they are not enrolled in any course and are no longer studying.

The goal of the exploratory study presented in the sequel is to provide heads of programs and student advisors with information based on data that can help them design interventions to reduce the number of students dropping out.

15.3.2 Graduating Versus Dropping out

The data exploration presented in this section attempts to answer the following questions: How many semesters do students take to complete the degree? How long do they remain enrolled before dropping out? How are enrollments and marks distributed over the courses? How do students who drop out compare with students who complete the degree? This overview information is helpful to reduce dropout rates; it may be also useful to reduce the time taken to graduate, which is, however, not the focus of this study.

In this pilot study, we are interested in investigating whether students drop out of the degree. As seen above in the German context, a student might still be registered in a degree program but, in reality, no longer studies. Therefore, we explore the data to capture when students drop out from the degree: we have calculated how many semesters off completing students take in a row. It turns out that only 8.8% of the graduates took semesters off. For most of them (84%), the break lasted only one semester. 8.7% took two semesters off in a row. Only 4.3% took three semesters away from their studies in a row. Longer breaks only occurred very sporadically. Therefore, students who have not graduated and not enrolled in any course for more than two consecutive semesters in a row are students who drop out in this study. It should be noted that this definition might classify as drop out a few outliers who take more than two consecutive semesters off without having given up yet their studies.

For the period considered in this pilot study, 788 students graduated, 868 dropped out from the degree, and the remaining 620 students are still studying. Figure 15.1 shows how many semesters graduating students take to complete their degree. About 35% of these students need exactly six semesters and about 66% need six or seven semesters. The outliers needing less than five semesters are students who completed courses in another degree program and transferred those courses to the program studied here. Figure 15.2 shows the number of semesters students spend in the program before dropping out. The highest number is in the first semester and

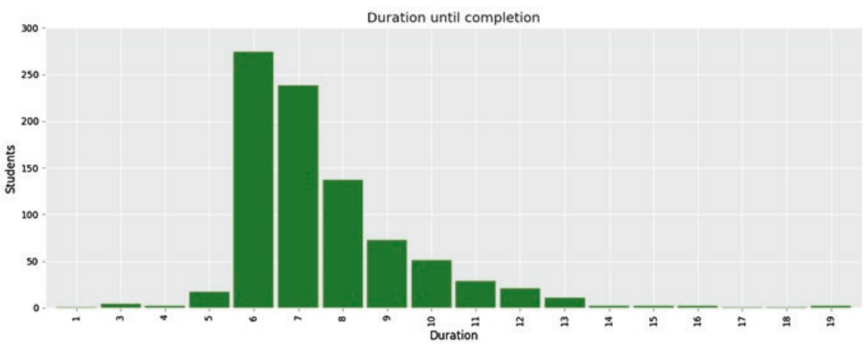

Fig. 15.1 Number of semesters until graduation

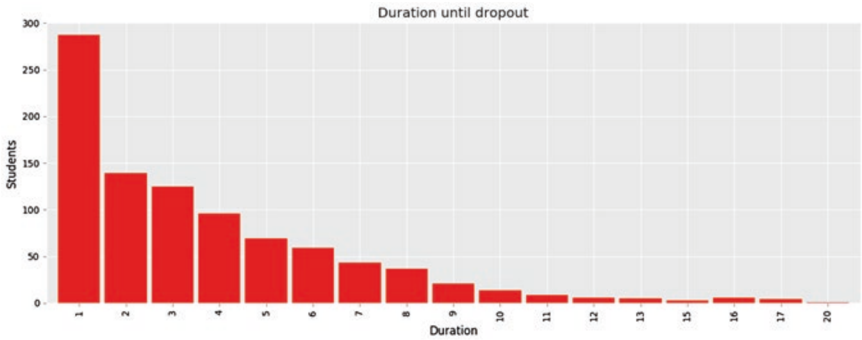

Fig. 15.2 Number of semesters until dropout

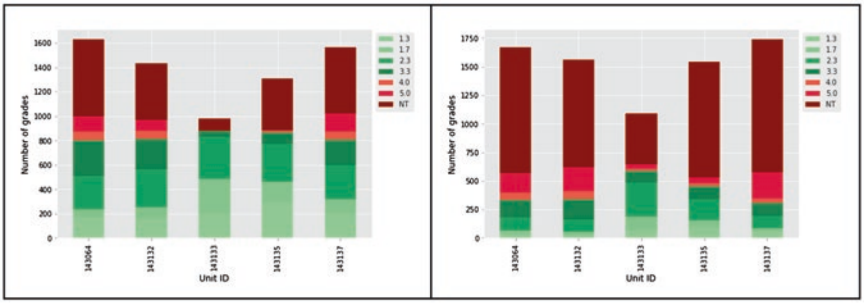

Fig. 15.3 Distribution of grades per course in the 1st semester – completing left, dropping out right

represents about 33% of the students who drop out, i.e., two-thirds of the students who drop out do so after studying two or more semesters in the program.

Based on Fig. 15.2, the focus of this section will now shift to the first semester, which contains only mandatory core courses for the study program. Figure 15.3 shows two diagrams, where the x-axis lists the courses from the first semester – denoted by their code – and the y-axis shows how many students have obtained each grade in each course. Note that a student may be counted several times in a column. For example, a student who does not take the exam at the end of the semester then fails the next exam and finally passes the next time with the mark 3.0 will be counted three times: once as NT, once as 5.0 and once as 3.0. The more a student is counted, the higher the column, which is an indicator of a difficult course. The different colors show the share of 1.3 (very light green), then 1.7 (light green), and so on till 5.0 (red) and finally NT (dark red) from bottom to top. The left diagram shows the counts for completing students and the right one for students who drop out. In all courses, the share of NT and 5.0 is much higher for students who drop out than for completing students. Notice that the scale of the y-axis goes higher in the diagram to the right (highest value 1750) than in the diagram to the left (1600), which means that the columns for students who dropout are even higher than shown in the diagram compared to the columns for completing students. Some students drop out although they received very good marks in some courses as every column in the diagram to the right includes a light green section that reflects students with the highest possible marks. One can also see that the courses Mathematics I (first and biggest column on the left of both diagrams) and Programming I (second biggest column on the right of both diagrams) have the biggest share of NT and 5.0 (failed) suggesting that these courses are more difficult because more students do not dare to attempt the exam or fail it.

15.3.3 Typical Completing Behaviors

In order to better address the high number of students who drop out and/or fail, it is useful to identify typical behaviors among completing students as doing so may provide a model of study to those students with difficulties and who might drop out.

To identify typical completion behaviors, the 787 completing students have been clustered. Students are represented by their marks and numbers of times they are enrolled in all mandatory courses. Elective courses are not included as prior research revealed that elective courses do not represent a barrier to students' success. This is partly due to the fact that students choose the courses they like the most from the pool of all elective courses. Marks and number of enrollments have the same order of magnitude, and, for both, the smaller the value the better (remember that 1.3 is a better mark than 1.7). Hence, these numbers have not been standardized for clustering. Clustering aims at grouping objects in clusters so that objects in one cluster are similar to each other and dissimilar to objects in other clusters. Clustering was undertaken using the classical algorithm K-means from the scikit-learn Python library. The K-means algorithm requires that the user chooses K, the number of clusters (see Han & Kamber, 2012). Using the technique known as the elbow curve (Han & Kamber, 2012) and the interpretability of the result, we fixed the number of clusters to four and number them 0, 1, 2, and 3. The centers of the four clusters are calculated as the average of all elements and depicted in Figs. 15.4 (grades) and 15.5 (number of enrollments). The courses are represented by their codes.

Cluster 3, the bottom black line, is the biggest cluster with 264 students. As reflected in Figs. 15.4 and 15.5, students in this cluster achieve the best marks in all compulsory courses; except for the case of two courses, they have the least number of enrollments and complete almost all courses within one semester. Cluster 2, the upper purple line, is the smallest cluster with 102 students and is almost the opposite of cluster 3. Students in this cluster have the biggest number of enrollments, the median in this cluster lies by 1.6, and, except for two courses, they have the worse marks. Students of cluster 0 (230 students) tend to have better marks than students of cluster 1 (191 students); in some courses, they have more enrollments; in other courses they have less. We have investigated further the number of enrollments in the different clusters with boxplots and found that students of cluster 1 tend to have more enrollments than students of cluster 0. Focusing on the marks only, these results bear strong similarities with those found in (Asif, Merceron, Ali, & Haider,

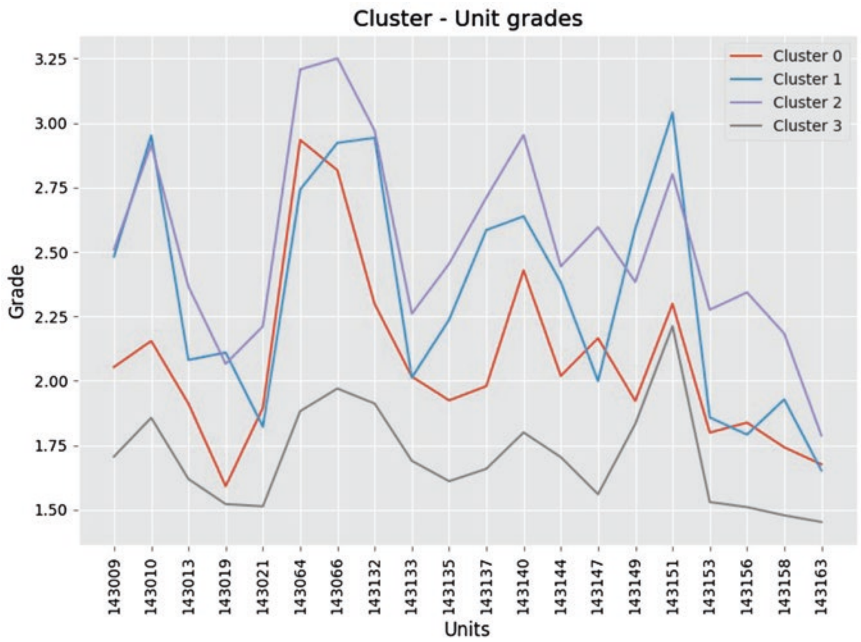

Fig. 15.4 Centers of the four clusters: grades reached in each course

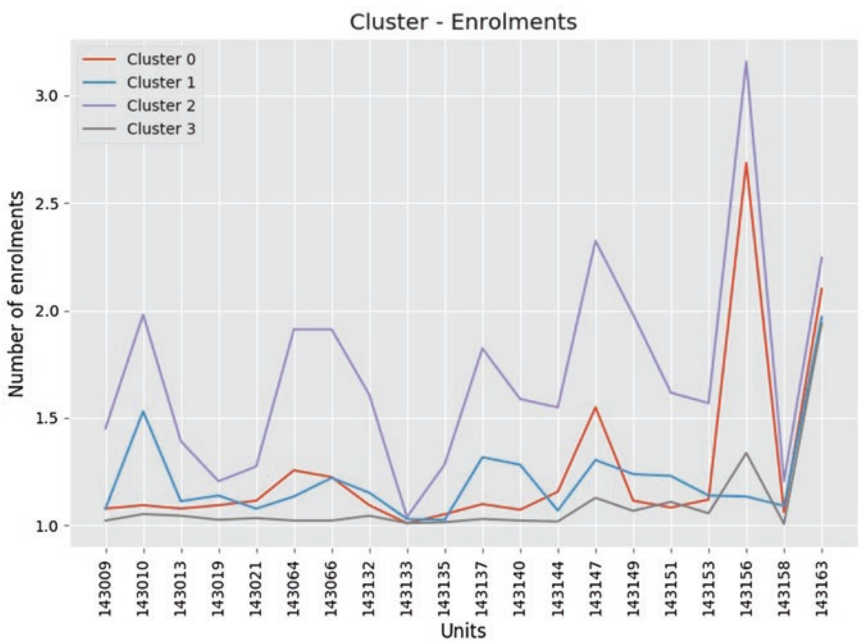

Fig. 15.5 Centers of the four clusters: number of enrollments in each course

2017): completing students tend to have the same kind of marks (good, average, or low) in all courses during the four years of their studies. Here too, students of cluster 3 have good marks, while students of cluster 2 have lower marks, and students of clusters 1 and 0 have intermediate marks in all compulsory courses of all semesters of the study program.

The number of enrollments per course does not reveal anything about the number of semesters necessary to graduate. Two students could have the same marks and enroll the same number of times, yet one could study part-time and needs 12 semesters to graduate, and the other could study full time and graduate in six semesters only. Further investigation shows that students in cluster 0 graduate the quickest, with a median of six semesters. It shows also that students of cluster 2 need the most time to graduate with a median of nine semesters. This result is similar to the finding of Campagni, Merlini, and Sprugnoli (2012)): students who take longer to complete the degree also have lower marks. Graduation time for students in clusters 0 and 1 is very similar: for both, the median is seven semesters.

15.3.4 Discussion

The data exploration shows that one-third of the students drop out in the first semester and that students continue to drop out in the next semesters. This indicates that interventions to reduce dropout rates have to target students at different time points of their studies. This pilot study suggests also that the reasons for dropping out are complex. One reason might be a lack of success as suggested by Fig. 15.3: students who drop out do not attempt or fail the exams in first-semester courses more often than completing students. However, some completing students do encounter difficulties from the beginning of their studies as shown by cluster 2. What distinguishes a persevering student (from cluster 2) from a student who drops out? Figure 15.3 shows also that students with some success in their first-year courses drop out. More research is needed to contrast and better understand what distinguishes students who drop out after one semester, two semesters, and three or more semesters from the students in cluster 2, who encounter difficulties but still succeed in completing their degree.

To build confidence within the university about this kind of research, it is important to involve all stakeholders. The first step involves gaining appropriate approvals from the data protection and security representative of the university (as has been done here). This study has been conducted with the help of six students who were giving their ideas, opinions, and points of view. All the results have been shown and discussed with the vice president of teaching and learning, three advisors/study program coordinators, and 12 faculty members involved in the study program. Their feedback was very positive. The pilot study is currently being extended to two other study programs to investigate invariants but also context-dependent constraints and results. This incremental and iterative process forms the basis for gaining more robust and trustworthy results and elaborates on the impact of diverse solutions for drop out avoidance, similar to results achieved by Georgia Tech University (McMurtrie, 2018).

These findings, though still limited, have already triggered ideas regarding initiatives the institution may put in place to reduce dropout rates. A first initiative is to introduce an information and counseling session at the beginning of the second semester, in addition to the one from the first semester, to provide guidance to students who are still in the degree program but might drop out. A second initiative is encouraging teaching staff to provide more support to struggling students and ensure their courses scaffold learning at the level of the learner. Another idea is to change the information activities for newcomers at the beginning of their first semester to help them overcome some anxiety that might build up in more difficult courses and provide better learning support. Finally, heads of study programs should be provided with data and diagrams similar to those of Fig. 15.3 as information for improving the design of the curriculum.

15.4 2nd Pilot Study

15.4.1 Context and Goals

The French project EOLE[2] (Engagement to Open Education – http://www.dune-eole.fr) aims at designing a different approach to education at the University, both in its modalities and in the enlargement of its target audience. The EOLE project includes the implementation and the test of learning analytics tools, under the responsibility of Université de Lorraine (France). The underlying goal is to support students' achievement by providing them with information on their learning activities: performance or behavior. To achieve this goal, a multi-profile team has been set up, including all the stakeholders of the LA project: teachers, students, vice-rectors, computer scientists, and researchers in data mining and data science, among others. This team works closely and has met regularly since the beginning of the project, 1year ago. The involvement of students in all steps of the project is a strong point of this project and of the approach adopted.

The LA action adopted in the EOLE project is divided into the following six traditional steps:

1. The design of a cartography of data sources, to determine which data is available and can be used in accordance with the General Data Protection Regulation (GDPR).
2. The development of a data infrastructure to store the learning traces.
3. The development of data mining algorithms to compute indicators from the data collected in both previous steps.
4. The design of dashboards to give feedback to students.

[2] French PIA DUNE call

In the EOLE project, it has been decided that each student can access course-level personalized dashboards. These dashboards display selected indicators that are presented and explained in the next section.

5. The support to teachers to structure their online courses.

   Most of the teachers involved in the EOLE project deliver face-to-face lectures and use the LMS platform only as a way to disseminate slides. One goal of the EOLE project is to develop a deeper usage of the LMS.

6. The deployment in real situations to test the pedagogical approach.

   An experiment was set up and started in September 2019, mainly with undergraduate students, in face-to-face or online teaching. The goal of the project is to evaluate if and how LA allow students to improve their academic performance and if they can help decrease dropout rates. To ensure broad representation, teachers from a diversity of disciplines are involved in the project.

It has taken the EOLE project a long time to reach this 6th and final step. In the following sections, we will focus on the fourth task of the project, i.e., the design of dashboards dedicated to students.

15.4.2 Design of a Student-Centered Dashboard

The literature defines self-regulated learning (SRL) as "an active, constructive process, where learners define their learning objectives and try to supervise, regulate and control their cognition, motivation behaviors, guided and constrained by their objectives and characteristics related to the environment" (Pintrich, 2000). In addition, Zimmerman (2002)) explains that the differences in learning success are mostly attributed to the self-regulation ability of learning, which are relevant to the initiation and maintenance of the learning process. Further, a recent study by Aljohani et al. (2019)) shows that student-centered dashboards increase student engagement (investment in time, etc.) more than teacher-centered dashboards (in the latter case, student engagement could be increased through the interaction between students and teachers). In this latter study, students can consult a dashboard giving them statistical, graphical, and textual feedback. The use of this dashboard has been tracked, and analysis shows that dashboard users are significantly more engaged (i.e., spend more time on the platform and have more activities on the forums).

As LA is a way to support students in the self-regulation of their learning, we designed a prototype dashboard that is targeting students. At the beginning of the project, students were invited to share their needs about setting up a learning analytics dashboard. A needs analysis was conducted with about 100 first-year students. The following list indicates the most recurrent needs in terms of indicators and features students expressed:

- Indicators should be sufficiently diversified so that every student can find those corresponding to their wishes.

Table 15.1 What feature students wishes in a dashboard?

Feature	Percentage of students (out of 88)
Individual progress	99%
Peers comparison	56%
Automatic advice	52%
Help other students	48%
Ask for advice	38%

- Obsession with indicators should be avoided.
- Indicators must be beneficial and easy to read.
- Indicators should value the advice between peers. Senior students should volunteer to mentor junior students.
- Advice about the methodology of academic work (organization, work methods) is welcome, not just help on course content.

Some of these comments have also been highlighted in a similar study (Schumacher & Ifenthaler, 2018). The comments allowed us to design the first student dashboard prototype, which was then presented to other students to obtain their feedback. More than 300 students, spread over several iterations, provided an opinion during the iterative and incremental co-design of the dashboard.

The dashboard is a tool made for the students' own interest, and it is not intended to constrain students. To ensure that it meets the students' interest, each iteration allowed students' opinions to be collected through a questionnaire. The first version of the dashboard (first iteration) was presented to 88 students along with questions about the features they thought they would use if they were made available. The results of this questionnaire are presented in Table 15.1. Although the literature highlights the comparison with peers, especially in higher education, only 56% of the students are in favor of this feature, i.e., nearly half of the students do not wish to compare themselves with classmates. In addition, five students (6%) expressed their fears and apprehensions about the impact of comparing themselves with peers in relation to their personal well-being. It was therefore decided that the peer comparison feature would only be displayed on demand by a student: students who want this feature have to explicitly request it on the dashboard. Other less requested features were not explicitly criticized by students, so we maintained them on the dashboard.

After three iterations, the final version of the dashboard has been designed (Fig. 15.6). It is also available at the following https://4gwzhg.axshare.com/#g=1&p=dashboard_aster2. Since this is an interactive and customizable dashboard, the best way to understand it is to interact with it directly online.

This dashboard displays indicators about the activity of a specific student in one of their courses. It is divided into two parts.

The first part (Fig. 15.6, left side) displays raw indicators of activity. This part is the most awaited functionality by the students: the individual performance (99% of students have declared they want it). There are three types of raw indicators in this dashboard:

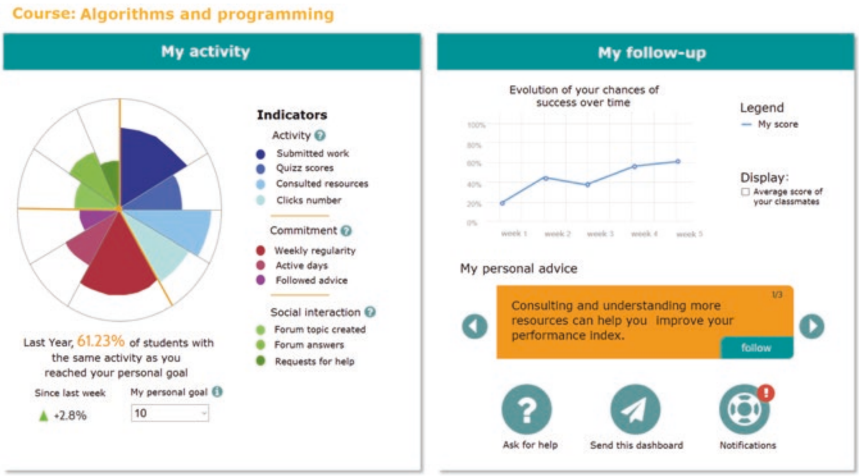

Fig. 15.6 Final version of the student dashboard

- Activity indicators (blue ones): number of submitted works, quiz scores, number of resources viewed, and the total number of actions on the course.
- Commitment indicators (red ones): number of active days, weekly regularity, and completed personal advice. The weekly regularity of a student has been adapted from (Boroujeni, Sharma, Kidziński, Lucignano, and Dillenbourg (2016), which shows not only that students easily understand the meaning of this indicator but also that they are interested in discovering if they are working less than in previous weeks. A personal advice, see the right part of Fig. 15.6, is a hint that is automatically generated from the learning traces; the system tracks whether students follow those hints.
- A correlation of 0.28 is observed between the weekly regularity that we have adapted and the course score. This correlation is calculated from the students' traces of activity enrolled in the course during the previous years and the final results of the students. With a p-value of 0.002, we can conclude that there is a significant link between the weekly regularity of student work and their academic performance.
- Collaboration indicators (green ones): number of created topics on the forum, number of answers, and number of times the student asked for help.

During the co-design iterations, most of the students put forward the fact that learning traces collected by the system only represent a partial view of their activity. Based on this feedback, the team decided to add an edit function, so that students can modify the indicators displayed on the dashboard. Thus, these data better reflect students' actual learning activity and students stay in control.

An additional indicator proposed in our dashboard, and requested by students, is the student's overall performance. Figure 15.7 shows this student's overall performance index. It is the odds percentage that a student achieves their personal goals.

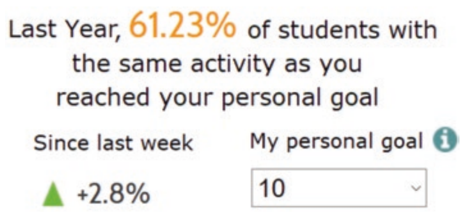

Fig. 15.7 The overall performance index and personal goal

The personal goal is the score (between 0 and 20, 20 is the highest possible score) that the student would like to achieve on the final exam.

We propose that students directly set their personal goals. So, the personal goal influences the student's overall performance and their odds of achieving it. For example, two students with the same value on two indicators, the one with an 18 as their personal goal, will not have the same odds percentage as a student with a 10 as their personal goal.

The second part of the dashboard (Fig. 15.6, right side) displays the evolution of the student's performance over time, in the form of a line chart. This is where students can choose to display the average performance of their classmates. Below this chart, personalized advice is provided to students to help improve their performance (orange rectangle). Students can choose whether or not they follow the advice, depending on their motivation. Finally, two action buttons allow students to ask for help. The first is dedicated to receiving help from the teacher. By clicking on this button, students accept to share the data displayed on their dashboard. The second one labeled "send this dashboard" only shares a capture at some time point of the dashboard associated with a question. Students choose who they want to share their dashboard with. A list of possibilities is proposed: a specific classmate, the class, a teacher, all teachers, etc. The last button is a notification queue to manage the actions of the first two buttons.

15.4.3 Usability of the Dashboard

The usability of the proposed dashboard has been evaluated with the System Usability Scale (SUS) (Bangor, Kortum, & Miller, 2008). Although this scale does not allow to strictly quantify the usability, the score obtained (between 0 and 100) allows locating the perceived usability of the dashboard by the student. 127 students took this test of the user experience. The results obtained are presented in Fig. 15.8.

We observe the 1st quartile at 65, the median at 75, and the third quartile at 85. The average score given is 74.12, the minimum 27.5, and the maximum 100. In UX Design Methods (Lallemand & Gronier, 2015), the authors propose an interpretation scale of the SUS score. Figure 15.9 presents the associated interpretation scale.

With an average score of 74.12, the dashboard proposed here is between "Good" (73) and Excellent (86), which is a promising result for our 1st live study, started in September 2019.

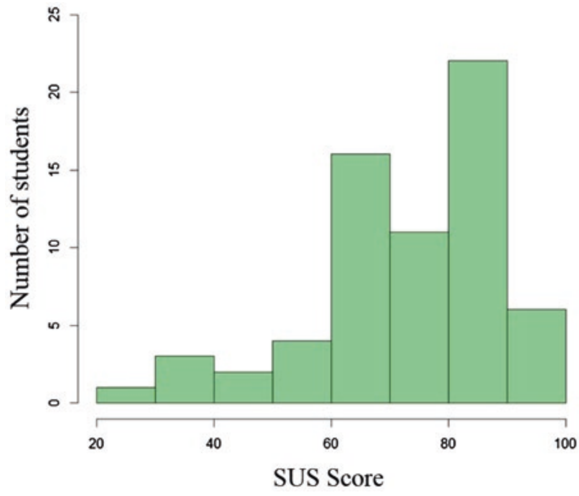

Fig. 15.8 SUS results distribution

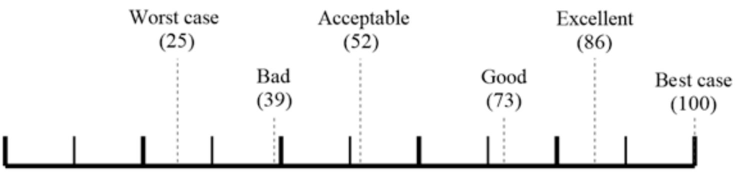

Fig. 15.9 Interpretation scale of SUS score

15.4.4 Discussion

The design of this student-centered dashboard has highlighted the differences in terms of students' expectations about the information to be displayed on a dashboard. Due to this diversity, allowing students to personalize their dashboard is a necessary feature for student adoption. In addition, there is a clear preference of students for factual activity indicators, based on raw observations.

Nevertheless, some of the students wish to set a personal goal for themselves and wish to receive personalized support to reach this goal. These requirements demonstrate the need of support for self-regulation learning for students. Besides, students seem to have less trouble asking for help through a dashboard (or a tool) than asking for help directly to the teacher during the class. Indeed, the "ask for help" feature is one of the first dashboard improvements students asked for. So, our dashboard is a way to fix one of the drawbacks of face-to-face teaching and may thus contribute to decreasing dropout rates.

The usability tests are also promising as they reveal a very good understanding of the dashboard by the students.

It remains to be seen how the students will actually use the dashboard and whether they will use the criteria they requested. We consider evaluating the use of this dashboard, not only in terms of frequency and regularity of usage but also in terms of the correlation with students' success, including an evaluation per indicator.

15.5 Conclusion

The two pilot studies presented in this chapter follow a similar goal of reducing dropout rates in higher education. To build confidence in the learning analytics that they implement, they both adopt an iterative and incremental methodology, and both follow recommendations from the community: (1) they involve all stakeholders in the design and implementation of their solutions as recommended in the Sheila framework (Sheila, 2018) and (2) they comply with the European General Data Protection Regulation (GDPR, 2018). These studies are complementary in the sense that they use different data about students, historical academic and activity data, and provide insights to different stakeholders.

In the first pilot study, the data of a degree program was mined, from its creation in 2005 to fall 2018. The analysis shows that one-third of the dropout cases occur during the first semester and that students continue to drop out after two, three, and more semesters, though there is a sharp decrease after the first semester. Comparing marks of the students who drop out and those of the completing students in the courses of the first semester, it is evident that completing students succeed better at the beginning of their studies than students who drop out. Clustering students according to their marks and their number of enrollments in all compulsory courses discloses a group of struggling students; these students need longer (median is nine semesters) to complete their studies, and their marks are in the second- or third-class honors, not in the first-class honors. This first pilot study is currently extended to include two more study programs and to predict students at-risk of dropping out of the degree (Wagner, Merceron, & Sauer, 2020).

What makes a struggling student persevere and complete the degree instead of dropping out? As already mentioned, Zimmerman (2002) explains that the differences in learning success are mostly attributed to self-regulation learning skills. Therefore, it is critical to support students in developing these skills. This is the aim of the second pilot study.

In the second pilot study, a dashboard was developed with and for students to support them in their studies. Students can see a summary of their activities in the LMS supporting the course every day. Students stay in control of what they see at their own request: they can update their score in some activity if they disagree with the visualized information. They can also set their learning objective and obtain the probability of achieving it. Furthermore, the dashboard displays tips for self-regulation, and a button is designed to make it easier for students to ask for help. This last feature is particularly important as it is known that students in need do not necessarily ask for help (Karumbaiah et al., 2019).

Based on the findings and lessons learned in each institution, we think that the next step is to integrate both solutions and conduct these studies on a common population of students to compare their usage of the dashboard and their academic performance, including their evolution through the semesters within their institution. A more advanced step will focus on the generalization of the findings from this next step to a larger set of European higher education institutions that may differ in the profile of their students.

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Chapter 16
Leadership and Maturity: How Do They Affect Learning Analytics Adoption in Latin America?

A Cross-Case Analysis in Four Latin American Universities

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16.1 Introduction

Higher education in Latin America has an urgent need for transformation, particularly in educating an increasingly diverse set of students (Ferreyra, Avitabile, Botero Álvarez, Haimovich Paz, & Urzúa, 2017; Knobel & Bernasconi, 2017; Reisberg, 2019). Although enrollment has expanded dramatically over the past two decades (Ferreyra et al., 2017), the region continues to adhere to a rigid and narrowly focused structure of programs (Knobel & Bernasconi, 2017; Reisberg, 2019). Latin American

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governments have implemented quality assurance policies to reinforce program improvement. However, a present issue is that not all universities have the capacity to continuously improve and innovate (Knobel & Bernasconi, 2017; Reisberg, 2019). As a consequence, students coming from socioeconomically disadvantaged backgrounds often have access to some lower-quality options, and an important percentage of them leave their programs in their first year (Ferreyra et al., 2017).

In this context, some researchers have suggested building capacity for institutional adoption of learning analytics (LA), so that Latin American universities can better leverage educational data to identify and meet students' needs (Cobo & Aguerrebere, 2018; Lemos dos Santos, Cechinel, Carvalho Nunes, & Ochoa, 2017). According to a recent study that assessed institutional needs for LA in Latin American universities, higher education stakeholders perceive that LA is a promising means for monitoring students' academic progress and workload at a curriculum level, in order to provide them with timely and personalized support (Hilliger et al., 2020). From current practice in the UK and other developed countries, researchers have argued that LA could become a valuable strategy for improving program quality, student performance, and retention rates (Gasevic, 2018; Sclater, Peasgood, & Mullan, 2016). As a result, there is growing interest in using LA to address similar educational challenges in Latin American and other developing countries (Gasevic, 2018; Sclater et al., 2016).

Although Latin American universities have started to measure and optimize teaching and learning processes through LA tools (Lemos dos Santos et al., 2017), there is still a long way to move from experimentation to full integration into institutional practice (Cobo & Aguerrebere, 2018). On the one hand, most efforts are still at an exploratory stage (Cobo & Aguerrebere, 2018), and most universities lack the maturity required for installing LA tools as an institutional capacity. On the other hand, only few universities have incorporated LA into institutional processes (Lemos dos Santos et al., 2017), which demonstrates a lack of leadership for pushing LA initiatives to address current educational needs. Considering that LA is still an emerging research field, its overall potential is higher than the actual evidence (Viberg, Hatakka, Bälter, & Mavroudi, 2018). Little is known about the leadership processes and the organizational maturity for adopting LA tools in diverse university settings. Thus, more cross-case studies are needed to understand how to transfer the potential of LA into universities with different levels of organizational maturity and leadership processes (Scheffel, 2017; Viberg et al., 2018).

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To enlarge the literature on LA adoption in Latin America and understand how universities of this region could evolve from experimenting with educational data to institutional transformation, this study presents and analyzes the cases of four Latin American universities. In this analysis, the following research question is addressed: *how do leadership processes and organizational maturity in different Latin American universities affect the adoption of LA initiatives?* These cases are part of a multinational project funded by the European Commission Erasmus+ Program, LALA project (https://www.lalaproject.org/). The project aims to build institutional capacity for LA adoption in the region, and one of its objectives is to create or adapt LA tools for Latin American universities (Maldonado-Mahauad et al., 2018). Thus, the LALA project offers the opportunity to explore how different institutions adapted and adopted similar LA tools.

To identify similarities and differences across the four cases, we conducted a cross-case analysis focusing on two dimensions: (1) leadership processes to effectively involve diverse stakeholders in the adoption of LA tools and (2) organizational maturity to analyze and act upon educational data. The leadership dimension is determined according to the definitions proposed by Dawson et al. (2018), which were built upon the complexity leadership theory (CLT) by Lichtenstein et al., (2006). This theory has been already alluded to in prior work to understand how leadership processes effectively lead to incorporation of LA tools at an institutional level (Tsai, Poquet, Gašević, Dawson, & Pardo, 2019). The organizational maturity dimension builds upon prior work conducted by Bichsel, (2012) and Siemens, Dawson, and Lynch (2013). These authors define organizational maturity as the capacity to work with educational data and develop LA tools to inform institutional practice. Further details about each case and its cross-analysis are explained in the next section, followed by the study findings and the lessons learned to facilitate LA adoption in Latin America. Thus, this study provides new evidence on the process of adopting LA in the Latin American context, aiming to contribute to it with useful insights about what it takes to move LA adoption forward in the region.

16.2 Methods

16.2.1 Research Design

In this study, we address the following research question: *how do leadership processes and organizational maturity in different Latin American universities affect the adoption of LA initiatives?* In order to answer this question, we followed a two-step procedure. First, we carried out a case study with four Latin American universities that had adopted LA tools at an institutional level. Second, we conducted a cross-case analysis to identify similarities and differences in terms of leadership processes and organizational maturity to analyze and act upon educational data.

16.2.2 Research Context

We chose four Latin America universities that are affiliated with the LALA project as our research context. These universities share a timeline for adapting and adopting similar LA tools, so it provides the opportunity to understand LA adoption in four different institutions in a common period of time. These universities differ in size, type of administration, and year of foundation, so their contrasts provided the opportunity to explore similarities and differences in organizational maturity and leadership processes. Also, two are traditional private universities in Chile and two are public universities in Ecuador, which allows comparing two different higher education systems.

- *Case 1: Adoption of NoteMyProgress in Pontificia Universidad Católica de Chile (PUC-Chile).* The PUC-Chile is one of the most prestigious pontifical universities in Chile and in Latin America. It was founded by a legislative decree in 1888, and it was conferred full academic and administrative autonomy in the late 1920s. Over the last century, it has become a large and selective institution, having currently 5 campuses and over 1200 full-time faculty members to serve 32,500 undergraduate and 5400 graduate students. Recently, this university started developing massive open online courses (MOOCs) and looking for new models to incorporate them as part of its regular programs. To support students in this process, the university launched an LA initiative to explore and support their self-regulatory abilities to deal with these new MOOC-based initiatives.
- *Case 2: Adoption of TrAC in Universidad Austral de Chile (UACh).* The UACh is a nonprofit traditional private university in Chile. Since its foundation in the 1950s, the university has focused on expanding higher education in the southern region of the country, priding itself as a preponderant social actor in widening educational access. Currently, the university has 16,700 undergraduate students, 850 postgraduate students, and 750 full-time faculty members. Due to the socioeconomic characteristics of its students, one of the main problems of the university is the dropout rates of the first-year students, as well as the time students take for completing their degree programs. To deal with that, in the past 2 years, the institution has been working on the implementation of an LA solution for student academic counseling.
- *Case 3: Adoption of a redesigned academic counseling system in Escuela Politécnica del Litoral (ESPOL).* ESPOL is a public polytechnic university that was founded in Ecuador in the late 1960s. The university has a focus on engineering-related degrees across eight faculties. The main campus holds approximately 1000 full-time faculty members and 12,000 students, including 10,300 undergraduate and 1700 postgraduate programs. This university has been working, in the past years, on a students' counseling tool to reduce dropout and failing rates among its students.
- *Case 4: Adoption of dashboards in Universidad de Cuenca (UCuenca).* The UCuenca is a public institution located in the center of the south region of Ecuador. It was founded by a legislative decree in 1867. The university's mission

is to train professionals and scientists committed to improving the quality of life in intercultural settings and in harmony with nature. Currently, it has five campuses that count with about 1200 full-time faculty members, 16,600 undergraduate students across 12 faculties, and 930 postgraduate students. This university had no previous experience in LA at the time of the study, but their leaders recognized LA as a powerful tool to support students in their learning process. As a result, two LA dashboards have been introduced to provide teaching staff and counselors with information about students' curriculum progress and academic performance.

16.2.3 Data Collection

We collected data in two phases. The first phase involved sending a questionnaire to four researchers affiliated with the LALA project (one researcher per Latin American university) to collect information about the adoption of LA initiatives. The questionnaire consisted of the following open-ended questions:

- What educational need was intended to be addressed with the LA tool adopted at your institution as part of the LALA project?
- Who did you have to involve and convince to adopt this LA tool?
- What was the process you undertook to adapt and adopt the LA tool in your institution?
- Is the adoption of the LA tool meant to enhance any existing process of educational support?

In the second phase, a follow-up questionnaire was distributed to the same researchers who have participated in the previous stage. The researchers were invited to provide information about the stakeholders that were involved in the adoption of LA tools, the processes undertaken, and the results obtained in each of the four tool development phases (Broos et al., 2020):

- Diagnostic phase: this phase (narrowed down from the initiation phase in Broos et al., 2020) is dedicated to understanding institutional needs for LA tools.
- Design/prototyping phase: this phase is dedicated to designing LA tools that can meet the needs identified in the diagnostic phase.
- Piloting phase: this phase is dedicated to piloting LA tools and evaluating the results.
- Scaling-up phase: this phase is dedicated to identifying actions that can embed the adopted LA tools into institutional processes.

In order to gain a comprehensive view of LA adoption in the four institutions, we triangulated the data collected from the two questionnaires with project documentation, including technical information and instructions about the adopted tools (https://www.lalaproject.org/demo/) and the project deliverable titled "Design of Learning Analytics Tools" (http://bit.ly/35yS93A).

16.2.4 Data Analysis

The data analysis also consisted of a two-step procedure. The first step was to analyze individual cases and create a detailed description of the tool development process. We hand-coded the answers to the two questionnaires with respect to the institutional need addressed by the tool developed, the stakeholders involved throughout the process, the processes undertaken for tool deployment, and the results obtained from each phase. The codes used were stakeholders, leadership processes (bottom-up and top-down), implementation phases (diagnostic, design/prototyping, piloting, and scaling up), and maturity of the tool implemented.

The second step involved a cross-case analysis to identify similarities and differences regarding (1) leadership processes to involve diverse stakeholders in LA tool adoption and (2) organizational maturity to analyze and act upon educational data. For this step, we used a schema to represent the current state of LA adoption in each university in terms of leadership processes and organizational maturity (see Fig. 16.1). The leadership axis indicates a spectrum between top-down and bottom-up leadership processes defined by Dawson et al., (2018) and inspired by the complexity leadership theory (CLT) by Lichtenstein et al. (2006). The top-down processes correspond to LA initiatives that are mainly led by senior managers such as vice provosts, without necessarily involving LA ground-level staff throughout the tool development process. In contrast, a bottom-up process corresponds to LA initiatives mainly led by ground-level staff, such as researchers, teaching staff, and counselors, without necessarily involving senior managers throughout the tool development processes. Organizational maturity is described as the capacity to

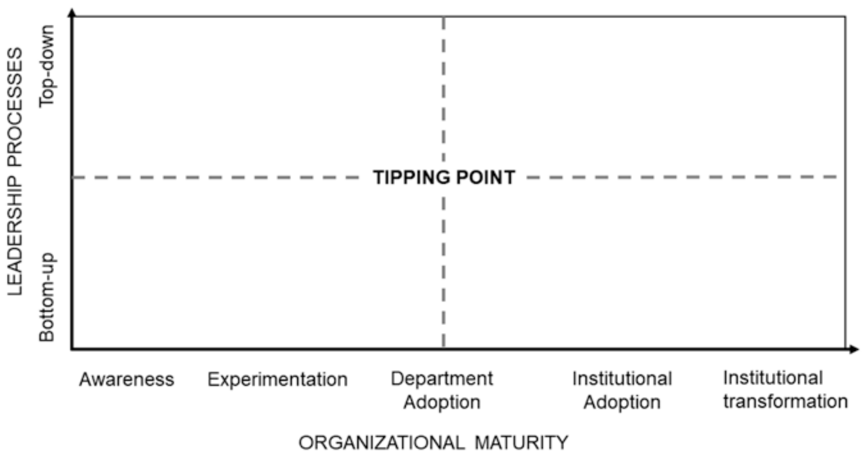

Fig. 16.1 Schema for comparing the current state of LA adoption in different institutions in terms of leadership processes and organizational maturity to analyze and act upon educational data. The tipping point indicates the state in which both senior managers and ground-level staff are interacting to effectively adopt an LA tool at a department level

work with educational data and develop LA tools to inform institutional practice (Bichsel, 2012). This axis is organized into five stages according to the concepts adopted from the LA sophistication model proposed by Siemens et al. (2013):

1. Awareness (basic understanding of LA tools and methods)
2. Experimentation (small-scale efforts for exploring how educational data could be used at a research or management level)
3. Department adoption (department efforts for integrating the use of educational data into staff and/or student practices)
4. Institutional adoption (institutional efforts for integrating analytics tools into staff and/or student practices)
5. Institutional transformation (institutional efforts for integrating analytics tools and evaluating its impact on student outcomes and learning and teaching practices)

16.3 Case Descriptions

Each one of the following subsections describes one of the cases selected for the cross-case analysis. Each case presents the leadership processes conducted for institutional adoption of LA tools, besides describing institutional aspects that reveal the organizational maturity for working with educational data and developing LA tools to inform institutional practice.

16.3.1 Adoption of NoteMyProgress in PUC-Chile

In PUC-Chile, LA researchers designed and implemented a tool called NoteMyProgress (NMP). This tool aims to support students' self-regulation strategies, in order to help them succeed in MOOC-based institutional initiatives. Through interactive visualizations, NMP offers aggregated data about the students' activity in the online courses and interactions with the course contents (see Fig. 16.2).

The need for designing and implementing NMP emerged from three research projects conducted by a researcher in the institution that aimed to understand student self-regulation strategies in MOOC-based initiatives. These three projects were also related with an institutional initiative launched in PUC-Chile to develop MOOCs using the Coursera platform and hybrid educational models to integrate them into traditional courses. Therefore, the interest of this LA initiative, in which data for MOOCs was leveraged at institutional level, was twofold: to understand students' self-regulated learning strategies and to propose solutions for promoting strategies to help students succeed in MOOC-based institutional initiatives.

The NMP was designed following the interactive learning design (ILD) framework created by Bannan, (2003). Table 16.1 summarizes all the phases followed for the adoption of NMP, from the diagnostic to the scaling-up phase. During the *diagnostic*

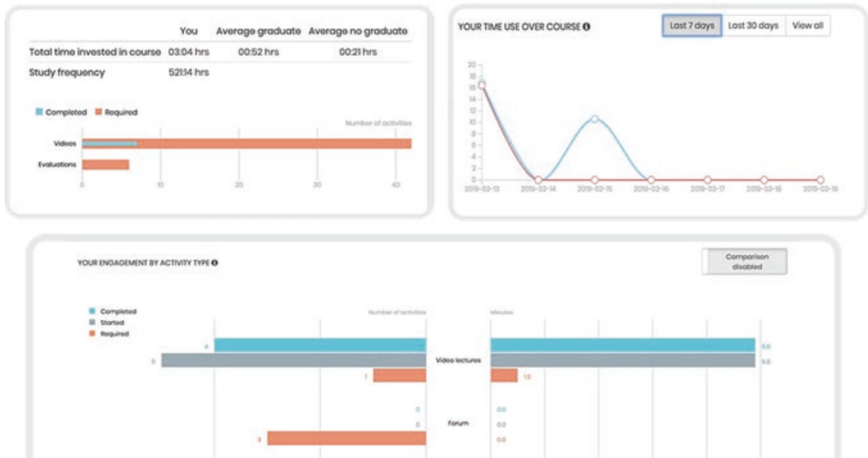

Fig. 16.2 Screenshot of the NoteMyProgress (NMP) tool, a learning analytics tool proposed at the Pontificia Universidad Católica de Chile (PUC-Chile) to support and promote students' self-regulatory abilities to help them succeed in MOOC-based institutional initiatives

phase, the researchers who were LALA project representatives conducted a literature review on analytical solutions for supporting self-regulatory strategies in online settings. With the results of this review, they developed the first version of the tool (Pérez-Álvarez, Maldonado-Mahauad, & Pérez-Sanagustín, 2018). In the *design/prototyping phase*, a first prototype of NMP generated 2 instrumental case studies for evaluating its usability and usefulness, one with 3 experts and 7 students affiliated to PUC-Chile and another one with 126 students from 10 different countries who registered in 3 MOOCs developed in PUC-Chile. The results of these instrumental case studies informed a new version of the tool ready to be tested in actual MOOC-based initiatives. Then, in the *piloting phase*, two pilots were proposed. The first one was conducted on three MOOCs created by PUC-Chile, collecting information from 236 students all over the world. The second one was conducted in four courses in Coursera created by Universidad de Chile. The results of the first pilot provided evidence on the effectiveness of this tool in supporting self-regulatory abilities in MOOC-based institutional initiatives. This evidence was used by LALA project representatives to start conversations with the dean and the associate dean for engineering education in PUC-Chile, initiating the *scaling-up phase*. The main objectives in this phase is to install NMP as a service of the engineering education unit, considering that the PUC currently offers 91 MOOCs with about 410.000 students enrolled.

16.3.2 Adoption of TrAC in UACh

In UACh, LA researchers developed an analytics tool called TrAC to support program chairs in their responsibility to lead academic counseling processes. TrAC provides program chairs with information about students' academic progress in relation

Table 16.1 Phases for the adoption of the analytics tool NoteMyProgress in PUC-Chile

Phases	Stakeholders involved	Processes undertaken	Results obtained
Diagnostic	LA researchers at PUC-Chile	Literature review on learning analytics tools for supporting self-regulated learning strategies	Requirements for an LA tool to develop students' strategies for self-regulated learning in MOOC-based initiatives.
Design/ prototyping	LA researchers at PUC-Chile LA experts and students from PUC-Chile Students from different countries	Design-based approach based on two instrumental case studies	A first version of a tool for the development of self-regulated learning skills
Piloting	LA researchers at PUC-Chile and Universidad de Chile Students from different countries	Evaluation of tool implementation in PUC-Chile and Universidad de Chile	Data collected from online and face-to-face activities to evaluate the use of the tool in different educational settings
Scaling up	Dean of engineering school at PUC-Chile Associate dean for engineering education at PUC-Chile Managers and teaching staff from PUC-Chile and other universities	Discussion with PUC-Chile staff and staff from other universities about the implementation of new experiences of the tool, besides installing it as a service in PUC-Chile engineering education unit	Proposal for scaling up the implementation of the tool at PUC-Chile and other universities

Each phase includes information about the involved stakeholders, the undertaken processes, and the obtained results

to the curriculum study plan and their academic performance. Figure 16.3 shows the dashboard provided to program chairs by TrAC, in which they can visualize the courses a student has to take, highlighting in green those that the student has already passed and in red those that the student failed. The main aim of this LA solution is to help program chairs identify students who are at risk of falling behind and eventually dropping out of a study program, in order to offer them timely support.

TrAC was developed in the context of the LALA project, and its design was based on the LISSA dashboard developed in• KULeuven (Charleer, Moere, Klerkx, Verbert, & Laet, 2018). In order to adapt LISSA to the UACh context, LA researchers followed an agile software development lifecycle (Chevreux, Henríquez, Guerra, & Sheihing, 2019) involving different stakeholders in a participatory design process. Table 16.2 summarizes all the phases followed for the design and implementation of TrAC.

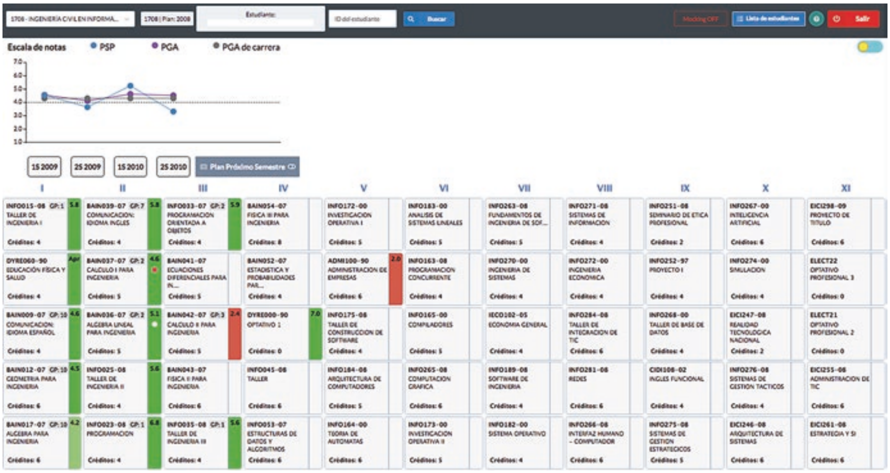

Fig. 16.3 Screenshot of the TrAC, a counseling LA tool developed at the Universidad Austral de Chile (UACh). This visualization shows the study plan of a student, highlighting in green those courses that the student has already passed and in red those that the student failed

During the *diagnostic phase*, the researchers who were LALA project representatives coordinated a set of participatory activities (as described in the institutional dimension of the LALA framework developed by Pérez-Sanagustín et al. (2018)), including interviews, focus groups, and questionnaires with different stakeholders: the learning support unit, academic registration unit, the IT office, and the different schools and program chairs. The results of this phase lead to a set of needs and requirements for the tool adaptation, besides identifying data access and privacy issues to be addressed throughout the following tool development phases. During the *prototyping phase*, these researchers coordinated several codesign sessions in which semi-functional prototypes were evaluated in order to develop, incrementally, a first functional prototype of the tool. The key stakeholders in this phase were the program chairs (intended final users) and the director of the undergraduate studies. This last actor played a key role, because he facilitated the socialization of the tool with the learning support unit, the academic registration unit, the IT office, and the program chairs of different faculties. At the end of this phase, a functional prototype of the tool was obtained for the *piloting phase*. In this phase, 17 program chairs used TrAC during course enrollment and withdrawal. The IT office was also involved as the stakeholder in charge of solving technical problems and registering possible improvements for next versions of the tool. At the end of this phase, data was collected and analyzed for analyzing the tool implementation. After the piloting phase, the data collected was analyzed for tool improvement, in order to scale it up at an institutional level. Therefore, LA researchers are still working with the IT office and the director of undergraduate studies in the *scaling-up phase*, in order to adopt the tool at an institutional level.

Table 16.2 Phases for the adoption of the analytics tool TrAC in UACh

Phases	Stakeholders involved	Processes undertaken	Results obtained
Diagnostic	LA researchers at UACh Teaching staff Students Program chairs Director of undergraduate studies IT office Learning support unit	Participatory activities, interviews, focus groups, and questionnaires conducted in the context of the LALA project	Needs for an LA tool to help students to make informed decisions based on their academic trajectory
Design/prototyping	LA researchers at UACh Program chairs Director of undergraduate studies IT office Learning support unit Academic registration unit	Agile software development lifecycle based on iteration and semi-functional prototypes	Validated design of the TrAC tool (including data integration)
Piloting	Program chairs/teaching staff IT office	Surveys and focus groups with program chairs	Data collected to evaluate the use of the tool
Scaling up	Program chairs/teaching staff Students Director of undergraduate studies Learning support unit IT office Dean of engineering school	Collaborative work among LA researchers, the IT office, and the director of undergraduate studies	Proposal for wide adoption of the tool, including students as new users

For each phase, this table shows the stakeholders involved, the processes undertaken, and the results obtained

16.3.3 Adoption of the Redesigned Academic Counseling System in ESPOL

In ESPOL, teaching staff had already an academic counseling system to help students with course enrollment and academic planning. This system provided teaching staff with valuable information, such as a report about the courses taken by

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Historial académico en linea

Buscar:

Año	Término	Materia	Promedio	Vez Tomada	Nota 1	Nota 2	Nota 3	Estado	Profesor
2017	2S	DESARROLLO DE APLICACIONES WEB	9.8	1	97.0	97.0	0.0	APROBADA	
2017	2S	INTERACCIÓN HUMANO COMPUTADOR	8.78	1	90.0	82.0	0.0	APROBADA	
2017	2S	METODOLOGÍA DE LA INVESTIGACIÓN EN COMPUTACIÓN	9.05	1	89.0	92.0	0.0	APROBADA	
2017	2S	PROCESAMIENTO DIGITAL DE IMÁGENES	8.85	1	93.0	84.0	0.0	APROBADA	
2017	2S	SISTEMAS DE INFORMACIÓN	8.9	1	92.0	86.0	0.0	APROBADA	

Fig. 16.4 Screenshot of the academic history report in the existing academic counseling system in the Escuela Superior Politécnica del Litoral (ESPOL)

students (academic history) as the one shown in Fig. 16.4. However, this system did not provide enough data nor visualizations to help teachers see the academic history of students and plan the courses for the upcoming semester, so it did not allow teaching staff to guide students as they enroll courses for the upcoming semester. Given this situation, the researchers who were LALA project representatives decided to develop new visualizations to improve this tool. Table 16.3 summarizes all the phases followed for the adoption of the new visualizations for the academic counseling system.

To redesign the system, the researchers who were LALA project representatives adopted an iterative and user-centered methodology, which combined design thinking concepts with human computer interaction (Ortiz-Rojas, Maya, Jimenez, Hilliger, & Chiluiza, 2019). Firstly, in the *diagnostic phase*, these researchers involved the vice provost for academic affairs to obtain his approval for educational data gathering and his support for the system redesign. They also involved teaching staff, students, and other middle managers in participatory sessions, including focus groups, interviews, and questions (as described in the institutional dimension of the LALA framework developed by Pérez-Sanagustín et al. (2018)). As a result of this phase, a list of needs was collected and translated into requirements for a new version of the tool. Secondly, the researchers started the *design/prototyping phase*, in which they run several meetings with teaching staff. The meetings were organized following a methodology based on design thinking principles, providing staff members with different prototypes of visualizations to capture teaching staff perspectives.

Figure 16.5 presents a screenshot of the new visualization developed after iterating different prototype versions, which provides teaching staff with information about the study plan of their students. For every student, this new visualization highlights courses passed at first chance with a green checkmark, those passed at

Table 16.3 Phases for adoption of the new visualizations for the academic counseling system in ESPOL

Phases	Stakeholders involved	Processes undertaken	Results obtained
Diagnostic	LA researchers at ESPOL Vice provost for academic affairs Other institutional leaders Teaching staff Students	Participatory activities, interviews, focus groups, and questionnaires conducted in the context of the LALA project	Needs for redesigning the visualizations of the existing academic counseling system
Design/ prototyping	LA researchers at ESPOL Teaching staff	Use of an iterative methodology for software design based on design thinking principles	A first version of the new visualizations
Piloting/ scaling up	Teaching staff	Application of knowledge test and a pretest survey to collect information about tool visualization satisfaction, usability, and functionalities at the end of the training session offered to all teaching staff members	Data collected about the tool usability and the need for improvements
		Implementation of the new visualizations in the existing academic counseling system Posttest survey about tool visualization satisfaction	Data collection from teachers' perception and log files usage

For each phase, this table shows the stakeholders involved, the processes undertaken, and the results obtained

second chance with a yellow one, and those failed with a red cross. This new visualization evolved directly from a tool design phase to a *piloting/scaling-up phase*, because the vice provost requested the LALA project representatives to scale up the new version tool to the entire teaching staff. To avoid anxiety issues due to the changes in the current visualizations, all teaching staff members were invited to a face-to-face training session to help them use the new visualizations. This training session helped teaching staff to understand the need for redesigning the system, and they ended up convinced that the change was beneficial for students. LA researchers collected data at the end of the training session and after the tool was implemented across faculties, and the results show that teaching staff satisfaction increased with the implementation of the new visualizations.

As a consequence of the positive results, the LA researchers have already incorporated the new visualizations into the current academic counseling system, and these visualizations have already been used by approximately 300 teaching staff (who advise about 7000 students). In order to help students, the new visualizations are being used at the beginning and in the middle of each of the semester, and it is expected to evaluate further adoption of the tool by means of log data analysis and teaching staff feedback.

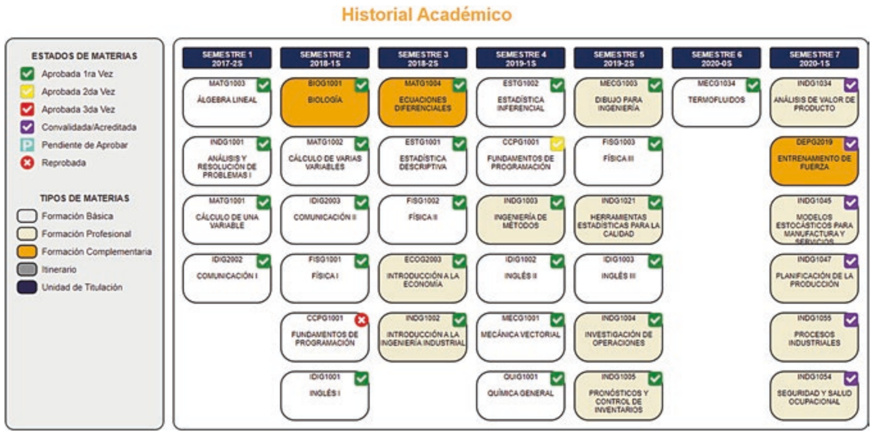

Fig. 16.5 Screenshot of the new visualization of the academic history in the counseling system adopted at the Escuela Superior Politécnica del Litoral (ESPOL). The green check mark highlights those courses of the study plan that the student passed in the first sitting, the yellow one those the student passed in the second sitting, and the red cross those the student failed

16.3.4 Adoption of Dashboards in UCuenca

In UCuenca, both decision-makers and researchers coordinated an LA initiative for developing a counseling dashboard from scratch, aiming to deal with first-year dropout rates. Since the university had no previous experience in LA, LALA project representatives decided to work collaboratively with the dean and the associate dean of the engineering faculty, in order to at least have department-level support for the adoption of this initiative. Table 16.4 summarizes all the phases followed for the adoption of this dashboard, which were also based on the LISSA dashboard developed in KULeuven (Charleer et al., 2018).

During the *diagnostic phase*, the LALA project representatives conducted different participatory activities, including questionnaires, focus groups, and interviews, with program chairs, teaching staff, students, and the IT director (as described in the institutional dimension of the LALA framework developed by Pérez-Sanagustín et al. (2018)). In addition to identifying the need for a counseling tool, the process of data collection was an opportunity to raise awareness about the potential of leveraging educational data. As a result, the IT staff got also involved, helping with data availability and technological resources. As a result of this phase, the LALA project representatives developed a report with the requirements for designing a counseling dashboard to provide teaching staff, counselors, and program chairs with information about students' academic progress.

During the *design/prototyping phase*, researchers developed two dashboards: one for teaching staff and another one for counselors and program chairs. Firstly, the teaching staff dashboard provides teachers with information about the academic

Table 16.4 Phases for the adoption of dashboards in UCuenca

Phases	Stakeholders involved	Processes undertaken	Results obtained
Diagnostic	LA researchers at UCuenca Dean of the engineering faculty Associate dean of the engineering faculty Program chairs of the engineering faculty IT director Teaching staff Students	Participatory activities, interviews, focus groups, and questionnaires conducted in the context of the LALA project	Needs for an LA tool to support the counseling process
Design/ prototyping	LA researchers at UCuenca Engineering students Engineering teaching staff Program chairs of the engineering faculty IT office Rector	Design-based approach based on several iterations with low-fidelity and high-fidelity prototypes	A first beta version of the dashboards
Piloting	LA researchers at UCuenca Students Faculties: engineering chemical sciences, hospitality sciences, economic and administrative sciences Teaching staff of the faculties: engineering chemical sciences, hospitality sciences, economic and IT office	Integrating the use of the dashboards in the faculties: engineering, chemical sciences, hospitality sciences, economic and administrative sciences Faculties' staff has been trained. Some people think using the tools could represent an additional workload	Data collected about the tool usability and the need for improvements
Scaling up	Program chairs/teaching staff Students Institutional leaders	Adaptation of the dashboards to the requirements of other faculties	Project proposal for institutional adoption

performance of the students in their course, so that they can implement actions to support students at risk of failing their courses. Figure 16.6 shows a screenshot with the information provided in this case. In particular, it shows a line for each of the students registered in a course and their performance in the course evaluations. Secondly, the counselors' dashboard provides academic information about the students' performance and progress according to their study plans. Figure 16.7 shows the study plan of a particular student, highlighting courses passed with a green line, courses failed with a red line, and courses currently being taken with a blue line. This dashboard also includes visualizations of the students' grade point average and the number of courses taken per semester. The idea was to provide information to

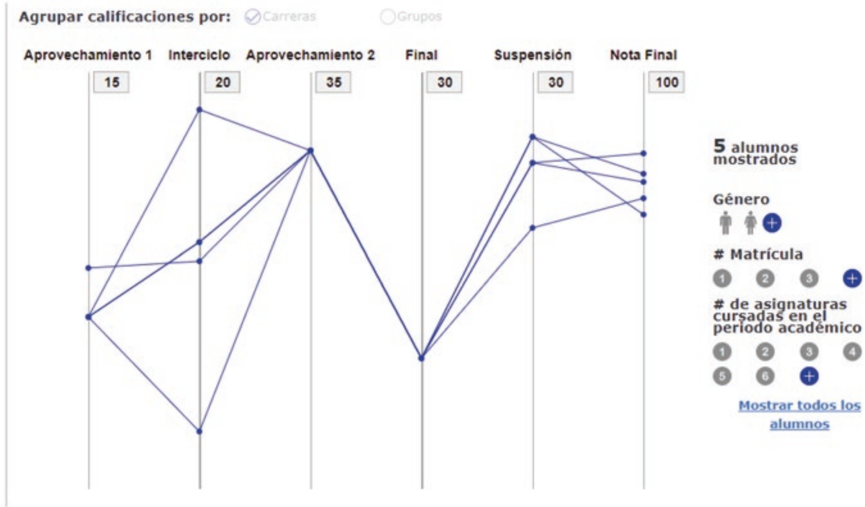

Fig. 16.6 Screenshot of the teaching staff dashboard developed by the Universidad de Cuenca (UCuenca). Each line corresponds to a student registered in the course, showing his/her performance in different assessment methods

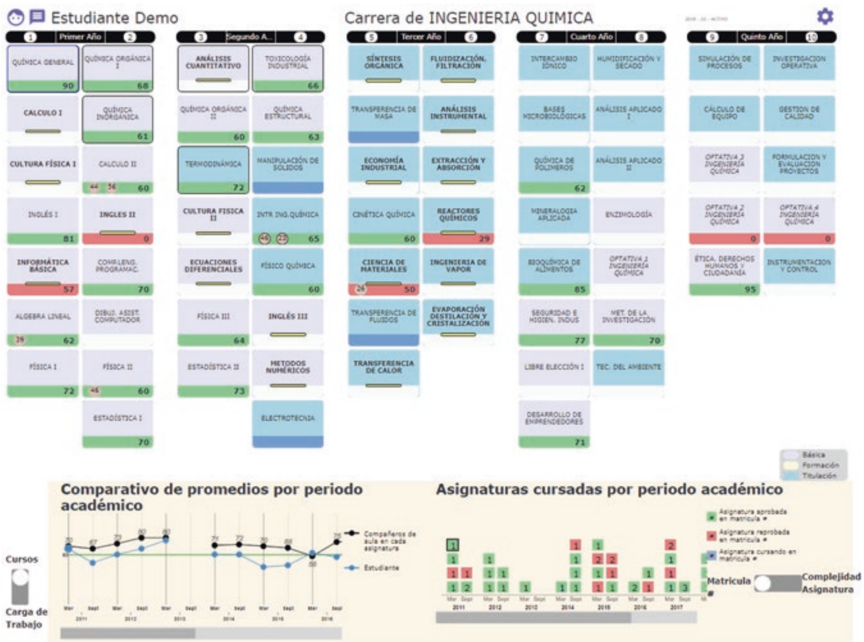

Fig. 16.7 Screenshot of the counselor dashboard developed by the Universidad de Cuenca (UCuenca). On the top, it shows different courses of the study plan, highlighting courses passed with a green line, courses failed with a red line, and courses currently being taken with a blue line. At the bottom, it shows students' grade point average and the number of courses taken per semester

the counselors and program chairs, so they can help students to make informed decisions regarding course enrollment and academic planning.

After several iterations, the LALA project representatives and the IT office had enough information to develop a first functional tool. This tool was presented to the rector to ask for support for the piloting phase. Although the *piloting phase* has not been conducted yet, researchers have already prepared a plan to pilot the two dashboards in four faculties, using real data of students' academic performance. The teachers' dashboard will be used by the engineering teaching staff, where each staff member will have access to academic information of the students enrolled in their courses. The counseling dashboard is planned to be used in counseling sessions among four program chairs and students enrolled in their programs. In this phase, the researchers affiliated to the LALA project will collect data before and after piloting, with the aim of understanding the impact of using the tool. If there is wide acceptance of the tool, the researchers plan to move forward to the *scaling-up phase* by promoting the use of the dashboards in other faculties. However, researchers already anticipate some barriers in this last phase, due to the lack of LA culture in the institution and the need for institutional processes in order to integrate the use of the dashboards into the daily practices of teaching staff, counselors, and program chairs.

16.4 Findings of Cross-Case Analysis

The cross-case analysis shows that the four cases differ in terms of leadership processes and organizational maturity. Figure 16.8 illustrates these differences by locating each case in a different position of the schema that we developed to represent the current state of LA adoption in diverse institutions. The location on the y-axis represents the leadership process implemented to involve stakeholders during tool development phases, while the x-axis represents the level of organizational maturity to incorporate the tool into institutional processes. Further analysis of how the leadership process and the level of maturity of each university affected LA adoption is addressed in the following subsections

16.4.1 Leadership

The cross-case analysis indicates that the leadership processes to involve stakeholders affected the progress of tool development phases in each university setting. In the case of PUC-Chile, the LA initiative emerged from a bottom-up process led by a researcher in the context of an experimentation. The predominance of ground-level staff facilitated tool development from the design to the piloting phases. However, the lack of involvement of other senior stakeholders in the process, such as vice provosts or deans, hindered tool scaling at an institutional level. The other extreme is the case of ESPOL, in which the LA initiative emerged as top-down process led by the vice provost. This top-down process facilitated the institutional

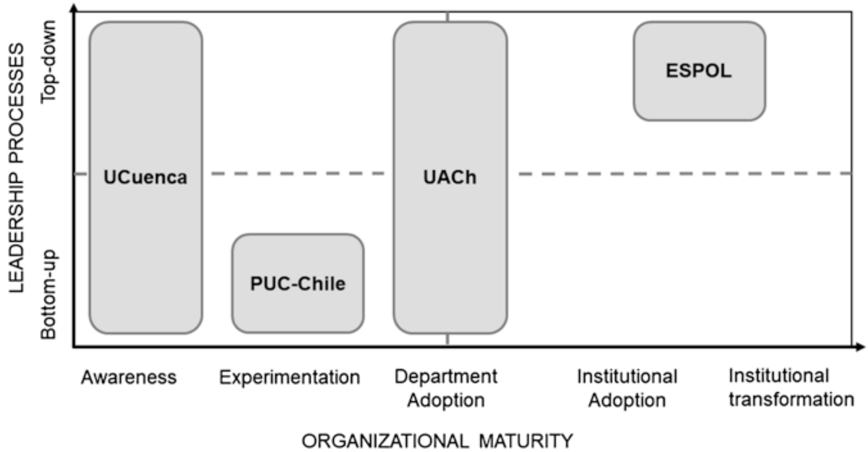

Fig. 16.8 Schema of the comparison of the four cases in terms of leadership and maturity levels

support needed for redesigning the existing academic counseling system. Yet, the lack of involvement of teaching staff members in the decision-making processes generated some anxiety during the piloting/scaling-up phase, since the initiative was presented as an institutional change that they had to accept across faculties. Then, the cases of the UACh and UCuenca are more balanced, considering that they combined bottom-up and top-down leadership processes to involve different stakeholders throughout the tool development process. In both cases, middle managers played crucial roles – such as the director of undergraduate studies in UACh or the associate dean of the engineering faculty in UCuenca. They not only involved other key stakeholders during the design and piloting phases, such as the program chairs and the IT director, but also placed a high priority on ensuring that the LA initiative met an institutional need. This confirms the importance of responsive leadership to create favorable environments to transfer the integration of LA tools into institutional processes (Dawson et al., 2018; Tsai et al., 2019).

16.4.2 Organizational Maturity

The cross-case analysis indicates that the organizational maturity of each university affected the leaders' capacity to incorporate the LA initiatives into existing institutional processes. In the case of UCuenca, the university leaders were aware (awareness level) of the promising use of LA tools, but they had no prior experience with LA applications. As a consequence, they faced challenges to determine which institutional processes would benefit from the use of the teachers' and counselors' dashboards they designed. At the PUC-Chile, the stakeholders involved had already some experience in managing and analyzing data collected from the students' interaction with MOOC content (experimentation level), but they faced challenges to scale up the tool as an institutional service for engineering departments. On the contrary, these challenges were not observed in the cases of UACh and ESPOL, which had a higher organizational maturity in terms of analyzing educational data to inform institutional practice. In both cases, the stakeholders involved in the project had already identified challenges in their academic counseling processes as an evidence-based practice that could benefit from the use of an analytics tool. Moreover, both institutions adopted an LA tool to help students with course enrollment and academic planning (Gasevic, 2018), aiming to boost retention rates as a consequence of supporting students' decision-making at an early stage (Sclater et al., 2016). So far, UACh has only widened adoption at a department level (department adoption), whereas ESPOL has scaled up their system to an institutional level (institutional adoption).

16.5 Lessons Learned and Conclusion

This study has briefly outlined four cases of LA initiatives conducted in Latin American universities in four phases: (1) diagnostic, (2) design/prototyping, (3) piloting, and (4) scaling. We used a cross-case analysis as the methodology to identify similarities and differences across the four cases. This analysis was based on prior LA studies that used the complexity leadership theory to better understand the role of leadership processes and organizational maturity on the adoption of LA initiatives at an institutional level. On the one hand, findings indicate that the leadership processes affected tool development progress in each university setting. On the other hand, the level of organizational maturity of each university affects their leaders' capacity to identify institutional processes that could incorporate LA tools.

In order to transfer the potential benefits of LA into higher education practice, we identified a tipping point in the institutional adoption of LA initiatives. This tipping point represents the moment in which university leaders have identified at least one academic process that could benefit from using an LA tool, along with the combination of bottom-up and top-down leadership processes to engage diverse stakeholders throughout the tool development phases. In the schema that compares the four cases (see Fig. 16.8), UACh is located across the y-axis because it illustrates this point in which different stakeholders had already identified an existing process to incorporate an analytics tool (the student counseling process). By engaging middle managers, such as the director of undergraduate studies and the director of the IT office, UACh researchers have been capable of developing a tool that is smoothly transiting to being scaled up at an institutional level. According to the implications of these findings, LA project representatives need to collaborate with middle managers, considering that they play a key role in facilitating the involvement of ground-level staff and senior managers throughout the different tool development phases.

From the systematic case description and the cross-analysis conducted, we extract two lessons learned that might guide other higher education institutions on how to start an LA initiative. First, it is recommended to consult a variety of stakeholders about institutional needs in order to identify an existing process that benefits from the use of LA. This consultation processes will not only raise awareness on the potential of LA tools among diverse stakeholders but also serve as a trigger for initiating an institutional cultural change toward the use of data for supporting evidence-based decision-making. Second, it is recommended to combine bottom-up and top-down leadership processes to move tool development forward – from its conceptualization to its institutional adoption. This approach implies engaging middle managers – such as deans, IT director, and undergraduate studies director – throughout tool development phases, so they can place a high priority on developing and promoting an LA initiative at an academic unit, in addition to involving other key stakeholders such as IT staff and program chairs.

Although the cross-case analysis presented in this study was supported on a theoretical basis, there are limitations that should be taken into consideration before the findings and lessons learned are extended to other Latin American contexts. Considering the limited number of LA initiatives in the region, it is currently challenging to evaluate to what extent the four universities represented in this study are similar to or different from other higher education institutions all over Latin America. In order to address this limitation, we examined universities that differ in size, type of administration, and year of foundation, representing contrasting higher education systems. Besides, the cross-case analysis was based on LA literature, interpreting prior work conducted by Bichsel (2012), Siemens et al. (2013), and Dawson et al. (2018).

Still, future work should analyze how the graphical schema presented in this chapter represents different LA initiatives in different Latin American universities for further generalization of the lessons learned. In order to better understand implications and mechanisms of adopting LA tools in varied contexts, more research is required to evaluate how this schema applies for planning, analyzing, and comparing LA initiatives in other universities. Still, the findings presented in this chapter extend the current research on LA adoption in Latin American universities by analyzing how LA tools are designed and implemented in different institutions of the region, exploring the implications of LA adoption in terms of leadership and organizational maturity.

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Chapter 17
Adoption of Bring-Your-Own-Device Examinations and Data Analytics

Showing the First Results of a Case Study at Brunel University London

Robyn Fitzharris and Simon Kent

17.1 Introduction

Assessment is an essential element of the learning process (Boud & Soler, 2016), and the use of technology in assessment is growing, acting as a major driver for change throughout teaching and learning (Farrell & Rushby, 2016). Different approaches to e-Exams have been explored, but more recently it has become possible to deliver high-stakes examinations to students using their own devices. The bring-your-own-device (BYOD) examination approach uses a locked-down browser environment[1] installed on students' own laptops to prevent them from being able to access resources online, or on their device, for the duration of the exam.

Adopting BYOD examinations across a higher education institution (HEI) brings potential benefits to students, administrators, and faculty. Students are able to take examinations in a way they are used to writing and on familiar device; administrators can reduce manual handling and cost of running a paper-based system and; academics benefit from legible scripts, automated marking, different assessment types, and flexibility during marking, especially with multiple markers. The latest approaches to BYOD examinations also open up a completely new

[1] Respondus Lockdown Browser

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source of data which can be analyzed to improve educational outcomes. To ensure integrity and reliability during an exam, the software systems used to deliver BYOD examinations store snapshots of student progress every few seconds so that work can be recovered should hardware or network failures occur. While this functionality is intended to protect student work, as a side effect it is possible to analyze the snapshot data to observe how students' work develops through the exam. With a paper system, student activity during examinations is a "black box"; only the final output is available. In a digital system, it is possible to collect second-by-second activity, view intermediate exams scripts, and analyze the final output.

While offering many potential benefits, the implementation of an institution-wide BYOD examination platform is not a trivial undertaking. The adoption of digital examinations requires a whole-institution approach to develop technological infrastructure, appropriate policies and processes, strategies to transform assessment, and the engagement of multiple stakeholders (students, academics, and administrators).

This chapter draws on the experience of deploying the first UK-based institution-wide BYOD examination platform. This chapter will provide a case study of successful implementation of digital examinations and the possible uses of the newly arising data for education data mining. The types of data analytics include readability analysis, text mining, document structure, plagiarism detection, document similarity, and analysis of student's approaches to examinations.

Computer-based tests for both summative and formative assessment are becoming well accepted. Many well-known virtual learning environments such as Blackboard and Moodle incorporate some form of assessment tool, and bespoke systems have been developed within universities, such as Rogō at the University of Nottingham (Burr, Chatterjee, Gibson, Coombes, & Wilkinson, 2016). These systems have been well used in medical degrees which make use of multiple-choice questions (Al-Amri & Ali, 2016). While such systems have been successful, they require skilled development teams and good local support mechanisms. In recent years, commercial products which target a broader range of examination types (e.g., essay questions, short- and long-answer questions, classification questions, image highlighting, etc.) have come to the market. Examples include Wiseflow, Inspera, and DigiExam[2] which all focus on the delivery of digital examinations through a bring-your-own-device (BYOD) approach.

BYOD digital exams bring with them a number of benefits such as the efficiency and sustainability of removing of paper, legible examination scripts, security of scripts, and accessibility. The focus of this chapter is that digital exams also open up a new class of data for use in learner analytics. Traditional approaches to learner analytics have used static data from student record systems and assessment submissions and outcomes; the data relates to the end product, not the process. Digital exams have the potential to provide dynamic data about how a student develops their work.

[2] DigiExam (https://www.digiexam.com), Inspera (https://www.inspera.com), Wiseflow (https://uniwise.dk)

The remainder of this chapter addresses digital examinations and data analytics in three ways. Firstly, because digital examinations are an enabling technology, we discuss the challenges of implementing a BYOD digital examinations system within a higher education institution. It is anticipated that other adopters might learn from past experience to ensure successful and rapid adoption in future settings. Secondly, we present some early work on understanding the type of data and analytics that are available from the modern BYOD digital examination software. Finally, drawing on our initial experience applying data analytics to dynamic examination data, we propose possible future lines of research which should be explored.

17.2 The Evolution of Digital Examinations

Most traditional, pen-and-paper examinations are run in a closed environment. With the rise of the Internet, proponents such as Eric Mazur argue that academics in higher education should be testing creativity and analytical skills, rather than recall (Siddiqui, 2018). While there are valid arguments for running open exams that offer an experience that is better aligned with the modern workplace, there continues to be an overarching requirement for digital exams to be as secure as paper. This means they should be run in an environment whereby students cannot access their notes and online resources or collude with others in the completion of their assessment.

Traditionally, this has meant running examinations in a very controlled environment. Fluck and Hillier (2017) observe that the definition of an e-Exam on Wikipedia was:

> a timed, supervised, summative assessment conducted using each candidate's own computer running a standardized operating system.

At the time of writing, this definition still remains, and while some universities continue to control the exam environment by provisioning large examination rooms of university-owned computers, there are a number of universities now adopting BYOD approaches to e-Exams.

BYOD digital examinations transform the traditional method of running high-stakes examinations using pen and paper to a digital form. A JISC[3] report (Gilbert, Gale, Wills, & Warburton, 2009) identified that e-Assessment existed only in pockets of good practice in individual departments or schools. The sector is currently at a turning point at which early adopters are introducing BYOD digital examinations at institutional level, often with internally developed solutions. It is possible that the current rise in institutional adoption is enabled by the availability of off-the-shelf, software as a service (SaaS) solutions from a number of vendors. From a technology point of view, these SaaS solutions remove the need for institutions to host the software on their own machines, maintaining and upgrading the software and hardware

[3] The Joint Information Systems Committee (JISC) is a UK not-for-profit company that supports higher education institutions with advice and research on digital services to support education.

as required. All this can be outsourced to the solution provider on a cost-per-use basis making the adoption of BYOD digital exams much simpler from a technical perspective.

The current growth area for digital examinations is in the BYOD approach through which students bring their own laptops in which to complete their assessments. Students are required to install a small lockdown browser through which they access the examination while restricting access to the Internet and from the files and applications on their computer for the duration of the examination. While such an approach means that a certain amount of control is surrendered, it benefits from being far more scalable as a way to adopt digital examinations and consequently to access the data that such systems contain. While the SaaS offerings make the installation of BYOD digital examinations much easier, the migration of paper to digital exams within an institution is a significant undertaking which requires careful management of technical and nontechnical factors.

17.3 BYOD Examination Implementation Case Study

The implementation of BYOD digital exams at Brunel University London followed an iterative approach starting with a small-scale pilot with 156 students taking a written sports science exam, growing to institution-wide adoption over a 4-year period. Brunel is a university based in London in the UK. It has three academic colleges and around 14,000 students. The exam platform adopted at Brunel University London is WISEflow by UNIwise Aps. UNIwise is a private company which works with educational institutions worldwide to switch to BYOD digital exams. WISEflow is a cloud-based software as a service (SaaS) solution which works on students' own devices and supports all work processes for examinations.

A successful capacity building pilot in the Department of Computer Science in 2016/2017 with around 900 students resulted in the submission of over 2000 individual exam scripts across 22 exams. Based on the success of these pilots, BYOD examinations were adopted across the institution: the College of Engineering, Design and Physical Sciences in 2017/2018, extending to the College of Health and Life Sciences in 2018/2019 and finally the College of Business, Arts and Social Sciences 2019/2020. During the 2018/2019 academic year, 2721 unique students had taken 79 exams, resulting in 7219 unique submissions. It is anticipated that this will double in 2020/2021.

WISEflow's architecture is based on a multi-redundant setup without "single point of failure" bottlenecks. The database layer is built up as a cluster with at least three nodes, in three different data centers, where there is write and read access to all nodes in the cluster, ensuring that the asset data is always stored on at least three physically separate locations. As noted above, this is set up to ensure that the system doesn't fail during key times such as during an assessment and allows previous points in time to be restored.

Institutions using WISEflow can access data collected for their examinations via the WISEflow API, which returns queries in JSON form. The data can be linked to a specific user or to a specific examination. Initially, the data collected was focused on practical elements of managing a cloud-based system but has developed based on customer feedback and requests. An example of this is the ability to identify which students have accessed their feedback; this isn't an essential component of the system but is of interest to educational institutions and is therefore collected.

17.3.1 Infrastructure

The basic requirements for delivering examinations at small scale can easily be accommodated by the standard infrastructure of most universities. There are some special considerations regarding wireless networking and power which need to be considered.

17.3.1.1 Wi-Fi

During a BYOD examination, students require a continuous connection to the Internet. This is to ensure that snapshots of their work can regularly be uploaded to the cloud to protect against device failure. The examination platforms are typically robust to short-term network failures; however, it can be inconvenient for students and invigilators who receive regular notifications of a lost connection. When providing Wi-Fi coverage to an exam location, it should not only be sized based on the number of expected candidates but also take into account the number of other Wi-Fi-enabled devices that may be active in bags and pockets and even carried by other students and staff walking past the examination venue. We have found that providing double the number of Wi-Fi connections provides a satisfactory level of service.

17.3.1.2 Power

When using a BYOD strategy, the most likely device used by a student for an examination is a laptop. Modern laptops with effective energy management have long battery lives that can easily last the length of the examination. However, unless an institution can afford to provide modern laptops or insist on laptops of a certain specification, it is necessary to provide some supplementary power. Some institutions provide mains power sockets at each examination desk; however, this is a costly solution. It is relatively quick and easy for students to raise their hand and move on-demand to a desk with power. The data in Fig. 17.1 was collected during six separate examination sittings run at Brunel University London in 2017. Session 1 and 2 had students from multiple modules in the exam session which is why the

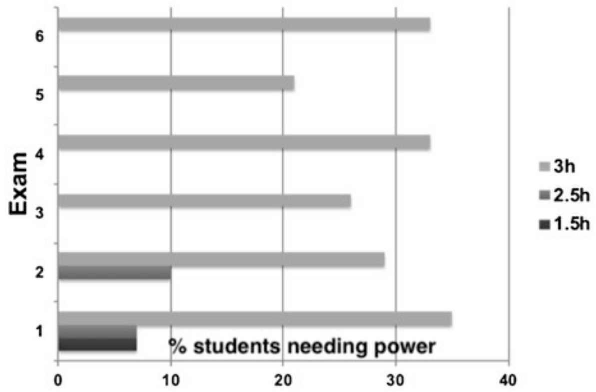

Fig. 17.1 Devices running out of battery during exams

exams were of different lengths. During sessions 3–6, only students from a single, 3-hour examination were present. All of the six sittings included 3-hour examinations, but some also had shorter 1.5- and 2.5-hour examinations. The percentage of students needing to move from battery alone to a mains socket remained at 10% or below for 1.5- and 2.5-hour examinations. As examinations lengthened to 3 hours, the requirement increased significantly. This data should be used by academics and institutions to consider (i) appropriate examination lengths and (ii) the amount of backup power sockets required for a given examination sitting.

17.3.2 Human Factors

Tomas, Borg, and McNeil (2015) recognize that much previous research focuses on specific tools and contexts. While this impacts successful adoption, the most significant barriers relate to the acceptance of digital examinations by the various stakeholders.

There are three clear stakeholder groups involved in the adoption of digital examinations:

- Students
- Administrators/professional staff
- Academics

Each group presents a significantly different set of challenges and demonstrates a different "perception profile" when they are first exposed to and subsequently become acquainted with digital examinations.

17.3.2.1 Students

Any change in the means of assessment should have a positive impact on the student experience. Ultimately any change to learning and teaching should have a positive impact on the outcomes for students. It is also important to consider the student's perception of digitizing the examination process. In most part, the reaction from students is ambivalence. They do not typically see assessment moving to computers as a significant concern and expect the university to make sure it works. Once they have experienced digital examinations, their expectations are raised that all assessments should be in this form.

17.3.2.1.1 Outcomes

In terms of outcomes, it is difficult to undertake research in a truly controlled environment. In an examination carried out during a pilot, 156 sports science students were given the opportunity to use pen-and-paper or to bring their own laptop. The exam was a 2-hour, written examination in which students had to write two essay questions. Of the sample, 113 students arrived in the exam hall with a device on which to complete their exam. The remaining 43 completed the process on pen and paper. As such, the students had been through an identical experience, with an identical assessment; only the examination medium had changed. Although the sample was small, we could not see any significant difference in the performance of these students.

17.3.2.1.2 Perceptions

As with all stakeholders, there are a wide range of perceptions exhibited by students with some stating a significant preference for pen and paper. However, in general our experience has been that students are somewhat ambivalent to the move from pen-and-paper to a digital medium. Anecdotally this can be observed when asking students at the end of the exam, "How did the exam go?" In most cases, the response will relate to the subject matter rather than the fact that the exam was digital.

These observations are reinforced by Dermo (2009) who undertook a thorough investigation into student perceptions of digital assessment and found that the results showed a normal distribution with a slight positive attitude. Most students were grouped around the midpoint of the five-point scale. It should be noted that this study related specifically to multiple-choice assessments with randomly presented questions. The respondents were most concerned about how fair the random selection was, again showing that they are more concerned about content than the medium of delivery. Hillier (2015) also reported positive experience from students across multiple exams, with respondents rating the e-Exams 4 out of 5 on a Likert scale.

17.3.2.1.3 Typing Versus Handwriting

A concern that is raised about digital examinations is it will not be fair to a student who cannot type as fast as they can write. There is evidence that poor fluency in handwriting under exam pressure correlates with lower performance (Connelly, Dockrell, & Barnett, 2005). Arguably this effect may be exacerbated as students use handwriting less as they move through primary and secondary education and into higher education. A study at the University of Edinburgh compared typed versus handwritten examination scripts during a mock examination (Mogey, Paterson, Burk, & Purcell, 2010). Students could choose to type (24 subjects) or handwrite (11 subjects) their answers. The results showed that students who typed their work tended to write more words; however, this did not correlate with their reported typing speed.

In Hillier's (2015) work, students were also assessed as to when they experienced discomfort when undertaking paper exams. Most students were affected by discomfort in their writing hand after 70 minutes; however, some were affected as early as 45 minutes.

Another issue relating to typing versus writing is that of legibility. This is discussed in Sect. 3.2.3.2.

17.3.2.1.4 Accessibility and Disability

A key driver for the adoption of digital examinations for some universities is the increasing number of students that request the use of a computer during an exam as an appropriate adjustment for a disability. This adjustment is no longer necessary if the use of a computer, especially the student's own computer, is the norm rather than the exception. In our experience, it is very important that those responsible for supporting students with disabilities should be well informed about the features of the adopted examination platform to ensure that the correct adjustment is made. Without the early involvement of disability support staff, students may be given adjustments which are inappropriate, for example, the automatic adjustment for an autistic student might be to allow them to use a computer in a special lab space, whereas when digital examinations are the norm, it is possible that the student could sit with the main cohort because the accessibility features of the examination software and the availability of spell-checkers mean that no special adjustment is required.

17.3.2.1.5 Device Ownership

When pursuing a BYOD approach, it is clearly important that students have access to the necessary devices on which to undertake their assessment. A study undertaken at Brunel University London during the main examination session in 2017 found that 80% of students reported that they owned a Windows or Mac OS laptop suitable for use during BYOD examinations. Some students chose to have a desktop computer and some a tablet device. Affordability was also an issue. As universities have a strong widening participation agenda, it is important that a suitable strategy is in place to ensure that the 20% who do not have a device are not disadvantaged. This is part of a wider debate on BYOD in higher education. While students may have personal access to newer and better computers than are available in their universities (Traxler, 2016), however, disadvantaged students may not have the same access; the Brunel study found that of the 20% of students who did not have a device, this group was four times more likely to have applied for financial hardship funds.

17.3.2.1.6 Promoting Adoption by Students

To ensure a smooth transition to digital examinations, students should be involved as early as possible in the process. Those taking part in early trials can act as champions and reduce any transitional concerns which the wider student body may have.

It is obviously essential that students are prepared for their first experience of digital exams. During the 2016/2017 academic year, around 900 students were involved. When offered multiple opportunities for mock exams, drop-ins, and clinics during the rollout of digital examinations at Brunel University in 2017, the rate of attendance at these preparatory sessions was only around 50% (Table 17.1). Students in their first year of study were least engaged, possibly because the assessments had less impact on their degree classification. Despite the lack of engagement, the overwhelming majority of students arrived at the exam venue either ready to complete the assessment or with the assumption that technical support could be readily provided in order for them to complete the exam.

17.3.2.2 Administrators and Professional Staff

Staff who are associated with the administration of examinations have been most positive about the introduction of digital examinations. Their behavior over the period of implementation closely mirrors Gartner's hype cycle (Linden & Fenn, 2003). An adapted version of the hype cycle showing the adoption of BYOD digital exams by administrators is shown in Fig. 17.2. Their "technology trigger" is their initial training to use the system. They are typically optimistic about the introduction and can predict positive outcomes in terms of a reduction in manual processing

Table 17.1 Student engagement with BYOD exam practice sessions

Year of study	Engagement %
Bachelor year 1	22
Bachelor year 2	46
Bachelor year 3	51
Masters	49

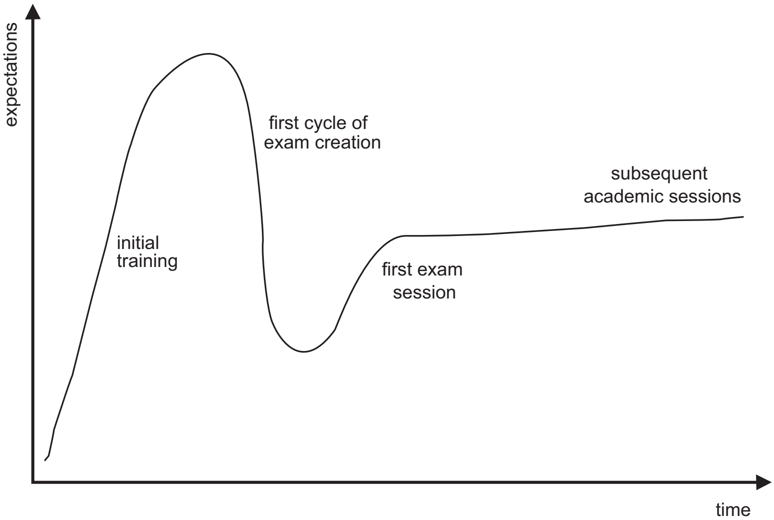

Fig. 17.2 Gartner's hype cycle for administrator adoption of BYOD exams

of paper. When the staff first start to use the software, there is a significant up-front change in their practice creating examinations, allocating roles to students and staff and providing support. The up-front investment by these staff is rewarded by a consequential reduction in manual processing such as reproducing examination papers and collating, distributing, and managing examination scripts. They are also able to exercise much better oversight of the overall examination process because they are able to monitor the assessment process in one place, as the digitized assessment artifacts all reside within a digital system rather than being distributed across the offices, homes, and vehicles of the markers. This allows professional staff to allocate more time to supporting their academic colleagues and the students.

Administrators are significant because they drive the adoption process for other users. It is useful to understand the way that they react to the technology, and that positive expectations from them are realized in a short timeframe.

17.3.2.3 Academics

Academics face the most significant change in practice when digital examinations are adopted. Digital examinations have the potential to impact every aspect of the process of setting and marking an exam, in doing so challenging long-standing practice. Unlike their professional colleagues, the return on their initial investment is less immediate, and it can take a number of cycles before clear benefits are realized in terms of security of scripts, improved legibility, and improved flexibility when multiple markers are involved because scripts do not need to be physically exchanged. These are discussed in more detail below.

17.3.2.3.1 Exam Creation

Digital examinations have the potential to allow for more interesting examination types which can draw on the use of multimedia and the use interactive applications to provide a much more authentic assessment experience. However, while it may seem appealing from a pedagogic perspective to rush into the use of such exam types, it may be better to focus on transforming traditional paper exams in the first instance as this will simplify the transition to digital examinations for less technologically adept individuals.

17.3.2.3.2 Exam Marking

Ideally the academic should provide their feedback and a record of the grading or scoring of the student's work digitally. This requires a significant change in practice for those who are used to marking work using a red pen. There tends to be significant learning curve for academics moving to a digital assessment system which can cause significant opposition. The effort required to mark digitally does reduce over time and can benefit from the use of rubrics and in some cases semiautomated marking for some question types such as multiple-choice questions, labeling tasks, or questions requiring the identification of hotspots on images.

On the positive side, work which is typed by students is far more legible compared to handwritten work. There is evidence that markers have a different perception of handwritten versus typed work (Mogey et al., 2010). This may be because they are used to how many pages of handwriting student would typically produce, whereas typed submissions will typically look shorter. In the study, the markers tended to grade the handwritten scripts slightly higher than the typed ones; however, there was a more significant difference in grading between individual markers than there was between handwritten and typed scripts.

For large cohorts, it is common for marking to be undertaken by multiple markers. A digital system lends itself well to this approach because unlike paper the markers can all work simultaneously without having to coordinate the swapping of scripts.

17.3.2.3.3 Promoting Adoption by Academic Staff

The steep learning curve will generate opposition from academics. The institution needs to accept that some time will be taken for academics to adapt and to be able to realize the benefits of a digital system. It is best to minimize the barriers to entry by initially just migrating traditional styles of paper on examination to digital format. In this way this academic can write an examination paper as they usually would, and rather than being printed, it is simply delivered to students in electronic form.

Usually champions can be identified who are prepared to readily adopt new digital examination platform. It is important to support these individuals because they play a valuable role in providing support to the less enthusiastic individuals and consequently reducing some of the opposition.

17.4 Bring-Your-Own-Device Examinations Data Analysis Case Study

Delivering a BYOD examination requires coordination from multiple stakeholders including academic staff, professional services staff, and students. Each stakeholder will engage with BYOD examinations from a variety of perspectives and face varying challenges during the process of adoption. Between these stakeholder groups, activity happens across the whole assessment and feedback lifecycle (Fig. 17.3), and, while BYOD systems will vary in their architecture and precise data captured, it is necessary to collect an audit trail of activity documenting actions, including who has completed actions at what time, before, during, and after an examination, to allow any issues to be reviewed at a later date.

Now that BYOD exams have been adopted at Brunel University London, this audit trail of activity is available for analysis and provides a large dataset for exploration. The initial analysis undertaken focuses on activity during the exam, which is arguably the most critical time for a BYOD system as any technical issues are likely to cause high stress for students who are already in the stressful situation of a time-limited summative assessment. As explored in Sect. 17.3.2.1.5, a number of students arrive to exams with devices which are inappropriate and may not have battery power which can last for the whole exam. While providing the appropriate infrastructure and power sockets to these students can be a solution, there are also other risks in terms of Wi-Fi or network difficulties which may cause problems during an examination. To mitigate against this WISEflow saves students' progress during an exam, allowing for a student to continue their assessment on another device and continue from the latest save point. The saved version of each script is available after the exam, and analysis has focused on analyzing this "dynamic" data to explore the evolution of an exam script. This area was selected as a first avenue for exploration as it may provide benefits for learners.

Fig. 17.3 Assessment and feedback lifecycle diagram

17.4.1 Methodology

This analysis used intermediate exam scripts from a 90-minute spring 2019 examination undertaken by students in the Department of Computer Science. The exam was selected as it required long written answers by students, rather than multiple-choice questions, and had a reasonably large sample size (n = 175). All data was anonymized prior to analysis and occurred after the assessment, and marking process had been fully completed. Each student script is saved either every 30 seconds during an examination or every 100 characters typed, whichever comes first. If a student does not make any changes between the 30 seconds' save, then the save is discarded; all saving happens automatically without student intervention. This approach to saving differs from those used by software such as Google Drive or Office 365 which use keystroke logging to record every adjustment or change to a document. The granularity of keystroke logging allows for visualization of document evolution; some early work exploring documents written in Google Drive uses keystrokes and cursor position to develop branching tree diagrams (Perez-Messina, Gutierrez, & Graells-Garrido, 2018). The data used in this analysis is not as detailed, as there may be changes which occur within each 30 seconds or 100 characters which are then changed back, e.g., typing a sentence and then deleting again. Therefore, an alternate visualization approach has been adopted which uses the time since the start of the examination on the x-axis and other variables on the y-axis.

The first variable calculated for each student was the numbers of characters in each script; this was completed in Python using the Natural Language Toolkit (NLTK) library; this count was then compared to the previous script to calculate the changes between scripts. This approach attempts to crudely highlight periods of time during the exam where students are either writing (indicated by a positive character change), editing, and deleting (indicated by a negative character change) or not doing anything (indicated by no change). This approach is a "surface-level" approach (Cohen, Ben-Simon, & Hovav, 2003) which is open to criticism for its hyper-simplicity (Condon, 2013; Shermis & Burstein, 2013) and the fact that it does not provide suggestions for improvement (Riedel, Dexter, Scharber, & Doering, 2006). It has been used here as a simple tool to initially explore the data; there are a number of considerations that need to be resolved before further in-depth analysis of BYOD exam data, including but not limited to privacy and ethics, at which point more advanced techniques can be applied.

17.4.2 Results and Discussion

Three students were selected at random to provide a "first look" at the data. The first student (Fig. 17.4) shows activity from the start of the examination with an immediate increase of ~90 characters. Across the examination, the student fairly consistently wrote ~130 characters between each save with four spikes of above 200

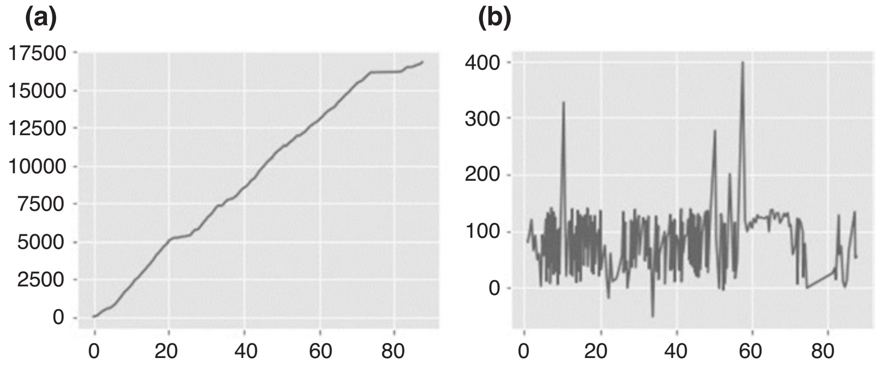

Fig. 17.4 (**a**) Volume of characters and (**b**) changes between saves for one randomly selected student during a 90-minute exam (student 1)

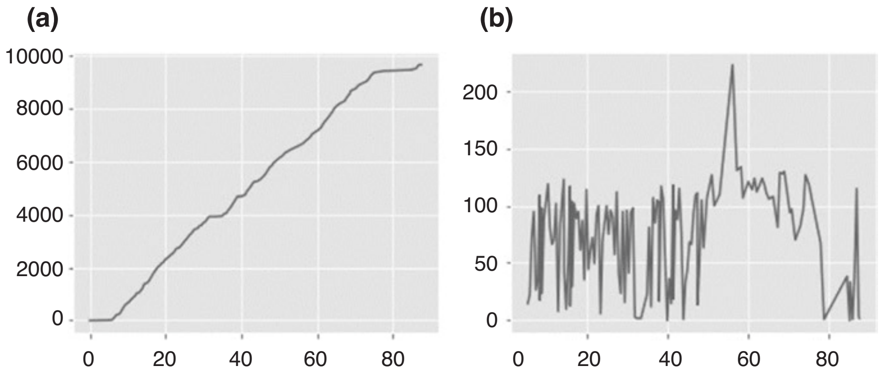

Fig. 17.5 (**a**) Volume of characters and (**b**) changes between saves for one randomly selected student during a 90-minute exam (student 2)

characters; these increases may be caused by the student cutting and pasting text between sections in their script. At the 20-minute mark, there are signs of the student pausing, as the gradient of the total characters line flattens, and negative values for character change indicate deletions. After 75 minutes, the student takes another break before making some final amendments. The final character count is ~17,500 characters.

In contrast to the first student, student 2 did not start writing immediately, and the character count begins to increase from the 5-minute mark (Fig. 17.5). Student 2 doesn't have any negative values for character change between scripts, indicating any text deleted was subsequently replaced within the 30 seconds between saves. Combined with the slightly slower start, this could indicate that this student planned its answer before starting to type and subsequently had less need to make large changes to their answer. This is in contrast to student 1 who starts immediately but then makes subsequent amendments. The period between 50 and 80 minutes shows

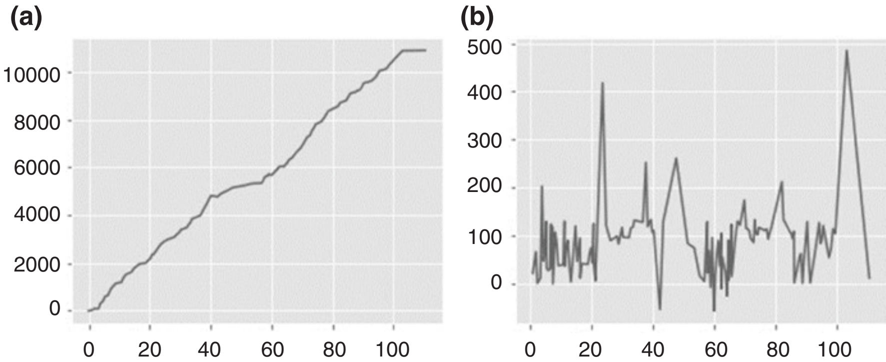

Fig. 17.6 (**a**) Volume of characters and (**b**) changes between saves for one randomly selected student during a 90-minute exam (student 3)

a high intensity of writing without pause, and at 80 minutes the student takes a break from writing before making some final amendments. This indicates the student allocated some time at the end of the exam to review and reflect on their answers. The final character count is ~10,000 characters, which is notably lower than student 1.

The third student has more time in the examination than the first two students and is given up to 117 minutes, indicating the student was allowed 30% additional time which is likely an adjustment due to disability (Fig. 17.6). The student wrote consistently until the 40-minute mark before making an amendment resulting in a negative character change. The student then appears to slow down until the 60-minute mark, indicated by the low number of data points, before making further negative adjustments. The student makes a large change to the script just after 100 minutes and then appears to make no further changes to the script. The total character count is ~11,000 characters.

These three students show different patterns of activity when completing the same examination. The first writes the most content and appears to take breaks during the assessment. This could be indicating the student taking time to review the content written or reviewing the assessment material. The second student is slower to start writing, possibly taking time to read the assessment material or time to mentally plan their answer. Once they start writing, student 2 then shows less evidence of making large adjustments to the script. The third student shows a blend of characteristics of the first two students as they started writing immediately, like student 1, and pause to amend and make deletions in the script like student 2. Further work is required to identify whether these patterns are meaningful and genuinely show difference in students' behavior. At present, the interpretation is without confirmation from the students about the approaches they were taking. Further analysis could allow for identification of "types" of student approaches, such as those that take time to plan their answers before writing and those that write first and then edit after. If types of student approaches can be identified and correlated to outcomes, it could be used to give feedback and advice for students to improve their performance in exams.

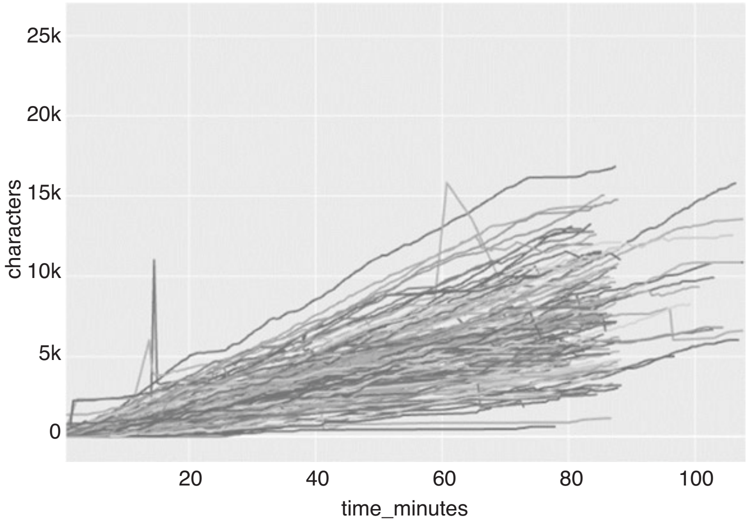

Fig. 17.7 Character count for a cohort of students during a 90-minute examination (n = 175)

Plotting the data for all 175 participants shows variation across the cohort (Fig. 17.7). The total characters written vary between ~1000 and ~ 17,500 characters – the student who has written the most is coincidentally likely to be student 1. The median value for final character count appears to be ~7500 characters. The number of students with extra time can be seen by the records continuing beyond 90 minutes. The concentration of data points for all of the students makes further interpretation difficult, and further work is required to develop appropriate visualizations to provide further insight.

The same difficulties of interpretation arise when plotting the character change data for the whole cohort (Fig. 17.8). The plot is dominated by very large changes between saves for a small number of students. As noted above, these large changes may be due to copying and pasting text within the document. By visualizing the data in this way, it makes it possible to identify any unusual behavior, and the individual saves could be inspected to understand what has happened. Otherwise, the only point to note is that negative data points can be seen across the timeline indicating various editing activities by a range of students.

The analysis of character counts provided a first look into the possible uses of WISEflow data. Data is collected by WISEflow throughout the whole assessment, and feedback lifecycle and consideration is now being given to other data analysis which is now possible. The areas we are intending to explore are:

- The use of natural language processing techniques on student exam scripts to provide automated feedback which could be provided either to markers or directly to students
- Further analysis of script development to identify if there are any patterns for successful students

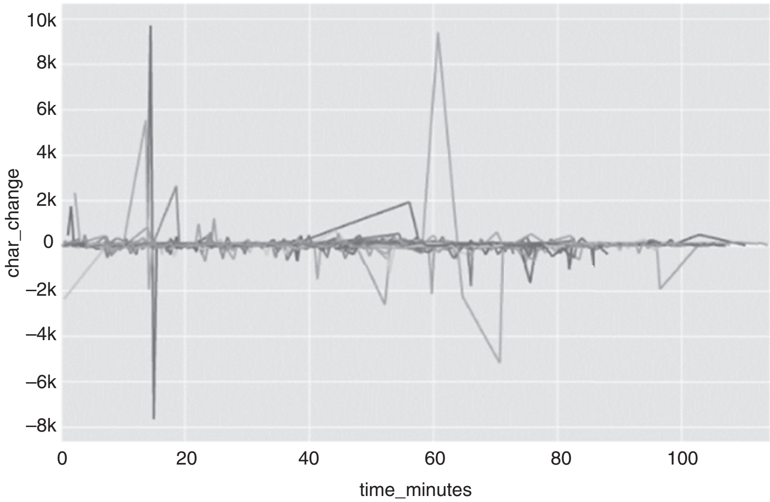

Fig. 17.8 Changes between saves for a cohort of students during a 90-minute examination ($n = 175$)

- The time taken for students to complete exams to identify whether exam lengths are appropriate
- Whether students view their feedback and identify which students are not engaging

Before undertaking further analysis, there are a number of areas which are important to consider.

17.4.3 Areas for Consideration

Analysis using data generated by BYOD exams relates to staff, students, and the learning environment, with data being collected based on activity by users of the system. Data collection of user activities in systems is not unique to BYOD examinations; analytics approaches using student data in higher education have relied on engagement data, such as with online learning materials (Atherton et al., 2017; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). The use of the data arising from BYOD exams of the type discussed in this chapter is therefore likely to face similar challenges to that of learner analytics data. A systematic review of learning analytics and associated challenges highlighted seven areas which are also important to consider for BYOD exam data (Avella, Kebritchi, Nunn, & Kanai, 2016):

- Data tracking
  Data tracking relates to implementing systems to monitor behavior. The lessons learned from this case study show the challenges that can be faced by institutions

implementing BYOD exams. While the number of institutions adopting BYOD exams remains low, the possible impact of any analysis or tools developed is limited.

- Data collection
  It is also important to consider that different institutions will use different BYOD exam providers, which may be commercial tools or HEI specific. The variation in tools means that the data collected is likely to vary. This will limit the replication of analysis between institutions and make widespread analysis more difficult.
- Evaluation process
  In this case study, the analysis of BYOD data has occurred after the assessment process has been completed, but future users may require the data to be analyzed more quickly in order to be useful. Any systems set up to evaluate, process, and clean the data will need to be able to work quickly and cope with data being produced in large bursts, for example, during examination weeks at institutions where the volume of data produced will be much higher.
- Data analysis
  Any analysis produced will need to be understandable to its intended audience. Learning analytics systems have used dashboards to communicate information which have been perceived as useful by staff and students (Ali, Hatala, Gašević, & Jovanović, 2012; Scheuer & Zinn, 2007). How can BYOD data be presented to staff and students? The analysis at cohort level has already shown challenges in presenting data for a large volume of students.
- Learning sciences connection
  A link to learning sciences is required to understand how the data could support learning development and improve teaching and learning. This is key to understanding the impact of the use of BYOD data and the value of it. Ensuring that the use of the data is for activities with clear intentions designed to have a positive impact and backed up by research can also help discussions of privacy and ethical issues with using the data.
- Emerging technology
  BYOD exam platforms are still an emerging technology which means that critical discussion of their use in education as well as analysis of BYOD exam data is limited. It is important to critically discuss and consider a range of views before prioritizing moving ahead with further analysis.
- Ethical and privacy issues
  The final and arguably most critical challenge is that of ethical and privacy issues. In order to work with the data, it is essential to adhere to legal frameworks, which bring complexities including requirements for users to have the ability to opt out of data collection and access all data collected about them. At present, data is collected for the purposes of system operation, and opting out is therefore not practical; however, when the use of the data moves into being used for analysis, then users should be informed and provided with the option to opt out of their data being included in analysis. Given the context of examinations and the fact that some of the users are students, it is also important to consider

the power dynamic in this situation. Students will have to continue to use the system for the examinations, and by opting out, they may be concerned that there will be a negative impact for them. It is therefore important to carefully consider the phrasing of any privacy and data consent forms. This can be eased by clearly identifying the intended impact and benefits of analysis before implementation. An area for consideration and development is the production of an ethical framework for using BYOD data or principles to adhere to, ideally developed in consultation with users similar to those produced for learning analytics (Slade & Prinsloo, 2013).

17.5 Conclusions and the Future of Exam Analytics

This chapter is not the final word on BYOD exam analytics. Higher education is at an early stage in adopting BYOD examinations and learner analytics and at an even earlier stage in combining them. It has been the intention of the chapter to offer some "lessons learned" to assist other institutions in their adoption of BYOD digital exams and to showcase the type of data that could be made available from such systems. These lessons learned are summarized in Table 17.2.

Initial work with student exam scripts has provided a first insight into student behavior during examinations. Comparing the characters typed between students over the course of a 90-minute examination showed different patterns by students which may be indicative of different approaches to planning, reviewing, and editing. The analysis remains at a simplistic stage, relying on the use of a "surface variable" (Condon, 2013) to differentiate between students, thus limiting the feedback that can be produced. Analysis at cohort level is limited by the large volume of information presented on one graph making it difficult to discern meaningful patterns. Despite these weaknesses, the analysis provides a first exploration of the data and a foundation for further work to build on.

From the initial work undertaken, it is clear that there are many routes future research could take. Within social science, health, and education, analysis of the available data could reveal cultural differences in the way people write in different countries, in different subjects, and at different levels of education. Further work could also be undertaken on typing speed and its relation to outcome. It could also be interesting to consider how education systems prepare students appropriately for communication in a digital world through handwriting and typing from kindergarten to university and beyond.

A key theme for future work is on how the data can be used to improve educational outcomes. To what extent can dynamic exam data be used to predict outcomes automatically or at least to assist with the automatic quality control of human marking? Can such approaches help to inform the decision about length of examinations? Why run a 3-hour examination when the ability is demonstrated after an hour-and-half?

Table 17.2 Lessons learned from adoption of BYOD exams at Brunel University London

Stakeholder	Issue	Lessons learned
Infrastructure owners	Wi-Fi	Double the number of Wi-Fi connections to help with network connections
	Power	Supplementary power can be provided for everyone, but it is easiest if students move to a desk with power only when needed
Students	Views	Students are generally ambivalent about using their own device for examinations
	Typing speed	There is no clear difference in writing speed for handwriting vs. typed
	Accessibility	Using their own device can impact which adjustments are required, so ensure early discussion to ensure any changes can be acted on
	Device ownership	Have spare devices for students to use, and don't assume students have their own BYOD exam system-compatible device
	Promote adoption	Have training available for those that need it
Administrators and professional staff	Adoption	Much of the effort required to implement a new system will be up-front with the benefits realized later, but this happens within a very short timeframe
Academics	Exam creation	Focus on transferring assessments from their pen-and-paper form first, and then focus on different approaches to assessment
	Exam marking	Typed text has benefits of being more legible, but it takes time to adapt to digital marking. The benefits are big for multiple markers
	Adoption	Use academic champions to lead the way and show benefits

Tools such as OpenEssayist (Van Labeke, Whitelock, Field, & Pulman, 2013) offer advice to students based on static analysis of their work; could the dynamic data from a digital exam provide in-exam feedback to a student? Would this even be useful or a distraction? Can this kind of data be used to cluster students with different approaches to writing for specific support with their writing, if their approach is detrimental to their exam outcome?

There are a number of areas to consider and discuss before moving forward with the use of BYOD exam data. Development of a common approach to data analytics using BYOD exam data may be limited by the lack of a singular BYOD exam platform, resulting in variation between the data collected and available for analysis. Once the data is available, tools need to be developed to process large quantities of possibly messy data and present it in a way that is understandable to stakeholders. This is unlikely to be a simple process, and there is also therefore a question of prioritization: is the use of BYOD exam data a priority for education institutions? The argument for prioritizing analysis of BYOD exam data can be helped by having a clear rationale behind any analysis and linking it to learning sciences research to understand the intended impact and outcomes. This will be supported by further research in BYOD exams as an emerging technology, which should include critical discussion of the benefits and disadvantages of using BYOD exams and their data, from a range of perspectives, particularly those of staff and students. Involving staff and students in the discussions is also important when considering ethical and privacy concerns. As the owners of their own data, users should be involved in deciding what is and isn't an appropriate use of data and ultimately be given the chance to opt out. The development of principles for ethical use of BYOD exam data is particularly significant when considering the essential role of assessment in the learning process (Boud & Soler, 2016), and care must be taken to avoid any unintended negative impacts on the learner.

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Chapter 18
Experiential Learning in Labs and Multimodal Learning Analytics

Anke Pfeiffer, Vlatko Lukarov, Giovanni Romagnoli, Dieter Uckelmann, and Ulrik Schroeder

18.1 Introduction

Lab-based experimentation plays a major role in engineering education because it allows to achieve important pedagogical objectives by directly applying theory to practice, and, as such, it enables learners to manipulate the physical environment and to understand its constraints and real-world problems (Feisel & Rosa, 2005). Laboratories are complex teaching and learning environments, as they can be broadly defined as places that provide opportunities for experimentation, observation, and practice in a field of study. Laboratory-based learning is also considered a way to accompany the digital change in engineering education (Uckelmann, 2012). It enables students to directly manipulate materials, electronic components, sensors, energy, and information and provides adequate opportunities to apply their knowledge and efforts to find creative solutions for real problems with the provided laboratory equipment. In the last decades, networks of labs have emerged as a promising way to overcome some disadvantages of lab-based education (Ma & Nickerson, 2006). Lab networks consist of remote and virtual laboratories, and they are currently widespread and adopted in many different areas (e.g., chemistry, physics, biology, engineering, and many others) (Orduña et al., 2017). Remote and virtual labs can be defined as artificial environments where lab-based experiments can be reproduced independently from time and location, i.e., students might perform

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those experiments remotely and at any time (Heradio et al., 2016). Students and teachers have shown appreciation for lab network solutions, due to their ease of use, portability, and efficiency.

Experience-based learning (EBL), also known as experiential learning, is a theory based on Kolb that can be associated with lab-based learning due to many intersections (Kolb, 1984). The work of Kolb describes how these four phases– experience, reflection, conceptualization, and experimentation – create an experiential learning cycle. In general, the continuous relationship between these EBL phases explains an experiential learning process, where the phases build on and influence each other (Kolb, 2014). It is acknowledged by the scientific community that EBL is particularly suited to lab environments, where both experimentation and experience can be carried out in an efficient and organized way (Abdulwahed & Nagy, 2011; Haertel, Terkowsky, May, & Pleul, 2013). Further, modern labs are more and more digitized environments, where learners produce various types of learning data. A recent and promising way to deal with those types of data is multimodal learning analytics (MLA). MLA combines together three different concepts: multimodal teaching and learning, different forms of data, and computer-based analyzes on those data (Worsley et al., 2016). Broadly speaking, MLA utilizes different forms of data, i.e., traditional and nontraditional ones, to model the way students learn in complex learning environments (Worsley, 2018). The goal of this study is to address how MLA can support experiential learning in lab-based learning environments and especially in lab networks of virtual and remote labs.

The starting point of this research concern was formed by considerations within the BMBF-funded project Open Digital Lab for You (DigiLab4U). The digitization in the engineering field, marked with buzzwords like Industry 4.0 (I4.0) and Internet of Things (IoT), refers to profound economic changes and heralds a paradigm shift that will profoundly change production, services, business processes, and education and will challenge them to a "digital offensive" (Stifterverband, 2016, 2019; VDE, 2016). The remainder of the paper is organized as follows: in Sect. 18.2, we will provide the theoretical background, by introducing lab-based learning and experiential learning as a pedagogical framework for a laboratory environment. In Sect. 18.3, the acquisition and advantages of MLA for laboratory-based learning are exemplified. Section 18.4 focuses on the question of how MLA can be used in laboratory-based learning environments to support experiential learning in engineering education, and it draws the conclusions of our work.

18.2 Theoretical Background

The theoretical background is organized into three sections. The first section outlines the foundations of lab-based learning, the second section describes experiential learning as a viable approach in laboratory-based learning scenarios, and the third section outlines the basics behind MLA.

18.2.1 Lab-Based Learning

In order to effectively prepare students for scientific and practical handling of relevant content, such as IoT systems, for example, they need deep theoretical knowledge as well as relevant skills and competences for the professional practice. Both can be acquired particularly well in laboratory-based experiments and scenarios (Bruchmüller & Haug, 2001; Feisel & Rosa, 2005; Haug, 1980; Pleul, 2016). The use of laboratory equipment offers students the opportunity to handle relevant facilities and machines of their future professional careers and to gain theoretical and practical experience in experimenting with the equipment, methods, and research processes of the engineering area (Bruchmüller & Haug, 2001). The laboratory can foster students' understanding of scientific concepts, science inquiry skills, and their perception of science. It can also provide students an environment where they can work cooperatively and collaboratively in small groups to explore and investigate technical and scientific conditions (Hofstein & Lunetta, 2004). In general, it can be stated that laboratories have an essential role in engineering education. This is due to the need of applied science education to provide hands-on skills and to comprehend design, experience, exploration, and enquiry processes, as well as problem-solving and analytical thinking. All these elements can be fostered and trained in lab-based scenarios (Abdulwahed & Nagy, 2011). Terkowsky, May, and Frye (2019) clustered competence requirements of the working world 4.0 (I4.0) in a competence grid in order to classify laboratory-based teaching and learning environments in engineering courses. The grid showed that, besides the acquisition of classical professional competences, laboratory experiments can also address interdisciplinary aspects of competence for different professional practice situations. This includes social competence (e.g., teamwork), self-competence (e.g., working self-regulated and self-responsible), and methodological skills (e.g., handling big data) that are equally important for the IoT field and the learning processes in higher education (Schaper, Schloemer, & Paechter, 2013). In addition to real lab environments, virtual and remote laboratories can provide several advantages such as remote and virtually continuous access, spatial and temporal flexibility, as well as the freedom to learn at one's own pace. Beyond that, learners can reiterate experiments without wasting resources in a safe environment. Thus, we can state that virtual and remote labs provide new opportunities for learning, teaching, and research. Labs are a necessary and useful possibility to engage students with their future learning environments and foster the development of professional competences (Haertel et al., 2013; Terkowsky, May, Haertel, & Pleul, 2012). Their research shows, that learner support, corresponding learning resources, and tutor interaction that are included in a pedagogical framwork, can result in higher learning outcomes and richer learning experiences. Recent developments in the fields of IoT and I4.0 led to the implementation of innovative lab infrastructure in different higher education contexts, e.g., GOLDi-lab (TU Illmenau), WebLab-Deusto (University of Deusto), Go-Lab (among others, University of Twente), LabsLand (among others, Universidad Nacional Abierta y a Distancia), and many others. Laboratories play an essential role for the acquisition of competences in this field, because they can deploy hands-on skills and involve elements of design, experience, exploring and enquiry processes, as well as problem-solving and analytical thinking (Abdulwahed & Nagy, 2011). To exploit appropriately the advantages of laboratory-based content in engineering sciences, an experiential-based learning approach was chosen.

18.2.2 Experiential Learning in Laboratory-Based Learning Scenarios

Experiential-based learning (EBL) is an approach that can especially be used for the acquisition of lab competencies in the engineering education, because it meets the requirements for students in laboratory-based learning environments and it provides a process-oriented procedure that supports the reflection of lab experiences. The relation of EBL and lab-based learning focuses on designing, building, and operating a laboratory infrastructure with the aim to support the theory-praxis transfer (Konak, Clark, & Nasereddin, 2014; Verner & Ahlgren, 2004). Furthermore, EBL is based on a constructivist approach and can provide impulses and ideas for the methodical-didactical implementation of the laboratory curriculum. Beside real hands-on labs, EBL methods can also be embedded in remote and virtual laboratories. Haertel et al. (2013), for example, used the experiential learning approach for the acquisition of interdisciplinary competences in a remote lab and to support the transfer of theory and practice through company contacts (Haertel et al., 2013). The University of Loughborough implemented the experiential learning approach in a virtual laboratory for process control to increase the conceptual understanding and the design skills of the students (Abdulwahed & Nagy, 2009). Depending on the mode of the laboratory, the learning spectrum can vary from preparation for the use of the real laboratory infrastructure (virtual) toward the enhancement of the laboratory experience with digital components (remote, augmented) to acting in safe environments or to repeat experiments as often as necessary (virtual) without causing additional costs (Alkhaldi, Pranata, & Athauda, 2016). Kolb defines experiential learning as “the process whereby knowledge is created through the transformation of experience.” For him, knowledge results from the combination of grasping and transforming experience (Kolb, 1984, 2014). In this sense, learning is a process of adoption, where knowledge is created and recreated continuously (ibid.). For Kolb, experiential learning is not just an educational technique that simply adds experience in the institutional context. He rather understands learning as a cyclical process, which he describes in four modes: concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 2014; Kolb & Kolb, 2009), as it is depicted in Fig. 18.1.

The circle visualizes the four modes in two dialectical related ones of transforming experiences. Concrete experiences made by a learner in dealing with the environment in general or with an object in particular are the basis for a closer look from

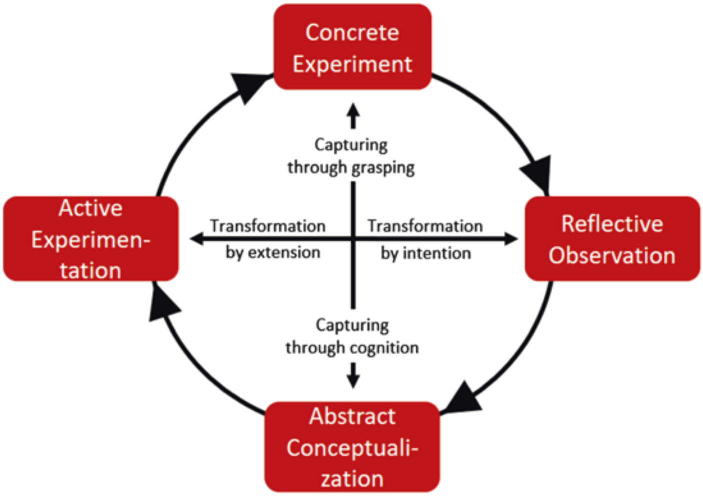

Fig. 18.1 Kolb's (2014) learning cycle

different perspectives, i.e., for reflected observation. The learner tries to put these observations in context, in "if-then relations," through inductive approaches. As with a puzzle, the individual parts or experiences and observations that have been analyzed are transformed into an image or a theory or abstract concept. In a fourth step, the theory is verified or falsified by a deductive process. This can only be done by testing the hypotheses, by active and concrete experimentation. From the result of this examination, new impulses or new experiences result (Kolb & Kolb, 2009). The optimal learning takes place when learners have adequate balance of these four stages during their learning experience. It is not necessary to start with a concrete experience. Rather, the learning process can begin in any of the four phases, but ideally it should include all phases and be spiral in nature. Experiential learning in laboratory-based environments offers a variety of method-didactic starting points and opportunities to stimulate learning and research processes like project- and problem-based learning, self-regulated learning, competence-based learning, research-based learning, or situated learning. In the DigiLab4U environment, the students are immersed in real, remote, and virtual labs in which they are tasked to solve practical problems, exercises, and own projects concerning IoT and I4.0 and discover solutions by experimenting with tools, materials, and artifacts. Therefore, an experiential learning approach was chosen and combined with lab-based learning principles. Experiential learning promotes the support of broad-based knowledge and overarching competences. It is based on the assumption that direct practical involvement with a learning object enables meaningful learning (see Markowitsch, Messerer, & Prokopp, 2004). For this reason and in order to support holistic learning processes, the experiential learning approach builds the pedagogical framework for the design of the lab environment in DigiLab4U and serves as focus for the survey of learning analytics.

18.2.3 Multimodal Learning Analytics

One of the core intentions of learning analytics (LA) is to understand and improve learning by using learning data. Ideally, this data exists as traces from digital tools on a personal computing device that learners use to perform various learning activities. However, in many scenarios, learning activities and the process of learning happen within environments which do not readily develop these digital learning traces. Usually, to be able to capture and analyze the learning processes within these learning environments, multiple signal sources have to be captured, processed, aggregated, and analyzed to produce traces that outline and describe the learning activities and user interactions of the learners within the learning processes. One specific scenario in which learning data comes from different physical sources is within laboratory-based learning. This challenge is not exclusive to this scenario, and there already exist substantial research publications and results within the field of LA which handle learning scenarios in which traditional log-file learning data are collected by online systems and combined with learning events and artifacts which include physical presence and interactions, gestures, gaze, speech, or writing (Ochoa, 2017). This combination of learner traces from these data sources into a single analysis is the main objective of a subfield called multimodal learning analytics (MLA). The main goal of MLA research is to extend the application of LA tools and services in learning contexts which do not readily provide digital traces and learning data. This includes, in lab-based learning environments, gestures, facial expressions, cooperation with peers or the manipulation of the lab itself, etc.

Moreover, the characteristics and properties of these learning contexts cannot be described by a single source of data traces, but a combination of several modes and sources are vital in understanding these particular learning processes (Ochoa, 2017). One specific learning setting in which there are hardly any (scientific) findings and research in LA is using MLA in hybrid laboratory environments in connection with experiential learning. This learning scenario affords the learners a physical presence within the lab (or virtual presence), physical movements and physical interactions within various lab artifacts, components, lab machinery and equipment, as well as a variety of learning artifacts from the learning platform, to conduct learning exercises and experiments as part of their learning process and experience. Such scenario includes the following so-called modalities within MLA, presented by Ochoa (2017): digital log files, actions, movements, gestures and motions, and gaze. In the following sections, we succinctly describe them and, in the subsequent sections, their practical implementation and application within the MLA technical infrastructure.

Digital log files (or simply log files) are log files and digital interaction traces the learning system creates whenever it is used by the users (i.e., learners). These digital traces (or logs) are most of the time captured automatically and neatly stored within the persistent storage of these learning systems. This type of learner data is abundant, and the challenge to collect and analyze it is relatively low compared to the other learner data modalities. When learning outside the system (in our case in the lab), the students have the opportunities and freedom to study, collaborate, and cooperate outside of the online learning environments. These learning activities cannot be logged or quantified and as such can go unnoticed from the LA processes (Lukarov, 2019). This constraint has to be accounted for and captured through the rest of the data modalities, and the aggregation and synchronization of the different learning traces has to be clearly conveyed through the analytics results to avoid misinterpretations and, more importantly, avoid teaching interventions based on these misinterpretations. Actions are body movements captured by sensors and cameras (video recordings) in MLA. They are intentional movements which are learned and usually are part of a thoughtful process putting previous knowledge in motion for the purpose of learning within the learning environment. In many cases, actions involve the use and manipulation of tools and physical artifacts and have a predefined sequence, a type, or a degree of correctness. These different kinds of actions usually can attest to the level of mastery that the learner has achieved in a given skill, and their analysis can be used as a proxy to determine the understanding the student has about a given procedure or experiment (Ochoa, 2017). Movements (body movements), gestures, and motions (including posture) are jointly referred as body language, and all three separately and combined provide different types of information about an individual (Bull, et al., 2013). Posture is the position of a person's body (or parts of the body) in a given point in time and as such can provide information about this person's internal state. Gestures and motions are conscious and coordinated movements of different body parts, especially the head, arms, and hands which communicate a specific meaning. They can be inconspicuous or exuberant, depending on the scenario, and usually serve as alternative emphasizing channels for providing feedback within the learning process. Opposite of the gestures and posture, motions are (mostly) unconscious and usually uncontrolled changes in the body position or body parts of a person which also reveal the inner state of a person during the learning process.

The structure of the courses in which lab-based learning scenarios are incorporated consists of three main parts: face-to-face sessions which convey theoretical knowledge to the learners; online learning activities for collaboration, cooperation, and formative assessment; and compulsory lab sessions for building practical knowledge and engineering lab skills. The relevance of MLA comes with the inherent nature of the learning scenarios within the labs because they are the place where theory and practice come into one and the learners have to build skills and conduct experiments and practical work as part of their course performance and, ultimately, part of their grade. Moreover, this hands-on approach for conducting experiments is done in real-time (students actively interacting with the lab equipment) which minimizes the opportunities for receiving feedback about their lab interactions and lab work, and in most scenarios they receive feedback very late in the course without the opportunity to change some aspects in their lab activities. This means that in many cases, the learners have poor/mixed results just because they do not know their way around the lab and know the lab's hardware work possibilities and the correct procedures for utilizing the lab equipment. On the other side, the labs at our disposal are digitalized with technology and equipment; they can generate learning data and events which can be logged and analyzed. The analyzed data can be used to provide feedback back to the students and the teaching staff about the lab-based learning aspects for the learning scenarios. Therefore, in our chapter, we would like to demonstrate the potentials and prospects of providing MLA tools and services in laboratory-based learning scenarios by collecting, combining, and analyzing learning data from these four modalities and use the MLA results to support the acquisition of skills and holistic professional competences of engineering students and enhance their laboratory-based learning experiences.

18.3 Learning Scenario Descriptions and Their Connection to Experiential Learning

In our research work, we have two lab-based scenarios which are incorporated into the curriculum of engineering courses for bachelor and master students.

18.3.1 RFID[1] Measuring Cabinet at the Hochschule für Technik Stuttgart[2] (HFT Stuttgart)

18.3.1.1 Overall Goal of the Scenario

In this scenario, the students learn to analyze and evaluate RFID measurements. They generate RFID measured values, such as the theoretical reading range or a 360° reading profile of an RFID transponder. During this exercise, the students work in a laboratory environment to perform a series of measurements using an industrial RFID measurement cabinet. For the preparation and the execution of the exercise-relevant learning materials, tests and tools are provided and connected via the Moodle learning platform. The use of Moodle allows the acquisition of data traces that are left by the learner during their learning process, and these data were currently evaluated in order to check the relevance for learning analytics purposes.

18.3.1.2 Lab Scenario

The RFID measuring cabinet is a testing environment for RFID UHF-Tags[3] (800–1000 MHz), and it is one of several industry-related applications that are provided as a learning resource for the I4.0 and IoT topics at the HFT Stuttgart (see Figs. 18.2, 18.3, and 18.4). The cabinet for RFID transponder comprises various vision sensors, and it is connected to a PC with Tagformance software that comprises a reading and writing system. It is connected to a PC with Tagformance software. In order to learn the correct use of the cabinet, the students get an industry-related, specific exercise. They can choose to check three different transponders (i.e., TBN

[1] Radio-frequency identification

[2] University of Applied Sciences Stuttgart

[3] Ultra-high-frequency Tags

Fig. 18.2 Transponder in RFID measuring cabinet

Fig. 18.3 Students working with the measuring cabinet

UHF "Delta" Tag, NXP Semiconductors A02, Impinj Monza 4D) on the same substrate or the same transponder on three different substrates (i.e., wood, metal, cardboard). This RFID application exercise allows, among others, sensitivity and orientation testing. Finally, they evaluate the gained data and analyze the efficiency of transponders to assess their ideal use and can give recommendations for their practical usage in the industry. Subsequently, the students prepare a standardized industrial test report to present their measuring results and evaluation. Usually, they work together in teams or small groups to carry out the test series in the lab environment (see Figs. 18.2, 18.3, and 18.4). Currently, an AR[4] application is being piloted at HFT Stuttgart that should additionally support the use of the measuring cabinet. Data traces that are generated in this context will also be used for MLA.

[4] Augmented reality

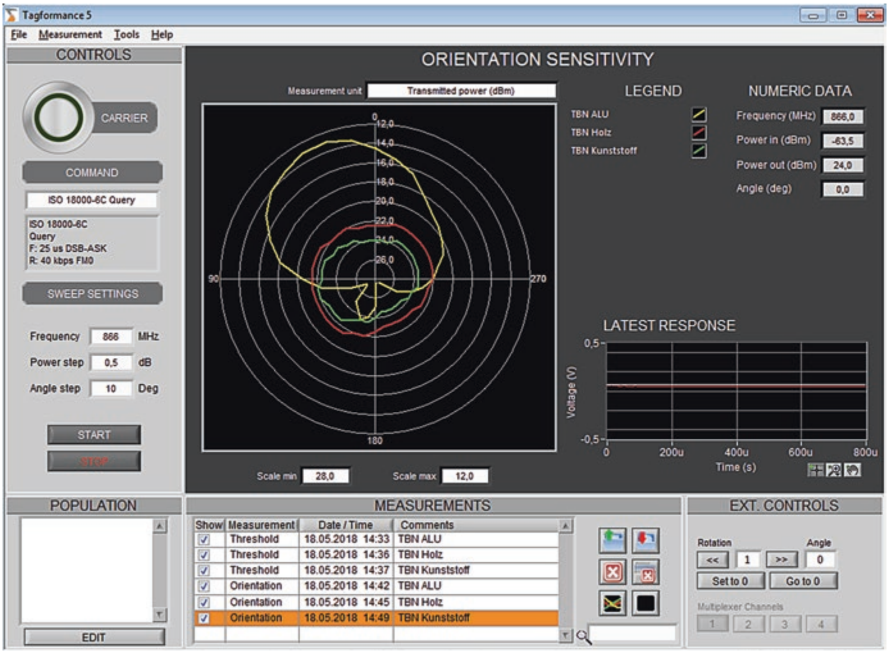

Fig. 18.4 Visualization of Tagformance test results

18.3.1.3 Learning Outcomes

The students show their ability to use the measuring cabinet according to the chosen task. Meaning they have to set up the software to fit the needs of the task. To do so, they have to understand what the different settings mean in order to get the desired results. For example, "transmitted power" or "theoretical read range forward" must be understood to explain what correlations between these two exist. The overall objective is that students are able to interpret their obtained results and document them in the standardized industrial test report. In the context of teamwork, they should also be able to develop, discuss, and document results together.

18.3.2 RFID Lab at University of Parma: Experimental Construction of RSSI Curves

18.3.2.1 Overall Goal of the Scenario

In this scenario, students must compare the theoretical RSSI[5] curve of an RFID tag moving at constant speed in a stable electromagnetic field, as they have learned in theory, with the one that can be obtained in the field from an industry-like scenario.

[5] Received signal strength indicator

The RSSI value is a measurement of the power present in a received radio signal. Although this value can be calculated quite easily in theory, its distribution in real life depends on several factors, such as frequency, topography, and environmental conditions, among others. Therefore, real-life data are often quite different from theoretical ones.

18.3.2.2 Lab Scenario

This scenario is tested in the RFID lab in Parma, on the closed-loop roller conveyor, which is equipped for moving and handling cases for picking activities. A picture of the conveyor is reported in Fig. 18.5, while Fig. 18.6 shows the positioning of RFID antennas on the conveyor (IMPINJ IR1000 RFID reader equipped with three CAEN WantennaX005 far-field antennas). A total of nine cardboard boxes are used for the experiment, namely, one group of three cardboard boxes per each produc, and three

Fig. 18.5 Overall view of the closed-loop roller conveyor in the RFID lab

Fig. 18.6 Positioning of the far-field antennas in the RFID lab

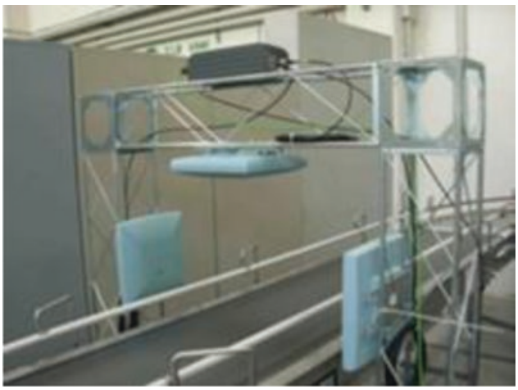

Fig. 18.7 RF-friendly jeans used in the experiment

different products. Products have been chosen due to the different behavior in the electromagnetic field: (i) jeans trousers (so called RF-friendly,[6] a solid material that does not interfere with the field); (ii) water-filled containers (RF-absorbing), with a great absorbing capacity of the electromagnetic field; (iii) tins of tomato sauce, food products with a metal packaging (RF-reflecting).

The three boxes of each group are placed on the roller conveyor and are moved on the closed loop. Every full round of the conveyor is a cycle. The roller conveyor is operated at a constant speed of 2 m/s, and the RFID reader and antenna settings cannot be changed during any cycle, but only between different cycles. Products of each group perform five cycles with the same reading power of the antenna, and then the power is increased by the reader in order to obtain new results. Therefore, 5 cycles are carried out for each of the 5 different power levels, for a total of 25 cycles per each product type. The packages of all products are identified by the same type of tag, called tag #1 (i.e., RFID UHF EPC[7] class 1 gen2 tag, 53 × 34 mm, tag Ucode7, produced by SmarTrac), positioned on the side face that looks at the outside of the roller conveyor. Each package differs for the serial code of the tag, in order to have a precise reference within the same group. In the first test, namely, #1.1, RF-friendly products are used, as it can be seen from Fig. 18.7, and the power of the reader is set to the minimum value (step 1 at 18 dBm). At every cycle of the three boxes, a set of RFID reads is performed and an empirical RSSI diagram can be built for each box and with the reading of each antenna. These values are of course affected by the reading power. A diagram is built with three curves, one for each of the three antennas. The reader is set in continuous reading mode with a time-out of 3 seconds: time $t_0 = 0$, the reading start time, is calculated per each cycle when the box is sensed by the photocell located upstream to the antennas. The photocell gives the input to switch the reader on at t_0. The reader is then switched off at $t_f = t_0 + 3$ s. The average time on which the RSSI curve is built is defined as t_m,

[6] Radio-frequency-friendly

[7] Electronic Product Code

Fig. 18.8 RF-absorbing water containers

Fig. 18.9 RF-reflecting metal-packed food product

calculated as the time in which the intensity of the signal received by the reader reaches its peak. After the 5 cycles, 15 RSSI diagrams are obtained for each box, 45 diagrams in total, i.e., 3 boxes times 3 antennas times 5 cycles. The remaining cycles are performed with the reading power increased at 3 dBm steps (i.e., from 21 dBm at step 2 to 30 dBm at step 5). The test is performed as described, and the RSSI curves are built, evaluated, and compared. In tests #1.2 and #1.3, the same procedure as for test #1.1 is carried out, respectively, loading on the conveyor the second (i.e., containing water containers, as in Fig. 18.8) and the third group of packages (i.e., containing cans of food product, as in Fig. 18.9).

18.3.2.3 Learning Outcomes

Typically, students perform the experiments in a collaborative way that is in groups of two to four students, according to the characteristics of the class. Every group of students is expected to set up the experiments to be performed, collect data from the field, and cluster data to build experimental RSSI curves and analyze them effectively and draw conclusions. This means that students are expected to understand the differences between transmitting and receiving power, the meaning of RSSI values, and what are the factors that influence it and, notably, the differences between theory and practice, i.e., the impact of moving objects and people, of the surrounding environment, and of other sources of noise and their effects on RF reflection and absorption on the electromagnetic field and on RFID reading results. Finally, every group is also asked to propose further developments to the experiment, possibly identifying new or broader goals with suggested improvements.

18.3.3 Connecting Experiential Learning to Lab Learning Scenarios

Appropriate computer technology (e.g., learning management systems, remote labs, virtual lab, etc.) can be used, among other things, to provide simulations and acquire data to analyze, correlate, and present results (Feisel & Rosa, 2005). This enables a wealth of insights and feedback opportunities to initiate transfer and reflection processes, on learning and teaching (Gašević, Dawson, Rogers, & Gasevic, 2016; Ifenthaler, Mah, & Yau, 2019). A central objective of the implementation of DigiLab4U is to provide the students with innovative industry-related lab scenarios and to increase their theoretical-conceptual and technical knowledge in the field IoT and I4.0. With the experiential learning, the project follows a holistic approach that will support likewise all phases of the experiential learning cycle in contrast to other research projects, which have mostly focused on supporting one aspect (see Abdulwahed & Nagy, 2011; Wyrick & Hilsen, 2002). We therefore propose according to Gunstone and Champagne (1990) a laboratory design that encourages students to ask questions (especially in coaching hours with the teacher), to reflect back on their learning (as they communicate their questions and progress with the teacher and peers), to develop new hypotheses (in teamwork), and to design experiments to test them by themselves. Table 18.1 illustrates exemplarily how EBL can be integrated for lab-based learning within the lab scenarios of the two universities.

The laboratory-based goals and activities are operationalized in order to assign them to the phases of Kolb's learning cycle. With the proposed holistic approach, students should be able to gain the more practical-technical skills via experience and experimentation, as well as the more theory-based conceptual and reflective skills. By combining the scenario with MLA, it is aimed to support individual learning paths, so that students with less skills in the field of experimentation, or that have problems in conceptual understanding, can be supported effectively. The data traces that are left by the students in the several EBL phases in Moodle, in the lab environment, or by practicing with the VR[8]/AR equipment can be used to support and guide individual learning paths of students.

[8] Virtual reality

Table 18.1 Integration of EBL within the lab scenarios at HFT Stuttgart and University of Parma

Experience-based learning	Lab-based objectives (HFT Stuttgart)	Lab-based objectives (University of Parma)
Concrete experience: Capturing a learning object through direct grab and grasp and conduct an experiment setup.	The students can place a transponder on a corresponding substrate with the right (horizontal, vertical) orientation within the RFID measuring cabinet. The students are able to set up the software to measure the transmitted power and start the system.	The students are able to set up the experiment and the hardware and the software for data collection, i.e., they can generate and collect data in a practical context. While the experiment is running, the students experience which data can be collected and in which format.
Reflective observation: Transformation by intention.	The students observe and document the measuring results. They have to figure out by testing and observing how much power is needed to activate the tag. They have to reflect why certain transponder on certain substrates serves the best.	The students observe and document RFID reading results with different products and different reading powers. They also observe from the field the impact of variability, i.e., time shifts and different sources of noise. They ask themselves what causes differences between theoretical knowledge and practical results.
Conceptualization: Capturing through internal cognitive processes.	The students have to establish a connection between the indications "transmitted power" and "theoretical read range forward". They have to describe the process and document their results.	The students are able to understand the reasons behind the differences between theoretical and practical RSSI curves.
Experimentation: Transformation through extension.	The students have to decide which transponder and which substrate work best for a self-chosen case study and explain their decision. They present and discuss the results of their experimentation results with peers and teacher.	The students will be capable of designing and testing industrial processes with reliable results of auto-ID technologies for process automation. They present and discuss the results of their experimentation results with the teacher.

18.3.4 Enhancing Lab Learning Activities with Learning Analytics

LA is currently increasingly implemented in laboratory-based scenarios, and the research results show that it can be useful for various use cases. Hawlitschek, Krenz, & Zug, 2019 collected LA data for laboratory-based learning to analyze dropout factors in laboratories, while Venant et al. focus on students' awareness of their learning performance to engage learners in deep learning processes (Broisin, Venant, & Vidal, 2016; Ifenthaler et al., 2019). One of the first successful attempts of implementing LA in lab-based learning scenarios was conducted at the Technical University of Ilmenau, where they collected data about the learning process during the interaction of students with an LMS, which was coupled with an online assessment tool that provided automated feedback (Wuttke, Hamann, & Henke, 2015). In order to explore and analyze the potential of LA for the lab-based learning environment in DigiLab4U, the selected scenarios were matched with experiential learning. The phases from Kolb's learning cycle, which can be enhanced with appropriate analytic results in the chosen lab scenarios, are currently in the conceptualization and reflective observation phase. In these phases, the students use information and perform activities which can be enhanced with analytics results deriving from the analysis of the learning events generated from the students.

The learning cycle starts with the preparation phase on the learning platform where students have to access and review relevant learning resources prior going to the lab and conduct the analysis and evaluation of RFID tags and measurements. The students also need to complete electronic tests and exercises and review the actual lab procedure and steps for conducting the experiments. This means that before going inside the lab, the students have to have an individual abstract conceptualization of the actual experiment. In connection to LA, the learning platform has built-in data collectors which will collect learning events for each individual, and this data can be analyzed to provide feedback back to each student about his situation and readiness to go in the lab and do the concrete experimentation. The next step of the scenario is to go inside the lab and conduct the actual experimentation with the RFID tags. In the current setup, the students have three possibilities. The first possibility is to go directly in the lab and conduct the experiments with the RFID measuring cabinet right after the initial preparation with the resources provided on the learning platform. Their activities within the lab will be collected via sensors, and the student's hardware interactions and measurements data can be collected for each individual and later used for providing feedback based on data analytics. The second possibility is to practice the entire experimental setup within a simulated VR environment, which was developed as part of the project. The virtual environment is an exact virtual replica of the physical measuring cabinet, and the student receives a relevant industry-related specific exercise so that she can practice the correct use of the cabinet. The activities within the virtual environment are logged for each individual student and then transformed into learning events and can be analyzed to provide analytics-based feedback to the student whether she is doing the correct steps and provide a suggestion back to the student about her preparedness to conduct the experiment. The downside of this possibility is that there are no data and measurement results to analyze in the subsequent stages of the experiment (observe, analyze, and interpret measurement results). The last possibility is to conduct the experiment directly within the physical lab with AR support. The student wears the AR glasses and is guided through the steps of the experiments. The activities within the physical lab environment are logged for each individual student and then transformed into learning events and can be combined with their physical interaction and experiment data, and as such their activities are analyzed to provide analytics-based feedback to the student about her work. Here, as well as in the VR environment, there is the possibility to provide immediate analytics feedback during the activities and execution of the steps of the experiment.

The same can be observed within the second learning scenario in the RFID lab at University of Parma. The steps from Kolb's learning cycle of transforming experiences which can be enhanced with appropriate analytics results are the conceptualization and reflective observation steps. The initial step of Kolb's cycle in this situation is to understand how the physical environment and conditions within the lab affect RFID signal strength performance. Again, the learning cycle starts with the preparation phase on the learning platform where students have to access and review relevant learning resources prior to going to the lab and conduct the experiment. The students have to create groups and together review the actual lab procedure and steps for conducting the experiments. This preparatory step is important to get familiar with the lab and the technical setup of the lab because they need to map their theoretical knowledge to the physical lab components which have influence and control over the antenna frequency, the topography of the lab, and the physical and environmental conditions in the lab. This preparatory step is based on activities and resources available on the learning platform, and these activities produce learning events for each individual, and this data can be analyzed to provide each student with the feedback about his situation and readiness to go in the lab and do the experiment. Unlike the scenario of the measuring cabinet in Stuttgart, the RFID lab in Parma is more complex, and there exist a lot more possibilities for conducting an incorrect experiment. Hence, the students will immensely benefit from including VR/AR technology within the lab to learn the correct steps and sequences for conducting a proper experiment and gathering good and usable data to build RSSI curves. The student wears the AR glasses and is guided through the steps of the experiment within the complex lab environment. The activities within the physical lab environment are logged for each individual student and then transformed into learning events and can be combined with their physical interaction and experiment data, and as such their activities are analyzed to provide analytics-based feedback to the student about her work. It can be observed, from the described enhancements of the scenarios with LA, that the interconnected hybrid learning environments will generate a wide range of analogue and digital learning-related data that must be analyzed and the analytics results used to support and enhance lab-based learning experiences. More precisely, the learning activities in these labs include interactions within the learning platform online (including the wide range of learning resources and instruction); physical interactions with the lab equipment; and physical presence and movement in the lab including group work, time spent within the lab, various sensor data from the labs, formative and summative assessment data, and interactions and events from the AR/VR equipment installed for the interconnection of the labs.

The combination and correlation of this multimodal learner data has to be aggregated and properly stored within one central learning record store (LRS), and the data should retain its semantic value and ensure that the data is available for analysis and interpretation while conforming to current data privacy regulations within the EU.

18.3.5 Technical Infrastructure for Lab-Based Learning and MLA

The two lab-based learning scenarios described in this research are to be implemented within a networked lab infrastructure which has an MLA as core component. This networked lab infrastructure contains interconnected hybrid learning environments (digitalized labs) which generate a wide range of analogue and digital learning-related data. The connected labs infrastructure works as a hybrid learning platform that puts together physical labs in which experiments are conducted, a learning management system to provide the necessary learning resources and assessment instruments, and an AR/VR environment for remote experimentation and interaction with the physical labs. The labs are equipped with computers which are directly connected to the lab components and collect the raw experiment data from the experiments and have various sensors, cameras, and equipment and tools which the learners have to interact with for conducting the experiments as part of the learning scenarios. The AR/VR components act as a bridge between the software and hardware components of the lab infrastructure. They include two realistic virtualizations of the labs in which the students can practice the experiments for their labs and (maybe) remotely conduct experiments within the physical labs. They interact with the virtual components within the virtual environment, while the experiments are conducted within the physical environment. After the experiments are conducted, the students receive the raw data collected from their experiment, and they are supposed to analyze it and use it as part of the assessment component of the learning scenarios. The enactment of the physical experiments, lab staff wearing AR technology (in Parma) and a robotic arm (in Stuttgart), is executing the physical steps of the experiments. The learning scenarios supported by the infrastructure can be integrated into bachelor and master engineering courses where gaining practical knowledge and competences is part of the curriculum. The learning scenarios themselves are well-defined didactical units with goals and what kind of competences they aim to develop in the learners and are implemented and deployed within the networked lab infrastructure.

One can observe that in both learning scenarios, the students' work and success within the lab is based on how much effort they have invested in the preparatory work and how well they did on the preparatory electronic tests and assignments before going within the labs. Here the teaching staff can observe how different students prepare themselves before starting the practical experimentation. Additionally, the digitalized lab can provide a complete timeline and breakdown how each student (or student group) worked within the lab, and through data analysis, each experimentation session can be broken down into specific steps for further investigation and analysis to gain more insights which parts of the experimentation are good and which ones are problematic and need to be improved with more lab guidance, learning resources, and actual technician support. The combination of the results of these two aspects provides a holistic picture of the development of practical lab skills needed for I4.0.

The lab infrastructure is a web-based solution that provides a single point of entry for the learners and combines the following hardware and software components: learning management system, LA infrastructure, AR/VR components, and the physical labs. When one of the learning scenarios is implemented as part of a course, the learner logs in on the networked infrastructure and she has all the components available for learning activities. The learning management system contains the various types of learning resources, including interactive readings, video lectures, tutorials about the labs and experiments, quizzes, and other assessment instruments. Additionally, the LMS also serves as a place for the delivery of the learning analytics results in the form of a learning dashboard. The LA component of the lab infrastructure includes four main elements: the data collectors (event generators), the learning data warehouse, the analytics engine, and the delivery of learning analytics results. The data collectors are present and implemented in each component of the networked infrastructure as a module that generates learning events for each learner and sends them to the data warehouse as xAPI statements. The data warehouse uses the xAPI data standard as an underlying model for storing data because it standardizes the way the learning data and statements are saved from the different (software and physical) sources. All of the cameras and sensors, the AR/VR tech, the physical labs, and the LMS generate log events in a completely different structure, frequency, and modality, and several xAPI extensions have to be developed and implemented to capture and store them so that they capture these modalities and provide a standardized way which helps in retaining the context and detailed granularity of the learning activities. Once the learning events are generated and transformed into the appropriate format, they are stored in the data warehouse (in this case, a Learning Locker LRS) via the available REST API for management and manipulation of events. The combination and correlation of this multimodal learner data is aggregated and properly stored within one central learning record store (LRS), and the data should retain its semantic value and ensure that the data is available for analysis and interpretation while conforming to current data privacy regulations within the EU. The analytics engine comprises of different algorithms for analyzing the learner events and works as a batch analysis process which takes learning data from the warehouse, analyzes it, and stores the results. The delivery of results has a form of a learning dashboard within the LMS and delivers personalized results to each learner.

Concrete example can be the analytics process workflow for the RFID measuring cabinet learning scenario and its possible analysis and data visualization. The first step is to collect learning data, events, and activities which exist on the learning platform (Moodle), all relevant lab activities and lab results which exist in the measuring cabinet within the lab, as well as all available AR/VR data from the students' learning activities (presented in Sect. 18.3.4). As all these logs and events are generated; they are transformed into xAPI statements with distinct verbs to describe a certain learning activity, like the student created, answered, interacted, and as such stored within the LRS. One interesting analysis is to see the experiment activity break down into the four major activities that are required from the students to do as part of the scenario: prepare for the lab experiment, spend time in the

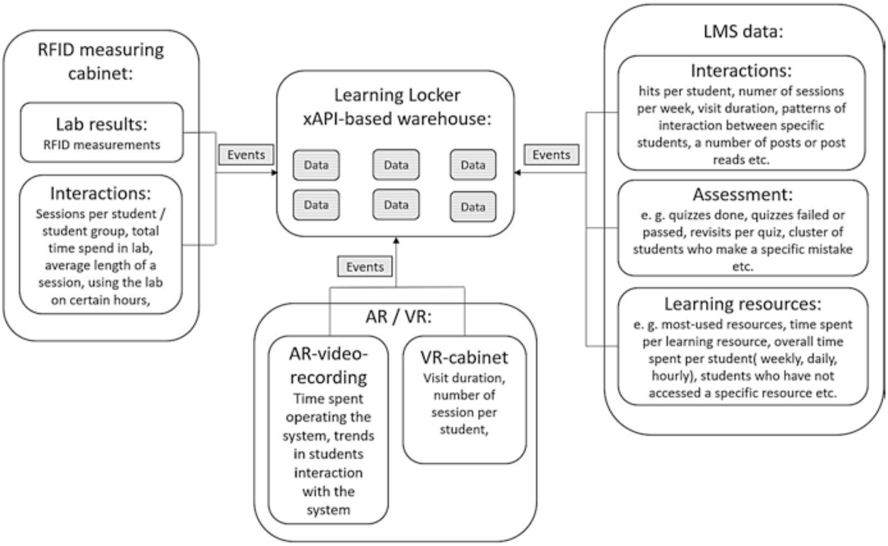

Fig. 18.10 Example: LA infrastructure for lab-based learning environment of the RFID measuring cabinet

lab experimenting, analyze and prepare the experiment results, and finally upload them on the learning platform. Figures 18.11 and 18.12 provide one possible visualization of the major activities for the experimentation as timeline over time. Each representation of these activities is clickable meaning that the user can delve deeper and observe how much work and effort she has invested for each of them.

The first iteration of the implementation, the LA for the lab-based learning environment, will be based on descriptive analytics due to the limited database that is currently available. For this reason, the aggregated data should provide insight in "What has happened?" and will be used to better understand current or past events. Therefore, the different databases (LMS, lab, VR/AR data, etc.) with their variety of coded, detailed data will be converted, like matching pieces in a puzzle to build a coherent, informative "learning" picture (Mustafina et al., 2018). In the second iteration, diagnostic analytics is planned to include among other things the analysis of data to inform and uplift key performance indicators concerning lab-based learning and analyze effective strategies to support students as well as learning management system metrics to improve the student engagement (SOLAR Society for Learning Analytics Research, 2020). The here-described technology setup and context will be used to support experiential learning approaches in lab-based learning scenario like the two outlined learning scenarios. The entire experimentation process, coupled with the immediate results they receive from the lab equipment and the physical and immediate feedback they receive from the environment, encourages the students to reflect upon their learning experiences and increases the possibility of developing new practical and problem-solving skills and improving existing ones. These results can also be used for individual tutorial support and coaching processes.

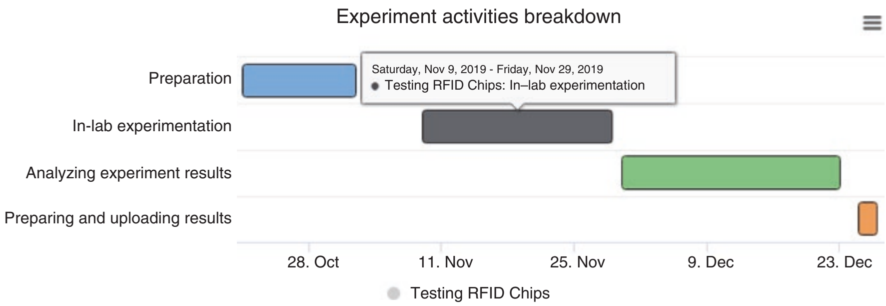

Fig. 18.11 Indicator showing the experiment work breakdown over time for a student

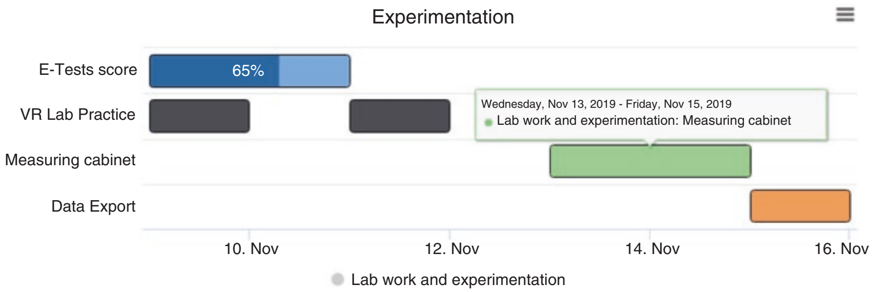

Fig. 18.12 Indicator showing the experimentation activities within the VR environment and the cabinet environment

Besides the feedback for students, MLA focuses on real-world learning contexts and can also provide relevant information for teachers and course designers for adapting and redesigning the learning environment, because the development of corresponding tasks for the lab environment can go hand in hand with the analysis of the available databases (Chatti et al., 2014). Apart from this, it is to be expected that for the more self-directed experiential learning phases, MLA can foster self-reflection and awareness and, by doing so, support valuable experiences for future tasks. The extent to which this can be achieved needs to be further evaluated within the project.

18.4 Discussion and Conclusion

Although the literature includes a variety of examples of including LA in lab-based scenarios, the approach that we chose focuses on the challenges of implementing MLA in mixed reality lab environments. In general, the scenario with the RFID measuring cabinet is a regular part of the course "Sensors" in the Bachelor (BA) Information Logistics at the HFT Stuttgart since 2017. The student evaluation results of the last semesters show consistently very good and good results concerning the possibility of using industry-related lab-based scenarios in their BA courses. Similarly, the lab scenario in Parma with the experimental construction of the RSSI curve was firstly introduced in the academic year 2017/2018 as a part of the elective course “auto-ID technologies in production and logistics.” The report produced by students at the end of lab activities contributed by 50% to the students’ evaluation for this specific course. Students’ grades, as a result of lab activities, ranged from fair to excellent, and the experimental part of the course was particularly appreciated by students. During the course of the DigiLab4U project, however, this lab scenario was reengineered, and it will be used systematically, starting from academic year 2019/2020. To do so, in fact, it is necessary to improve a current hands-on lab to a remote one, as to allow big numbers of students to access the lab (classes in management engineering in Parma might exceed 250 units). Similarly, in the following semesters, a remote, virtual, and augmented version of the RFID lab scenario at the HFT Stuttgart will be tested. Both these scenarios will then be evaluated and equipped with MLA, with regard to the learning and teaching processes within each scenario. These changes pose some challenges, but also benefits, which are summarized as it can be seen hereinafter.

Due to the database, which is still in development, the project will deliver in a first-step descriptive MLA data. With the help of this currently preliminary database, many possibilities can already be identified concerning how the experience-based learning phases can be supported in the future. For example, the descriptive data from the LMS can provide insights on how engaged students are with the provided learning environment and related digital resources. This data can easily be used by learners to reflect on their own learning process, and it gives teachers the opportunity to gain insight into important aspects of the learning process and to make results discussable. In addition to the support of reflective observation, it is considered that MLAs offer a range of data through the acquisition of movement patterns, handling, and interaction, which can be used in the context of active experimentation and concrete experiments. For example, the use of VR/AR equipment could deliver heat maps that visualize where the students’ attention lies and, in a later state of the analysis, if different student groups show similar patterns during their work in the laboratories. These kinds of data can moreover be used as one component for educational decision-making concerning the design of the learning environment as well as additional learning resources.

Overall, the students and teaching staff involved in these learning scenarios need easy-to-use analytics tools which provide a pleasant user experience and are not intruding on the lab learning experience. Moreover, MLA tools should also provide a simple interface and functionality, which is appropriate for the different user groups and which ensure continuous usage and incorporation in their online activities. The provision and access of such tools should be seamlessly integrated within the users’ online working environment and available at-hand without extra effort. The use and implementation of the networked lab infrastructure, and especially the newer technologies such as AR/VR, should feel natural to use and in place. The use of MLA that we propose here as part of the experiential learning approach can help the learner to reflect and plan their activities by becoming aware of their situation and actions within the experimental scenarios, comprehending what it is going on in them, and then plan future activities which can result in continuous learning and, possibly, in achieving better results and changing their learning behaviors in the lab. The experiential learning approach already includes cycles in which the learner has to reflect upon his knowledge, and LA have proven methodologies and potentials to actively support the learner in these reflective activities (in some cases, even directly within the experimental environment).

Furthermore, the analytics elements of the lab infrastructure should also provide added value for teachers, and this should as well be investigated in the future. Working, learning, and experimenting in a lab are an intricate process which requires experience and higher degree of freedom and the confidence to be able to execute the experiments within these scenarios. The only way to build this confidence and lab knowledge is to be immersed in the lab to practice and experiment with the lab equipment. LA can provide invaluable assistance by providing information about the students' activities and interactions with the provided learning resources and course material, whether the students are showing intrinsic motivation by engaging in continuous learning, and how well are they progressing with their experiments and lab activities. Moreover, LA can provide knowledge and support when the teaching staff is evaluating a course in terms of the applied didactic concepts, the chosen learning resources and resources delivery styles and their content, the formative assessment activities, and the results of the information distribution and the teaching and intervention activities during the course duration.

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Chapter 19
Web Analytics as Extension for a Learning Analytics Dashboard of a Massive Open Online Platform

Philipp Leitner, Karin Maier, and Martin Ebner

19.1 Introduction

The Internet as a provider for information and educational material plays a central role in the ubiquitous learning environments we all live in nowadays, and thereby, changing drastically how learning takes place now and in future. Identified as the future of education (Billsberry, 2013), massive open online courses (MOOCs) attract a lot of interest in the last decade (McAuley, Stewart, Siemens, & Cormier, 2010). MOOCs provide anyone with Internet access the opportunity to participate in online courses on a university level for free. Because of high demand, MOOC platforms have to deal with a large audience of a wide variety of people from all over the world (Romanowski & Konak, 2016). Regardless of the potential of this new learning format, there are also some challenges. While teachers can observe their students in a traditional learning environment and respond appropriately and immediately when needed, they are not able to do so in an online environment especially with a large number of participants. Therefore, the legitimate step is to observe and analyze learners' data in this new environment to grasp and understand this new way of learning and improving the underlying process. In this intersection of various academic fields such as education, psychology, education, and computer science, the term Learning Analytics (LA) was coined (Dawson, Gašević, Siemens, & Joksimovic, 2014). The goal of LA is to understand learning itself and the environment in which learning occurs, but additionally it can also be seen as the approach to optimize these factors (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013).

Although LA is a relatively new research field, one important outcome from previous research may be that there is no "one-size-fits-all" LA solution (Blikstein, 2013). Therefore, a requirements analysis of the stakeholders involved the university

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and the platform guaranteeing successful deployment and valuable results. In their literature review, Leitner, Khalil, and Ebner (2017) categorized the involved stakeholders into learners, teachers, and researchers/administrators. Although the learners are the main target group when talking about learning, our dashboard was specifically designed to support teachers and administrators to understand how learning is happening.

To achieve this, however, it is necessary to take a closer look at the activities of learners. The data records for LA come directly from the learning management system (LMS) used, where information such as the number of downloads or accesses to the system can be generated. Stored as log files or numbers in a database, this data and its sparse presentation may not be sufficient to answer the research question of how learners use MOOCs. A chain of processing steps is necessary to receive a human interpretable representation; this starts with identifying the traces left behind by learners, through data aggregation techniques within this learning environment, to data modeling, and the definition of key figures and metrics (Duval, 2011).

The Web Analytics (WA) plugin presented in this research work performs these steps by capturing the learner's interactions with the provided resources in selected courses on the Austrian MOOC platform iMooX, founded in 2013 (Kopp & Ebner, 2015). In addition, suitable indicators are defined which are to be presented to the interest groups. These are encapsulated as widgets and integrated into a LA dashboard named LA Cockpit.

This approach provides the opportunity for a sophisticated view on how learners interact with the learning material offered in MOOCs. Through behavioral analysis as well as associated metrics combined with the educators' experiences from face-to-face teaching, the dashboard supports teachers in the decision-making process on where to act and how to improve the learning process in general.

Taking into account guidelines and best practices from our previous research (Maier, Leitner, & Ebner, 2019), we have extended our framework to include also Web Analytics. Our overall goal for our LA Cockpit is to close the information gap that teachers in MOOCs have compared to real classroom learning situations and examine what can be derived from recorded activity traces in online learning environments. For integration into the existing framework, a subset of possible metrics was designed, on which the plugin explores appropriate visualization tools for the engagement and behavior of the captured learners. Further, the plugin aims to provide means of evaluation to improve the quality of the offered MOOCs by adapting the content and presenting it to the MOOC community.

Therefore, our main research question follows the goal of how such LA dashboard have to look like to assist especially teachers or any educators to understand the learning process of his/her learners in order to improve their teaching and learning behavior within a MOOC platform.

19.2 Related Work

The reuse of established tools from various research fields for educational data traces is increasing in the recent years. Those visualization strategies are using charts, graphs, or maps as presentation technologies for digital dashboards (Elias, 2011) which have been successfully adapted using educational data (Charleer, Moere, Klerkx, Verbert, & De Laet, 2017; Jivet, 2016). These learning dashboards have proven to be effective tools in aiding teachers and learners in the context of the learning process.

Based on the findings and earlier studies on the design of learning dashboards (Khalil, Taraghi, & Ebner, 2016; Leitner & Ebner, 2017), three recurring ideas can be worked out:

1. *Relevant metrics:* A very crucial step is finding suitable metrics for the target group. If it is not done properly, the tool will become overloaded, or the user will be discouraged, and therefore it would be useless to use LA.
2. *Visuals:* To make complex coherences understandable and visible to the users, it is essential to use appropriate colors for the different visualization types. Therefore, it is necessary to apply basic principles of interface design and ensure that aggregated data is not falsified.
3. *Interactivity:* Different views or filter options increase the usefulness of the tool for the users and speak to their curiosity. Interactivity is preferred over certain discontinuous numbers.

Furthermore, a suitable system has to be found which also supports the requirements of online use. Learning management systems (LMSs) are a good choice because they offer administration and serve as a provider for online resources. The market provides various paid as well as cost-free alternatives with the option of self-hosting on the universities own infrastructure or as software as a service (SaaS) cloud instance.

As part of the cost-free alternatives, open source implementations are particularly attractive. Three very popular products are challenging each other: Moodle, Open edX, and Canvas. All three are providing basic logging capabilities and visualization options. However, teachers and administrators must work with log files for more specific metrics and metrics if they want to go deeper into the data. It is a great additional effort to provide functions that go beyond the basic statistical figures and reports for the product providers. Therefore, the ideas and concepts of LA are slowly finding their way in the software. For example, Moodle offers various dashboard plugins with LA capabilities. Unfortunately, some integrate connections to external servers or promote their additional paid content.

Other plugins and projects such as Analytics Graphs for instructors are not applicable for a broader range of possible users. They lack in analytical features, customization options, or cover only specific use cases in their implementation.

All these dashboards are working with data produced by learners. Additional constraints for collecting, storing, and transferring this personal data apply. The increasing volume of data, often a by-product of online interactions, has brought new perspectives on privacy and property. The ownership of data has become a hot topic in the last years. Individuals started to claim the "right to be forgotten" (Elias, 2011), and people started to question the "almighty" algorithms over bias and validity. This rising awareness made it necessary to think about potential risk and benefits. This has recently been legally manifested in the General Data Protection Regulation (GDPR). The results are publications about guidelines, best practice, and good working examples. It is necessary to think about inconvenient questions regarding privacy and ethic usage before applying algorithms and tools on the data. This can be done by agreeing on an ethical framework or checklist such as the one by Drachsler and Greller (2016) when dealing with learner's data. Further, Khalil and Ebner (2016a) dealt with the challenges LA is facing and also pointed out the possibility of de-identification of learner's data (Khalil & Ebner, 2016b).

If a researcher wants to use LA, the rights of the data subjects must be questioned. Openness about intentions, distinction which data shall be collected for which purpose, storage and access rights with state-of-the-art software, and security standards are some points to think about. They need to be discussed with all stakeholders. Further training of academic staff is needed to ensure that all standards are met. Further, despite the promises and benefits of LA, it is necessary to discuss the critics on LA metrics, such as the loss of control over data traces. To mitigate the risk and compromise between the benefits and drawbacks, the DELICATE checklist can be used (Drachsler & Greller, 2016). As a consequence, dashboards should not only comply with the minimal requirements given by law or agreements from the institution. Moreover, it is necessary to think about the consequences of displaying metrics, classifications, and visualizations from the early stage of the design phase.

WA is used to obtain key information about the behavior of users on websites Rohloff, Oldag, Renz, and Meinel (2019) discussed in their research work about the possibility to use WA without compromising the learners' data privacy. In their test setting, they integrated Google Analytics in an MOOC as a proof of concept. The study showed that WA can provide useful insights and retrieve a large part of metrics relevant in context of LA for the stakeholders. Especially key performance indicators (KPIs) are easier to obtain from WA tools than, e.g., learner-specific metrics due to the fact that WA is not designed to retrieve user level information or providing LA data to individual students (Rohloff et al., 2019).

19.3 Concept of the LA Cockpit

The first version of the LA Cockpit was completed at the end of 2017 and entered the evaluation and test phase in an academic test environment the following year (Maier et al., 2019). Designed as a plugin for the LMS Moodle, the initial concept included requirements such as simple maintenance or modular and configurable system design. The target group was only administrators of the LMS. The focus was on demonstrating that Learning Analytics plugins can be used with open source resources and serve as a basic source repository for quick and easy extension.

The LMS Moodle already collects basic statistics about the system as well as data on interactions between participants with the learning objects and stores this information in the database. The first version of the LA Cockpit used these database tables to group and aggregate on daily basis. This basic metrics were encapsulated and visualized trough widgets. The MOOC administrator could add or delete these widgets. Besides presenting different visualization methods, it should also serve as a starting point for other key figures. The metrics showed system-wide key figures from the LMS. We interviewed the stakeholders, and together a list of feature requests was created. This list was decisive for the revision of the dashboard.

The new and extended version of the LA Cockpit is based on these existing daily aggregation mechanisms. Furthermore, it is improved by additional data tracks from outside the learning management system. Capturing interaction within the learner's browser environment enriches the data available in the LMS and provides opportunities for new metrics and widgets. The next section describes the basics of behavioral analysis and activity measurement. Further design changes, improvements to the LA Cockpit, and a new feature later called Web Analytics (WA) plugin are discussed in the next sections.

19.3.1 Activity Measurement

When designing learning analytic tools, the focus lies on how the content is going to be displayed and which key figures should be provided. In the environment of many online learners spread across different courses, the contact and interaction between teachers and learners is fundamentally different from the traditional face-to-face environment. Teachers receive feedback from the learners often only through their final grade or explicitly requested responses.

In addition to the implicit feedback of the interaction process, the teacher must be able to rely on the functions of the LMS. However, simple statistics of the system do not sufficiently reflect the actions of the learners. The LA Cockpit should reenact this cognitive connection between teachers and learners and allow teachers to use their pedagogical knowledge to work with the displayed information.

In order to measure different activities, a closer look must be done to the LMS itself. As data source, one can access the LMS resources in the form of database tables, logged events, and records of technical processes such as download count. This is often not enough to capture the manifold ways of learning, so a number of research studies (Blikstein, 2013; Spikol et al., 2017) try to make use of additional information (or multimodal data) such as speech, writing, or nonverbal interaction (e.g., movements, gestures, facial expressions, gaze, biometrics, etc.) during real learning activities to enlarge the data traces and to create metrics from. The internal state of the learning process is quantified by capturing its external representation of learning.

The focus of the LA Cockpit is on aggregated metrics rather than individual, single, and absolute values. The main goal is to create a context for teachers without classifications or complex predictive modeling. With the help of the Web Analytics plugin, the LA Cockpit hopes to visualize – not only quantify – activities within a course in an aggregated mirrored view from the user's perspective. Insights into what the learners are doing within a MOOC and what resources they are accessing can provide a starting point for further research.

In the next section, the details of the behavioral analysis approach with the Web Analytics plugin are discussed. Basic technical background of the LA Cockpit and the building blocks of the technology within its environment are discussed in Chap. 4.

19.3.2 Web Analytics

The LA Cockpit provides means of measuring, identifying, and visualizing the behavior of MOOC participants with an additional plugin built within this research study. Applying Learning Analytics only with the resources from the Moodle system is not enough, especially in the context of MOOCs. In the face-to-face classroom situation, teachers can observe, infer, and act upon the learner's behavior. Following questions must be pointed out:

- Do students struggle to find a certain resource?
- Do they need more time than expected?
- Do they answer their quizzes by going back and forth between video lectures and quiz questions?

In the online environment of MOOCs, the providing platform has no timely analysis capabilities of the interaction on the client side. Therefore, the Web Analytics plugin tries to capture the interaction within the browser window, aggregating the interaction and offering an additional data source from the learner's perspective.

Figure 19.1 provides an overview of the involved resources. The aggregation of data does not happen user-wise, but resource-wise beginning with the clients' browsers.

Within Moodle, multiple pages, distinguishable via their URL, represent one specific online learning course. Each URL is considered as a single resource. This means that for each accessed course page, the activities of the learners are logged and daily aggregated into the LA Cockpit database.

Using the web browser to access the learning resources, interaction can happen via different types of input devices, mouse, keyboard, touch input, or speech input, whereas mouse and keyboard interaction are considered as standard input devices. With mobile devices, the mouse is replaced by touch input, and a physical keyboard is simulated with a virtual one. The way those input devices are used can relate to our cognitive processes and also depends on the presentation of the content.

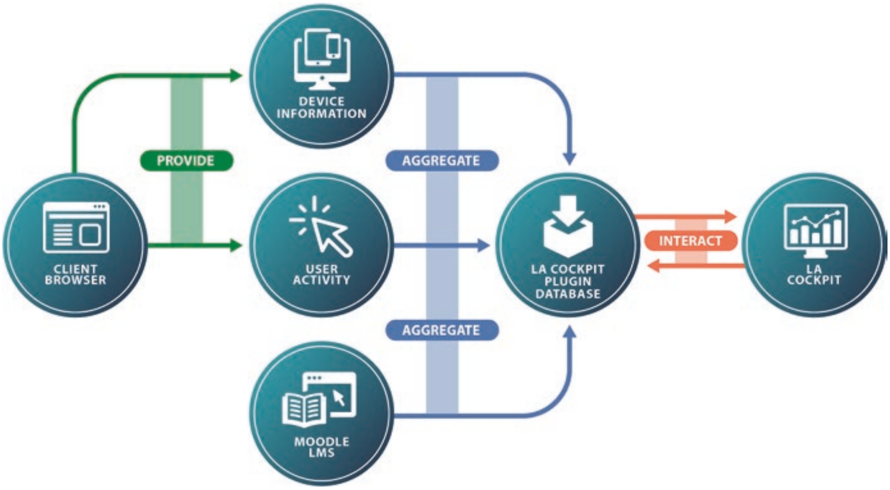

Fig. 19.1 Resource interaction of the LA Cockpit

From a technical point of view, behavior can be categorized into different events happening within the system. These need to be interpreted by the browser to react accordingly, e.g., a click on a button opens a pop-up. The triggered event gets forwarded and processed by the browser, where the WA plugin aggregates different types of events. The following events are aggregated with their timestamp attached:

- *Mouse Movement*. Aggregation for changing x and y coordinates of the mouse pointer.
- *Click*. A click (pressing of a button followed by a release) event as well as a target resource upon which the event has happened (e.g., button, link).
- *Key Event*. Timestamp for the key event and if any special keys are pressed (Shift, Alt, Control).
- *Scroll Depth*. Scroll depth is saved within a regular interval. This refers to the calculated percentage of the page the users have scrolled to, where the top of the webpage is considered 0% and bottom of the page would be 100%.

The main data provider is mouse movements. A mouse movement can be defined as continuous event sampled at consecutive points in time with according x and y coordinates, creating a discrete data trace over time. All visually guided movements (e.g., selecting, pointing, clicking) are formed through gestures with the mouse device.

In the WA plugin's database, a mouse movement is described by consecutive logged entries. The database field id refers to a consecutive log number, and a timestamp is the Unix timestamp of the triggered event, whereas event time is the JavaScript generated timestamp. The latter is calculated from zero, defined as the creation of the web document and is reset with a reload of the web document. The WA plugin saves both for redundancy reasons. The position of the mouse event is given by its values x-pos and y-pos, calculated from the coordinate system where (zero, zero) starts at the top left corner of the web document. For the metrics, the number of database entries grouped by these coordinates is used to generate the Heatmap value.

There are many different ways to use and consume web content; mouse movement analysis can provide the necessary data for the goal of the WA plugin to identify overlapping regions of interest. Especially as this collected data results from real-life situations and not from a controlled lab situation, previous research results about correlation cannot directly be transferred.

19.3.3 Metrics and Visualization

The aggregated data from the WA plugin still needs some further refinements before becoming usable within the widgets of the LA Cockpit. It might not be necessary or helpful to display all raw data in every detail. The target group should get widgets which are easy to interpret and to understand. Therefore, meaningful subsets of the information have been agreed upon, and the activity data will be represented with three new additional widgets: Device Statistics, Activity Calendar, and Heatmap.

These should provide the teacher with a starting point for discussions on how students interact with learning resources. The web analysis function is intended to enable researchers to create additional analytical functions of the LA Cockpit that are related to this behavioral analysis data set. Each metric provides a different perspective on the aggregated interactions; the foundations of the metrics and its visualizations are explained below.

19.4 Implementation

19.4.1 Device Statistics

In the evolution of the Web, the Internet began with a text-based system in which users navigated by entering commands. Nowadays, browsers perform this task for the user. When accessing resources, the browser acts as an agent and turns the action into commands. When loading resources, the browser on the client side identifies itself with the string User-Agent to the server.

In HTTP, the User-Agent string is used for content negotiation. The format is a list of product tokens/keywords, with the most important listed first. The HTTP header of the request specifies which languages the client can understand and which language is preferred, reflecting the language set in the browser user interface.

For the WA plugin, this information is used within the Device Statistics widget (Fig. 19.2). The character string of the browser User-Agent is stored the first time the user accesses the course. Afterward, the server analyzes all available datasets and returns sorted subsets to the dashboard for visualization.

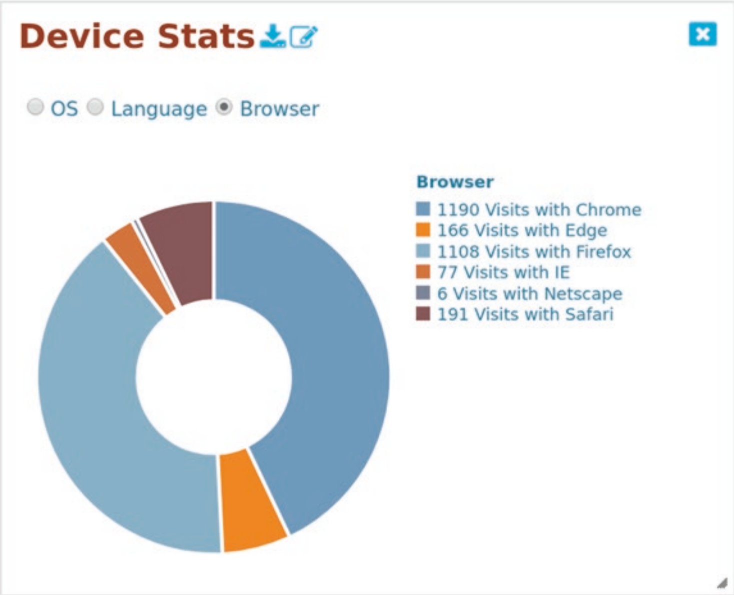

Fig. 19.2 Device Statistics widget

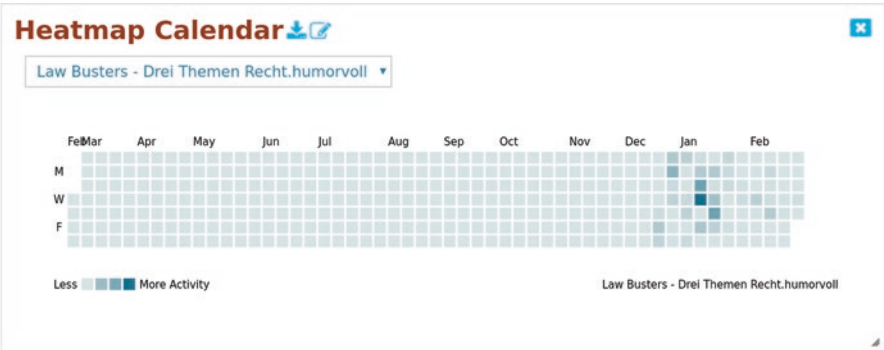

Fig. 19.3 Activity Calendar widget

19.4.2 Activity Calendar

For the Activity Calendar widget (Fig. 19.3), a basic aggregation of mouse events is performed. The count value of the activities for each day is calculated directly from the data traces in the database. All available events are stored on a daily basis as the calendar provides a daily overview. The year view is calculated from the current date that gives an overview of past activities within the last 12 months. The metric is aggregated on the server side according to the request sent after selecting a course to display the data.

Fig. 19.4 Heatmap widget

19.4.3 Heatmap

The Heatmap widget shown in Fig. 19.4 consists of two main parts. The activity data itself – visualized as traces between red and green – are aggregated from the WA plugin by analyzing the user's mouse activity. Since these widgets have to visualize complex relationships, the LA Cockpit uses state-of-the-art technology such as the D3.js framework. Without the displayed course URL, these mouse traces would be difficult to interpret. Therefore, it is necessary to provide the information layer presented to the user. The background image of the widget puts the captured data into the correct position, for which an elaborate process creates the screenshots. Then the widget itself presents only the list of URLs where background images are available to the target user.

19.5 Discussion

The revised and extended LA Cockpit for the Austrian MOOC platform iMooX was deployed for the first time during the MOOC "LawBusters – Drei Themen Recht. humorvoll." It started at the end of December 2018 and featured 3 weeks of video lectures, which dealt with law-related basics in an entertaining way through analogies from Science Fiction and Fantasy. Nearly 90 users took part in the course, where our goal was to provide a proof of concept for the LA Cockpit as well as getting feedback of the participants.

19.5.1 First Evaluation Results

The feedback on the LA Cockpit was collected via online surveys and was general satisfying. Especially, the basic concept of multiple dashboards proved beneficial when grouping different widgets to the individual liking of the target user such as on course basis. Yet, when managing a larger number of courses, the name as a distinction turned out to be not enough. Additional details such as date of creation could help finding the desired dashboard faster and so improve the satisfaction with the tool.

We got a similar positive feedback to the PDF report. It seems that despite the digital era, some teachers prefer paper over digital reports, or at least the possibility to print it out. An additional motivation might be that sharing course-related information without elaborate access and authorization process to the LA Cockpit. Also, the information in the note section received broad reception and is considered to improve the understanding of the different widgets. The adaptation possibilities of those texts to document own findings and observations proved useful. User adapted the text even for basic information related to the displayed metrics or visualization. In our case with the LawBusters course, the Christmas time left a distinct decline in activity on the platform, shown in Fig. 19.5. Even such general remarks can find their place in the note area and be used as documentation for later comparisons.

The user behavior was captured by the WA plugin and provides a large amount of information. At the moment, only a subset of this information is visualized in our metrics. The target group of researchers and administrators suggested that further details about the user experience in-course should be visualized. One particular example was the keyboard usage in the context of forum, which could give information about search bar usage to access specific learning materials. Nonetheless, the

Fig. 19.5 Login over time widget with notes

provided metrics were considered helpful by the target group and gave interesting insights to the underlying data.

As for the user group of administrators, the distribution of the operating systems and Internet browsers used was relevant. This significantly supports the testing and optimization of the platform. Teachers were more interested in the specific language settings of the participants. In our case, two thirds of the participants accessed our system with German language, whereas the remaining exclusively used English with American locales as their primary browser settings.

19.5.2 Limitations

The evaluation of the LA Cockpit also showed some limitations. In addition to keyboard and mouse, touch-sensitive input devices were used, which have to be handled differently depending on their type, such as mobile phones or tablets. Web applications may either process those touch-based inputs trough events or access them as interpreted mouse events. Our WA plugin was designed to only collect and process mouse, and mouse-interpreted events and thus touch-only events were not or only partially recorded. In addition, it is a technically complex task to completely cover the dependencies on the various combinations of operating systems and Internet browsers, including different versions.

A second limitation concerns the sampling of mouse events. User interaction takes place continuously in real time, with each logged event represented by a discrete timestamp. The data stream generated by the tool has a sampling rate that is influenced by various factors, primarily by the input device itself. A computer mouse has a polling rate, measured in Hertz (Hz), and a corresponding polling interval. They define how often the position is reported to the computer, which is usually once per millisecond. For example, 125 Hz means that the mouse position is sent to the computer every 8 milliseconds. In addition, a discreetly rated representation of the mouse movement that the event triggered within the web content could add another layer of inaccuracy. The mouse event is intercepted trough JavaScript in the WA plugin, where microsecond times for events would be theoretically technically feasible. However, in order to minimize current security threats such as Spectre (Kocher et al., 2018), browsers round the result of queried timestamps to varying degrees. Thus, the exact profiling of users is not feasible. However, the assumption that the entire data trace of a mouse movement is sampled at a lower rate has no negative effect on data aggregation and the visualization of behavioral analysis in the LA Cockpit.

A third limitation relates to the fact that there are different ways, depending on different cognitive processes and personal characteristics, to achieve the same goal such as downloading a learning resource or accessing a video lecture. For example, while browsing the webpage, the mouse pointer of the user could be like an anchor, resting at the top of a paragraph. Another user, on the other hand, can mark the passage along the text while reading, in order to copy it later. Using keyboard shortcuts to scroll through pages or browse the web page would also leave the mouse at a position that does not correlate with the center of the user's visual attention.

Several studies in the areas of mouse tracking, mouse movements and behavioral analysis have shown that the mouse pointer can act as a weak proxy of the gaze (Arapakis, Lalmas, & Valkanas, 2014) and offer a cost-effective alternative to eye tracking (Huang, White, & Buscher, 2012). The strength of the correlation depends on the design of the website (Clark & Stephane, 2018). Therefore, it is important to note that mouse motion analysis is not a suitable substitute for eye tracking studies. The equipment required for these studies is much more expensive and requires a predefined laboratory setting. These environmental requirements are not transferable to the target application of the LA Cockpit. However, mouse activity provides a suitable data source for checking the design of web pages and evaluating user activity in specific areas. For the WA plugin, these data traces are visualized within metrics to provide insight into remote processes that would otherwise not be observable.

19.6 Conclusion

The LA Cockpit, a custom LA dashboard was revised, extended by WA and deployed at the Austrian MOOC platform iMooX. It combines the collection, transformation, and visualization of data produced in the learning environment. Additionally, the focus during the design and implementation of the LA Cockpit was on a modular framework and thereby its extendibility and maintainability. Because of the complexity of LA approaches, the LA Cockpit has a number of tools and offers a highly modular dashboard that can be adapted to the different needs of the target groups.

The LA Cockpit contains basic key figures related to activities in the LMS itself. Through the extension of the WA plugin, it is possible to analyze the behavior of the participants and, thereby, let the target group infer on the way learners interact with the course and its materials. Therefore, the WA plugin uses a set of metrics to capture user activity. This behavioral analysis is done by aggregating different traces of the user in the browser. Three widgets aggregating a series of events and actions are designed to visualize metrics in the dashboard. The Device Statistics widget provides statistical information about the devices used, browser versions, and language settings. The widget Activity Calendar adds a temporary visualization element to the data. Displayed as daily calendars for the last 12 months, different colored fields match the activity level. With this view, it is possible to uncover recurring patterns of user contributions in online learning courses that may have gone unnoticed until now. The Heatmap widget uses the traditional concept of mouse activity heating cards, which display moving areas in different colors, from low activity areas with cold colors like blue to high activity areas in red. The widget is often used as a tool to check the usability of websites in terms of their design and provides another dimension of information. The most commonly used resources and regions of high interest can be visually inspected, giving teachers and administrators a quick overview.

All visualizations within the tool follow the core guidelines of dynamic and interactive presentation. With this concept, it is possible to let the user explore the data himself through the visualizations instead of presenting indicators that are difficult to understand and interpret. This exploration phase is crucial to enable the user to understand relationships that are otherwise not understandable due to large datasets or blurred by aggregated averages without the real dataset. All metrics have course-wide aggregation of data that focuses more on the learning process than on the individual's learning track. The resulting additional privacy does not affect the quality of the information provided by the tool.

In order to better understand the handling of the LA Cockpit and to include the opinions of the stakeholders, an evaluation in terms of usability and usefulness of the LA Cockpit was carried out. In particular, the target group of researchers and administrators provided valuable suggestions and further ideas for improving the LA Cockpit. The focus of these feature requests refers to the metrics and the data and not to the application of the widget itself. Nevertheless, there were common interests, such as touch compatibility, including video analysis and metrics, researching aggregated data with knowledge discovery methods, and providing thorough evaluation.

Further, there is a great need for a comprehensive evaluation of the LA Cockpit including a significant test user group. The next step in the development cycle would be not only feedback from the target group on what information they would like to receive but also on how to achieve useful results. An evaluation of the tool in terms of interface design, usability and user-friendliness, and the content displayed should be made. This may be achieved through technical improvements, where adding new widgets will be a quick next step in supporting future use of the LA Cockpit.

With the LA Cockpit and the WA plugin, a suitable framework for Learning Analytics was created. Such tools are essential to close the information gap between learners and teachers in pure online courses. Further research on this topic will prove to be advantageous as the results can be transferred to general e-learning environments that are gaining importance.

Developers are encouraged to add more metrics, expand the widget repertoire, or even transfer the LA Cockpit to other target groups, e.g., by shifting the metrics to the learners. The creation of a student-oriented dashboard version of the LA Cockpit would be possible by reusing the core components aggregation and visualization. Finally, the tool provides quantifiable insight into learners' behavior and learning process with MOOCs on the iMooX platform.

Further research and development can improve the widgets and add more features to the LA Cockpit. Useful additions can be made directly from the evaluations of the courses. Video lectures or quizzes provide motivation for key figures into aspects such as "number of video lessons seen" or "minutes consumed by video lectures." Since video lectures are a core component in the transmission of learning content, the next promising steps are the analysis of video consumption. This could extend the behavioral analysis of the WA plugins and provides the opportunity to gain further insight into the consumption of video content within MOOCs. After an in-depth evaluation of the interface design, customizing the visualization of the existing metrics and providing alternative types provide the opportunity to increase usability and satisfaction.

The more features and options a LA tool offers, the more important it is to have a clear explanation of the displayed data, key figures, and visualization. A Frequently Asked Questions (FAQ) section, which includes background information about LA, metric calculations, and design decisions for widget visualizations, could be useful for target user group.

Future research and improvements of the LA Cockpit should not only help learners in their learning process and close the feedback loop but also close the gap between learning, teaching, and research. As an actively used tool on platforms such as iMooX, it has the opportunity to gain qualitative insights into the application of LA among its target groups. The research community benefits from the LA Cockpit because most tools never leave their prototype stadium. With these next possible steps, we aim to improve the feature set but even more to reestablish the information channel between learners and teachers in online learning environments. Thereby, teachers get the opportunity to support and improve the learning process with current technologies to educate a larger group of learners than the traditional classroom environment would allow. This approach reflects the fundamental objective of LA to improve all possible parts of the LA life cycle Khalil and Ebner (2015) itself and let all stakeholders benefit from its application.

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Chapter 20
A Dimensionality Reduction Method for Time Series Analysis of Student Behavior to Predict Dropout in Massive Open Online Courses

Eric G. Poitras, Reza Feyzi Behnagh, and François Bouchet

20.1 Introduction

Distance education has a long history and has taken many forms since its inception. One of the popular models of distance higher education first emerged in 2008 when Stephen Downes launched a course on Learning Theory through the University of Manitoba, where 2300 online students took it for free, alongside 25 paying students. This type of course was later named a massive open online course (MOOC) by Dave Cormier. Since then, these types of courses have been offered by a vast number of institutions. MOOCs are web-based distance learning courses with the following characteristics: the courses are (a) massive, open to all, free, and online; (2) low- or no-stakes, no barrier to entry, no penalties for failing, no credits, accreditation, or certification; (c) asynchronous, learners are free to browse and complete assignments at any time or in any order; and (d) heterogeneous in both demographics and intentions (Gardner & Brooks, 2018a).

As of 2017, approximately 81 million students have taken part in at least one MOOC (Shah, 2018), and this number continues to grow over time. Despite the massive enrollment in these MOOCs, around 90% of students fail to complete the course (Jordan, 2014). The term attrition or non-continuation is commonly used to refer to the reduction in numbers of students attending a course. It is worth noting that determining that rate is not necessarily as straightforward as it seems,

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considering many students who register to a MOOC do not register with the original intention to complete the course (Gütl, Rizzardini, Chang, & Morales, 2014), whose motivation could include getting an experience with a MOOC, getting a sneak peek of a topic, or accessing some content. For students who originally intended on completing the MOOC, reasons for non-completion include course length (lower completion rates in longer courses), start dates (courses with start dates closer have high completion rates), and assessment types (auto-grading in the MOOC is associated with higher course completion) (Jordan, 2014). This high rate of dropout has been a cause for concern.

This work contributes to the field of learning analytics by examining the outcomes and effectiveness of various existing machine learning techniques in reducing and meaningfully interpreting students' clickstream data for the purposes of modeling attrition in MOOCs. In particular, the use of data segmentation and feature reduction techniques to engineer features that discriminate between students that are likely or not to withdraw from a course. In this chapter, we conceptualize early detection of students at risk of attrition as a time series classification problem and limit our review of the relevant literature to related works with regard to clickstream data of student activity. Next, we will outline the structure of the MOOC dataset we have used to model student attrition, along with the data preprocessing and processing techniques. Lastly, we will outline the contributions and limitations of our findings, along with practical applications toward the design of early detection systems implemented as dashboards for students, instructors, and advisors. Future directions for research will be proposed at the end of the chapter.

20.1.1 Research on Student Attrition Prediction in MOOCS

One of the most significant advantages of a MOOC concerns the use of the platform as a research tool to investigate issues such as student attrition. Among these, MOOCs capture rich, fine-grained, dynamic behavioral data as digital footprints of the students at scale; data that is not so readily available in other learning environments. These data are amenable to many techniques of computational analysis and predictive models. These data analytics are of interest to institutions of higher education, which need to gain insights into student behavior as a means to bolster retention and graduation rates (Schumacher & Ifenthaler, 2018). Existing studies of MOOCs have focused on different topics, such as motivation, retention and attrition/dropout, assessment, design, engagement, and self-regulated learning (in order), primarily using data from surveys, database, interviews, and discussion forums (Zhu, Sari, & Lee, 2018). From among 146 studies reviewed by Zhu et al. (2018), only 8 used the platform database as their only data collection method. This trend highlights the importance of research using students' trace data available from the MOOC platforms toward a sophisticated and in-depth understanding of students' learning behavior.

A number of studies have begun to investigate the use of predictive models as a means to detect the likelihood of students to dropout from a course and improve MOOC completion rates. Early identification of at-risk students who are more likely to fail or drop their courses is key to a successful learning environment (Romero & Ventura, 2010). Prediction of student success in learning environments has been one of the most popular and well-studied tasks in educational data mining and data analytics (Romero & Ventura, 2010). Educational data mining (EDM) is defined as the "area of scientific inquiry centered around the development of methods for making discoveries within the unique kinds of data that come from educational settings, and using those methods to better understand students and the settings where they learn in" (Baker, 2010). The data mining process involves four steps: (a) data collection, where students' interaction information is stored in a database and/or in a text log file; (b) data preprocessing, where the raw data is cleaned and transformed into a format suitable for data mining (which includes a phase of feature engineering with an impact on performance that can be much stronger than the choice of a particular algorithm); (c) data mining application, where data mining algorithms are applied, associated hyperparameters are fine-tuned to optimize performance, and analytic models are built to summarize and discover interesting patterns and tendencies in students' interaction information; and (d) results interpretation evaluation and deployment, where the model created in the previous step is interpreted and the filtered mined knowledge is used to make decisions about the students (e.g., a model trained to predict dropout on previously collected data needs to be integrated into the learning platform to provide online prediction on future cohorts of students) (Romero, Ventura, & Garcia, 2008).

In a recent review of the literature, Gardner and Brooks (2018a) surveyed 87 studies on predictive modeling techniques of success/dropout used in MOOCs. They classified the purposes of developing predictive models of student success in MOOCs as (1) personalized support and interventions, (2) providing adaptive content and pathways, and (3) data understanding. In terms of models used by researchers, Gardner and Brooks (2018a) identified discussion forum-based, activity-based, demographics-based, and learning-based models. Data used in predictive modeling predominantly constituted clickstream, forum posts, assignments, demographics, and surveys. Predominant platforms were Coursera, edX, Moodle, and XuetangX. Gardner and Brooks (2018b) found that clickstream data are more effective predictors of dropout compared to forum or assignment features in MOOCs; however, except for simple counting-based analysis of temporal patterns in clickstream data, existing studies have not tapped into much of the complexity therein. Feature engineering has been highlighted as an important approach and as a gap in existing research. In the following section, we elaborate further on a novel approach to engineer features that characterize clickstream data of student activity for the purposes of modeling student attrition in the context of the Open University.

20.1.2 Clickstream Data for Prediction of Student Attrition

The Open University Learning Analytics Dataset (OULAD; Kuzilek, Hlosta, & Zdrahal, 2017) is an anonymized dataset released under CC-BY 4.0 license and certified by the Open Data Institute that contains information about a subset of courses offered at the Open University, UK, from 2013 to 2014. It is freely available at https://analyse.kmi.open.ac.uk/open_dataset to support learning analytics research. Students are informed that their de-identified data is used for academic research purposes and could not opt-out of sharing their usage data. At the Open University, an online platform or learning management system like edX or Coursera is used to host distance learning courses referred to as modules multiple times during the year. Each presentation of a module is distinguished by the year and month of its starting date. A typical length of presentation for a module is 9 months. Students may interact with curricular materials prior to the starting date since module resources are made available a few weeks before the start of the presentation, and they sign-up for the module a few months until 2 weeks after the official start date. Each module usually includes several assessments and a final exam. A full discussion of the data selection, anonymization, and validation procedure to create the OULAD from the data warehouse is beyond the scope of this chapter; we refer readers to Kuzilek et al. (2017) for additional information. The resulting dataset contains information about 22 module presentations, 32,593 students, their demographic data and assessment results, as well as logs of their interactions in the form of aggregated clickstream data. The clickstream data consists of daily summaries of student clicks (10,655,280 entries) associated with curricular materials featured in an instructional module.

Kuzilek et al. (2017) distinguish between three types of data collected at the Open University: (1) demographic data that represents information about students, including their age, gender, region, previous education, and so on; (2) performance data about student results and achievements on modules; and (3) learning behavior data that reflects logged student interactions in the virtual learning environment interface or curricular materials. A basic data structure in OULAD consists of the number of times a student interacted with a curricular material identifier on a given day for a specific presentation of the module. Curricular material may take different forms such as HTML pages, PDF files, and so on. The course instructor sets a specific role for the material (e.g., data, external quiz, forum, glossary, page, activity, wiki, quiz, external link) as well as a start date from which the material is planned to be used in the module until a given closing date. Since separate dataset tables are connected using students as unique identifiers (or combinations of modules and their presentations, referred to as student-module-presentation triplets), the data structure enables researchers to align student demographic and registration data, assessment results, and logs of student interactions in the form of daily activity summaries. For the purposes of this analysis, we focus on student registration and assessment results and exclude student demographic information from further analysis of clickstream data. The day of student registration and/or unregistration from the module presentation is included in OULAD, with students who have unregistered have Withdrawal as the value of their final result. Furthermore, assessments vary in type, including tutor- and computer-marked assessments as well as final exams with a given cutoff day to submit the assessment and a continuous value for its weight, totaling in 100% for all assessments included the module. In the following section, we describe prior research conducted in preprocessing the clickstream data, not to argue for any particular approach, but rather to explain the concerns that motivated the use of the particular data segmentation and feature extraction techniques examined in this chapter.

20.2 Related Works

Much of the previous research on OULAD has focused on segmenting the clickstream data for early detection of students at risk of undesirable pedagogical outcomes, such as dropping out, failing a course, or not completing the first assignment. Data segmentation refers to how the clickstream data is partitioned into subsets for further processing. Past research suggests that the choice of moving time series windows for feature selection has been inconsistent, which is often due to the varying goals of a study from evaluating modeling approaches to deploying models with practical implications for instruction. Wolff, Zdrahal, Herrmannova, Kuzilek, and Hlosta (2014) used a time-driven basis to establish the window size, aggregating the clickstream data on a weekly basis. Kuzilek, Vaclavek, Fuglik, and Zdráhal (2018a, 2018b) aggregated student usage data on a weekly basis to predict subsequent week likelihood of course withdrawal or passive withdrawal, meaning that are neither actively studying nor withdrawn from a module. Markov chain models were constructed for the whole cohort of students, students who submitted the first assessment, and students who did not submit the first assessment. Alshabandar, Hussain, Keight, Laws, and Baker (2018) relied on time intervals, but adjusted for assignment submission dates by aggregating clickstream data into six intervals. Hlosta, Zdrahal, and Zendulka (2018) instead varied the labelling window size using predetermined time intervals while evaluating different machine learning methods to detect student failure. In other studies, researchers have relied on a single time series that captured each day of the module presentation (Heuer & Breiter, 2018).

In partitioning the clickstream data, feature extraction is commonly used to provide a high-level representation of the time series due to the high dimensionality, feature correlation, and large amounts of noise that hinders accurate classification. Furthermore, time series data is ordered, and there may be discriminatory features dependent on the ordering. To mention a few examples, Liu, Wang, Benachour, & Tubman (2018) extracted features that characterized the sum total of student interactions with three types of curricular materials across module presentations, including student download of PDF resources, reading course content, and participation in the forum space. Wolff et al. (2014), Alshabandar et al. (2018), along with Hussain, Zhu, Zhang, and Abidi (2018) broadened the categories of interactions to include forum, course content, pages, and glossaries, among others for the purposes of classification. To the best of our knowledge, only a single study compared the relative benefits of binary rather than continuous representations for daily usage in addition to additional metrics such as student demographics and geolocation (Heuer & Breiter, 2018). Hlosta, Zdrahal, and Zendulka (2017) engineered features such as the count of consecutive days with active sessions, first and last day that student was active, average and median clicks and number of materials visited per day normalized by all days, as well as the total number of active days. In combination with student interaction data, the features led to accurate prediction of likelihood to fail due to failure to submit the first assignment. In a subsequent study, Hlosta et al. (2018) achieved accurate rates of detection of students' likelihood of failure through explicit representations of students' tendency to submit assignments earlier than the due date while investigating different methods to sample examples and correct for class imbalance. Kuzilek et al. (2018a, 2018b) relied on the course plan to engineer features to characterize whether an activity was planned or not. Students with no planned activities were found to be more likely to do nothing from the plan next week and those who did nothing will do nothing next week in 2/3 of cases.

As was mentioned in this section, research on the subject of data segmentation techniques have been restricted to limited consideration of context-relevant factors to student attrition such as assignment deadlines and weight. Although student performance on assignments might affect decision whether or not to withdraw from a course, researchers have not adjusted data segmentation methods on the basis of such relevant factors in much detail. Another problem with previous approaches used to extract features is to reduce features that characterize student activity using categories of curricular materials to derive aggregate metrics. The discriminative power of this approach to reducing dimensionality might be improved through a statistical procedure that uses an orthogonal transformation to convert a set of potentially correlated interactions with curricular resources during a given time period into a set of uncorrelated principal components. We now turn to describing the method followed in a case study to address these research questions.

20.3 Experiment

The aim of this case study is to train and test a time series classification model as a means to detect the likelihood of student attrition in the early stages of course completion. It is difficult for an instructor to intervene when students are disengaged because of the lack of physical presence in distance learning courses at the Open University. Furthermore, we identified the most suitable approach to model student attrition by varying the type of machine learning classifier, data segmentation, as well as feature extraction methods. This case study considered the following research questions:

- Can we model student attrition based on the clickstream data by utilizing machine learning algorithms, and if so, which type of algorithm offers optimal performance in predicting the likelihood of dropping out from a module in the virtual learning environment?
- How early in the course completion can we accurately detect the likelihood of dropping out from a module in the virtual learning environment?
- Is it possible to represent the clickstream data by utilizing feature projection, and if so, do the extracted features offer optimal performance in predicting the likelihood of dropping out from a module in the virtual learning environment?

For the purposes of this case study, we limited the focus of our analysis to a subset of student interaction data where attrition was a prevalent issue. Student attrition, also referred to as dropping out from a course, was measured as whether or not students unregistered from a course. Unregistered students are assigned the label of "Withdrawn" as the final result, rather than "Fail," "Pass," or "Distinction," which for the purposes of analysis were merged as a single class label – "Not Withdrawn". A total of 496,181 interactions were selected from module CCC (i.e., STEM course, 241-day duration) and presentation 2014B (i.e., taken from year 2014, section B) due to the high incidence of student attrition. The attrition rate for this presentation of the course was 46.4% of students ($n = 898$ Withdrawn; $n = 1038$ Not Withdrawn). Further examination of the data shows that 250 students unregistered from the module before it began (i.e., day 0), while 648 students unregistered from the course following the start date of the module (i.e., registration entries ranged from −312 days to 227 days; see Fig. 20.1). Liu, Wang, Benachour, and Tubman (2018) reported a similarly high rate of dropout for another presentation of the same STEM module (i.e., presentation J), which suggests that withdrawal may be a systemic issue.

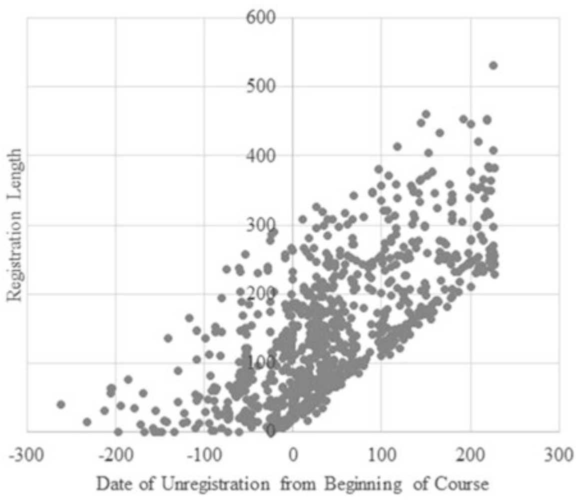

Fig. 20.1 Rate of course unregistration by date from the beginning of the course and the length of registration

Table 20.1 The assignment submission cutoff dates and weight in the final grade

Id	Type	Day of presentation	Weight
24286	CMA	18	2
24282	TMA	32	9
24287	CMA	67	7
24283	TMA	102	22
24288	CMA	137	8
24284	TMA	151	22
24285	TMA	200	22
24289	CMA	207	8

Notes: The day of presentation for each assessment was used as inclusion criteria for dataset preparation
CMA Computer-marked assessments, *TMA* Tutor-marked assessments

Alshabandar et al. (2018) argued that segmentation of the clickstream data should take into account assignment submission dates, as a critical, context-sensitive factor that might explain student withdrawal. As such, this case study examines the use of a variable-sized overlapping window (VSOW) to divide the larger clickstream data into smaller subsets for processing. The VSOW was set to segment the data based on the day of assessment presentations within the module, as shown in Table 20.1. The window was set to move from one assessment or segmentation of the data to the next in order to predict the likelihood of student dropout (e.g., less than 0 days, 18 days, 32 days, 67 days, and 102 days). In doing so, a total of 57, 87, 92, 113, and 141 features corresponding to the sum of student interactions with sets of curricular resources made available during each time period were extracted from clickstream data. This process was conducted until the total weight of assessments or segments included within the VSOW exceeded a threshold value of 40% of the total grade (i.e., 102 day of course presentation). The rationale for this threshold is to allow early identification of students at risk of leaving the course during "critical" moments – when module assessment results are delivered to students – and before students are at risk of failing the course. This method is particularly useful in terms of its practical implications, as instructors may be notified followed assignment due dates of the likelihood of students to withdraw from the module and how to intervene to provide help according to the procedure of Alshabandar et al. (2018).

The existing approaches to extracting features from the clickstream data have largely relied on the role of curricular resources to aggregate the clickstream data into higher-level representations of student interactions (Alshabandar et al., 2018; Hussain et al., 2018; Liu, Wang, Benachour, & Tubman, 2018; Wolff et al., 2014). Although this method reduces the high dimensionality of the clickstream data when transposed by curricular resources, it assumes that all curricular materials are of equal value toward attaining instructional objectives. It may be possible that subsets of resources that students fail to interact with may be less critical to attaining course objectives, while others are more essential, thereby serving as more discriminating features. In this study, we compare two formalisms for representing the clickstream data within each VSOW: (1) a vector of numerical values where each observed student interaction is potentially correlated across sets of course materials or (2) a vector of principal component values, where the identical set of observed student interactions is represented as a set of linearly uncorrelated variables called principal components, where each component is a linear weighted combination of the initial set of interactions. Principal component analysis (PCA) consists of a multivariate statistical technique to reduce the number of features in a dataset into a subset of dimensions. The components are ordered so that the first component explains the largest amount of variation in the original student interaction data. The second component is unrelated to the first and explains additional but less variation than the first component. The benefit of this approach is to reduce the number of materials that students interact with down to a subset of the original dimensions while still retaining information that distinguishes students that have either withdrawn or not from the module. In doing so, a total of 2, 4, 6, 8, and 11 principal components were derived from the original vector of 57, 87, 92, 113, and 141 features to characterize student interactions with curricular resources during each time period defined by the moving window. Instead of relying on a predetermined set of categories to identify curricular materials, the proposed PCA method infers categories by identifying sets of curricular resources that students commonly interact with on any given time period, as defined by the VSOW.

20.4 Results

To determine the most suitable modeling approach, past studies have often compared several algorithms to find an optimal solution while taking into account the type of feature extracted from clickstream data. Gardner and Brooks (2018a) distinguishes models in terms of activity-based features extracted from clickstream data ranging from simple counting-based features to more complex features that characterize temporal, sequential, or latent variables. As an example, Heuer and Breiter (2018) compared several counting-based supervised machine learning algorithms such as a decision tree, random forest, logistic regression, and support vector model to a majority class classifier as a baseline when analyzing daily aggregated activity in OULAD. Alternative approaches to modeling that also aim for early prediction include, but are not limited to, rule-induction, Naive Bayes, and Boosted Tree classifiers (Liu, Wang, Benachour, & Tubman, 2018; Hlosta et al., 2017, 2018; Hussain et al., 2018), Gaussian Mixture Model (Alshabandar et al., 2018), or variants of these approaches that either correct for class imbalance (Hlosta et al., 2018) or combine multiple models in an ensemble (Wolff et al., 2014). Kuzilek et al. (2018b) investigated a stochastic model describing higher-order sequences or patterns in student behaviors that were predictive of student attrition using a Markov Chain model. In this case study, we investigated four commonly used supervised machine learning algorithms, replicating a similar method found in Heuer and Breiter (2018). The different modeling approaches included the following: (1) decision tree (DT), which consists of decision rules inferred from the features; (2) random forest (RF), which fits several decision trees on different subsets of the data to obtain aggregate results; (3) logistic regression (LR), a maximum entropy classifier; and (4) support vector machine (SVM), which transforms the data into a high-dimensional space using kernels. Data analysis was conducted using the RapidMiner 9.2 implementation of each algorithm.

Estimates for the goodness of fit of each model were derived from a tenfold stratified cross-validation method to calculate the accuracy, kappa, precision, and recall metrics. Table 20.2 shows the summary statistics for goodness of fit of each model across each feature segmentation and extraction methods. In terms of the sparse representation of student interactions obtained from the use of principal components, we found that both LR and SVM outperformed both DT and RF in terms of predictive accuracy as measured on all metrics (e.g., Acc = 0.77 and 0.75 vs. 0.61 and 0.71, respectively). This finding is consistent with the fact that DT and RF models select the most relevant subset of features while partitioning the data and are therefore not as affected by the high dimensionality of the time series compared to LR and SVM. Although there are benefits to utilizing feature projection to reduce the dimensionality of activity-based features with regard to LR and SVM approaches, these modeling approaches failed to perform better than both the DT and RF models without the principal components.

The results show that the best performing model consists of the DT and RF models, attaining 78% accuracy and kappa of 0.53 with time series data collected in less than 102 days of registration to the module using the sum of interactions with sets of curricular resources. Further examination of the recall and precision metrics suggest that the model is well balanced in terms of detecting students either likely or not to withdraw from the course, with scores of 76% and 77%, respectively. Finally, the rate of accurate detection was comparable to those obtained with time series data collected in less than 67 days of registration for a module presentation lasting a total of 227 days, with accuracy rates decreasing to 76%. In other words, the models stand to accurately detect student likelihood of attrition after completion of three assignments, accounting for a total of 18% of the final grade, which is a reasonable baseline for intervention. Since the DT model provides a more parsimonious representation than RF, we conclude from our findings that it is the most suitable model to deploy for the purposes of early detection of student attrition.

20.5 Discussion

A predictive system enables an instructor to automatically identify students that are most likely to drop out of a course based on activities from that online module (see Hussain et al., 2018). This case study builds on prior research in automated detection of student attrition by investigating the use of context-sensitive segmentation windows and feature projection techniques from clickstream data to train and evaluate several common types of classifiers that can be deployed for real-time prediction. We demonstrated these techniques in regard to the OULAD dataset, where one

Table 20.2 Goodness of fit metric estimates across machine learning algorithm, data segmentation, and feature extraction (projection as principal components) techniques

Model	Metric	Data segmentation				
		0 days	18 days	32 days	67 days	102 days
		No-PCA feature projection (baseline)				
DT	ACC	0.62	0.60	0.61	0.76*	0.78*
	KAP	0.00	−0.01	0.01	0.48*	0.53*
	PRE	0.43	0.39	0.59	0.75*	0.77*
	REC	0.50	0.50	0.50	0.74*	0.76*
RF	ACC	0.61	0.60	0.61	0.76	0.78
	KAP	−0.01	0.00	0.02	0.48	0.53
	PRE	0.40	0.46	0.55	0.75	0.77
	REC	0.50	0.50	0.51	0.74	0.76
LR	ACC	0.60	0.63*	0.66*	0.72	0.73
	KAP	0.02	0.20*	0.29*	0.42	0.46
	PRE	0.53	0.61*	0.65*	0.71	0.73
	REC	0.51	0.60*	0.65*	0.71	0.73
SVM	ACC	0.62	0.60	0.62	0.64	0.64
	KAP	0.00	0.00	0.15	0.33	0.34
	PRE	0.41	0.49	0.60	0.70	0.71
	REC	0.50	0.50	0.57	0.68	0.69
		PCA feature projection				
DT	ACC	0.62	0.61	0.61	0.61	0.61
	KAP	0.00	0.00	0.00	0.25	0.05
	PRE	0.31	0.30	0.30	0.66	0.44
	REC	0.50	0.50	0.50	0.64	0.53
RF	ACC	0.62*	0.60	0.62	0.63	0.71
	KAP	0.00*	−0.01	0.05	0.09	0.36
	PRE	0.48*	0.31	0.66	0.67	0.72
	REC	0.50*	0.50	0.52	0.54	0.67
LR	ACC	0.62	0.62	0.63	0.73	0.77
	KAP	0.00	0.04	0.09	0.46	0.53
	PRE	0.31	0.53	0.55	0.73	0.76
	REC	0.50	0.52	0.54	0.74	0.76
SVM	ACC	0.62	0.60	0.60	0.70	0.75
	KAP	0.00	0.02	0.03	0.41	0.49
	PRE	0.31	0.36	0.37	0.71	0.74
	REC	0.50	0.51	0.51	0.72	0.75

Notes: Model evaluation metrics (*ACC* accuracy, *KAP* kappa, *PRE* precision, *REC* recall); Machine learning models (*DT* decision tree, *RF* random forest, *LR* logistic regression, *SVM* support vector machine); Feature extraction via projection method (No PCA, PCA); Data segmentation feature selection (1 Less than 0, 2 Less than 18, 3 Less than 32, 4 Less than 67, 5 Less than 102)
*Denotes the maximum value obtained within the segmentation window and across feature extraction techniques

of the courses offered at the Open University exhibited a high rate of attrition among students (Kuzilek et al., 2017). The analysis demonstrates that relatively accurate detection of the likelihood of students dropping out from a course can be attained within approximately 10 weeks of elapsed time or 20% of the summative grade point average for assignments submitted throughout the course. Using a predictive system in the form of a course dashboard, instructors can then intervene by providing assistance, contacting students via an advisory email or link to a survey asking about any issues and/or requesting course feedback. Instructors may also ask students about the effectiveness of curricular materials and their reasons for participating in the course. The communication taking place between instructor and student can serve to appraise the course load, whether it is reasonable, and steps that can be taken at an early stage to modify the course as a means to improve student retention.

Many recent studies (e.g., Heuer & Breiter, 2018; Hlosta et al., 2018; Kuzilek et al., 2018b) have shown a lack of consensus in terms of the segmentation method and window size to divide the larger clickstream data into smaller subsets for processing. In accordance with Alshabandar et al. (2018), we proposed an overlapping window that is adjusted for assignment submission dates with the aim of capturing a context-sensitive factor that may lead to student withdrawal from a course. To determine whether the proposed VSOW method is effective, we investigated the relationship between window size and the goodness of fit metrics obtained for several commonly used types of classifiers. The analysis showed that in the case of a VSOW, a minimum of 67 days of registration for a module presentation was necessary to attain the most accurate levels of detection. The findings suggest that is a suitable method to train classifiers as a means to inform instructors, allowing researchers to appraise the trade-off between detection accuracy and the shortest time window necessary to attain it. One of the main challenges of data preprocessing at the Open University following acquisition consists of deciding which segment of the clickstream data to use in the live stream. Further research is necessary in order to test the underlying assumption that assignment submission dates allow to distill features that differentiate among students that are more or less likely to drop out by comparing it to alternative methods. Researchers should also investigate techniques to identify novel factors by discovering statistical patterns in the dates of unregistration from a course, which may be informative (i.e., last day until students may drop out of a course without penalty, first class where instructor reviews the syllabus, and so on). The discovery of dates where students are more likely to unregister from a course across its multiple presentations can inform the adjustment of the size of each window in the proposed VSOW method.

To date, much of the available literature (e.g., Alshabandar et al., 2018; Hussain et al., 2018; Liu, Wang, Benachour, & Tubman, 2018; Wolff et al., 2014) has relied on predetermined categories of student interactions to extract features from the clickstream data by differentiating between types of curricular materials or resources. In contrast, some studies have been mainly interested in engineering features while comparing alternative representations, including binary and continuous variables (Heuer & Breiter, 2018); transformations via metrics such as average, median, sums, and normalized scores (Hlosta et al., 2017); as well as using domain knowledge to determine whether activities were anticipated or not given the course syllabus (Kuzilek et al., 2018b). Principal component decomposition on features derived from time series data has been previously used for anomaly detection (Hyndman, Wang, & Laptev, 2015), forecasting (Cornillon, Imam, & Matzner-Løber, 2008), and segmentation (Banko, Dobos, & Abonyi, 2011). In this case study, PCA seeks to describe a subset of the clickstream data using fewer features than those derived from identifiers of curricular materials or resources, which can reveal hidden structure or patterns in student interactions with these materials. The principal components are uncorrelated and represent the joint variance observed in student interactions with subsets of curricular materials and resources. However, the findings of the current study do not support the use of PCA as a feature extraction method. This can be attributed to the fact that although gains in goodness of fit metrics were obtained for a set of classifiers, those classifiers failed to outperform partition-based algorithms such as decision trees and random forest classifiers on the whole set of features derived from identifiers of curricular materials. As such, the choice of classifier is a more important factor in the detection of student attrition than the proposed feature extraction method. Other works on educational data have already highlighted the lack of effect of PCA in improving their results, for instance, when clustering students based on the questions they asked (Harrak, Bouchet, & Luengo, 2019).

20.6 Conclusions and Implications

An implication of this work is that the proposed method can help identify at-risk students and enable them with just-in-time access through an advisor or tutor dashboard to make appropriate interventions if necessary (see Hussain et al., 2018; Wolff et al., 2014). These include but are not limited to the following: (1) discuss their choice of withdrawing from the course; (2) understand the consequences toward attainment of academic or professional goals; and (3) gather information regarding alternative modules or curricular resources that may be of interest to students. To date, several studies have begun to examine the use of predictive systems deployed in higher education institutions. Course Signals at Purdue University takes into account students' performance, effort, prior academic history, and other characteristics in its predictive student success algorithm to identify students who are at risk of not attaining their full potential in the course and notifies the instructor to deploy meaningful interventions (e.g., send email, refer to academic advisor) (Arnold & Pistilli, 2012). Milliron, Malcolm, and Kil (2014) also reported on several case studies in the use of the Civitas Learning Illume analytics dashboard. One of the common themes in the reviewed studies regarding feedback to students was providing students with risk-assessment results along with practical advice on precisely what steps to take to improve and at other times offering them academic consultation. Practical and individualized student support is highlighted as key to the effectiveness of these interventions. A recent systematic review of 11 studies on the efficacy of learning analytics interventions in higher education (Larrabee Sønderlund, Hughes, & Smith, 2019) indicated that the studies found 6% improvement in final grades (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014), 10% increase in A and B grades (Arnold & Pistilli, 2012), a doubling of the likelihood of receiving a grade of C or higher (Fritz, 2011), and 11% and 25% higher retention (from before to after implementation of intervention) (Arnold & Pistilli, 2012; Cambruzzi, Rigo, & Barbosa, 2015). However, Larrabee Sønderlund et al. (2019) claimed that additional research is needed into the implementation and evaluation of such interventions as there is currently little evidence for the generalizability of the effects reported in past studies.

The transferability and generalizability of predictive systems of much published research in learning analytics is problematic (Baker, 2019). The decision tree model derived from this analysis relies on features derived from curricular resources that are specific to a given module, which raises the question of how the modeling approach may be applicable to other presentations, modules, or virtual learning environments. It stands to reason that prediction of student attrition for a given presentation may be transferable, thereby informing predictions made on the basis of future student activities. There is also the question of how the model trained on the basis of a particular cohort of students may apply to future presentations of a given module, but with a different cohort. To address these issues, the methodology followed in this case study could be substantially improved by (1) broadening the focus of the analysis and including module presentations with low attrition rates; (2) outlining feature extractions techniques that result in higher-order representations of student activities that are amenable to usage across systems; and (3) cross-validating the decision tree model using students, presentations, and modules in the OULAD dataset as batches to verify claims regarding the transferability of the resulting model. One of the main advantages of decision tree algorithms is that the rules are interpretable, but future research should also investigate how to design analytics dashboards where the decision-making process is made explicit and understandable for an instructor. The dashboard would ideally provide detailed information on how to intervene, what information to share with students, and any alternative approaches to support them.

This case study investigated the relationship between several factors regarding student interactions with a virtual learning environment as a means to design an early prediction system of the likelihood of students dropping out from a course. The high rate of student attrition in virtual learning environments such as MOOCs is well-known. Approximately 90% of students who enroll in such courses fail to complete them (Jordan, 2014). After taking into account for student intentions to complete or not a course, slightly more than half of students intend to achieve a certification of completion, and only 30% of them actually attain that goal (Chuang & Ho, 2016). Since MOOC enrollment and course offerings have steadily grown in the last 7 years (Shah, 2018), there is a need for research into predictive systems that are capable of early detection and intervention. Furthermore, these platforms allow for large-scale data collection that is standardized in its format, which enables the approaches alluded to earlier in investigating the generalizability and transferability of predictive models across cohorts, courses, and other relevant variables. Understanding the relative benefits of different sources of data may be most useful in improving the efficiency of predictive models (Gardner & Brooks, 2018a). Besides addressing the previously mentioned issues, future research should investigate the inclusion of other types of features such as those obtained from student demographic achievement data, text-based data from discussion forums, and social relationships in order to provide a more holistic understanding of student attrition across different modules.

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Chapter 21
Evidence-Based Learning Design Through Learning Analytics

Esin Caglayan, O. Osman Demirbas, Ali Burak Ozkaya, and Mehmet Sahin

21.1 Introduction

The information-age paradigm of education has led to the rapid adoption and pervasive spread of learning management systems (LMS). Large datasets are produced as instructors use the LMS to upload course content, post assignments and tests, and give feedback to learners. While using content provided by their instructors, submitting assignments, etc., students also create similarly large amounts of data, which are potentially valuable for assessing their levels of engagement with courses. The issue of measuring student engagement and its contribution to student success has opened the gate to Learning Analytics (LA), which has the potential for predicting and improving student achievement and retention through enhancing the quality of teaching and promoting learner autonomy. To date, most LA research has focused on student engagement, retention and achievement, while integrating analytics into learning design has received much less attention (e.g. Ifenthaler, Gibson, & Dobozy, 2018; Lockyer, Heathcote, & Dawson, 2013; Mor, Ferguson, & Wasson, 2015). However, learning design can benefit from LA, because, if interpreted correctly, data produced by the LMS has the potential to provide instructors with constructive and objective feedback regarding their design.

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21.1.1 Learning Design and Learning Analytics

The concept of learning design came out in the early 2000s when the need for more effective instruction methods became a topic of discussions in higher education. These discussions revolved around over- reliance on traditional, teacher-centered, large group lectures and the need for more student-centered and technology-enhanced teaching and learning (Lockyer et al., 2013). As a result, following the principles of socio-constructivist approach and adopting technology-enhanced approaches, the concept of learning design emerged, which also altered the educator's role from knowledge transmitter to a facilitator of student engagement with knowledge (Laurillard, 2008).

Learning design is defined as "the creative and deliberate act of devising new practices, plans of activity, resources and tools aimed at achieving particular educational aims in a given context" (Mor & Craft, 2012, p. 86). It enables instructors to make informed decisions about learning activities and the tools and resources needed to design those activities (Rienties & Toetenel, 2016). In order to measure the effectiveness of learning designs, and to make informed decisions about the instruction process, there is a need to identify the patterns of student engagement and this is where LA comes into play. In order to achieve better data-driven learning designs, LA data-mining is needed, and in order to assist better learning design initiatives, LA should incorporate educational research and theory (Gašević, Kovanović, & Joksimović, 2017).

As an essential part of learning and teaching processes in today's educational environments, LMSs contain large amounts of data and serve as online repositories of learning designs. Analytics modules used in LMSs to record and analyze vast data created by instructor and student interaction have the potential to provide new insights into curriculum and learning design, which not only help optimize student learning, but also may ultimately lead to improvements in learning culture and educational decision-making. This process may occur at different levels. While analytics can be used to evaluate individual courses, analyses at the program and institutional levels are also possible. The main idea in all the cases is to collect reliable data and use this data to provide useful feedback to instructors, educational technologists and decision makers. Measurement of user activity in specific sections of the LMS as well as correlating this activity with the student success can help instructors identify which materials they have uploaded have benefitted students more or which page-design is most user-friendly, and analysing the usage metrics of LMS in a school/department may allow educational technologists to identify an unused or ineffective software/tool so that they can remove/replace it, or it may even lead to a decision to reconsider the choice of LMS platform. Adopting a learning design approach enables instructors to articulate the design and intent of learning activities, which guides the interpretation of learning analytics data (Bakharia et al., 2016). As Nguyen, Huptych, and Rienties (2018) stated: "By capturing and visualizing the design of learning activities, the learning design approach could provide a pedagogical context to support interpreting and translating learning analytics findings into interventions" (p. 142).

It could be suggested that LMS course design plays a key role in determining patterns of student activity on LMS, and therefore, becomes an essential aspect of instructional pedagogy (Fritz, 2016). In order to measure the student engagement, and better interpret the student activity on the LMS, planned learning design activities such as assignments, assessments, and collaborative tasks need to be mapped with LMS usage. The study by Rienties, Toetenel, and Bryan (2015) concluded that instructors are not much aware of various aspects of learning design on LMS and design their courses "with an invisible blueprint in mind" (p. 318). However, the affordances that current instructional technologies offer should not be ignored, and teaching staff and learning technologists should adopt a learning design mindset in order to meet the needs of the new generation of learners. Despite the significant effect of learning design on student engagement, satisfaction and retention, research on learning design elements and approaches is limited.

One strategy involving the use of LMS analytics to support learning design at course level is to detect specific patterns in tool use, classify courses in the form of archetypes, and give instructors systematic and specific feedback considering these course design archetypes.

21.1.2 Course Design Archetypes

In order to discover archetypes of course design across institutions, Whitmer, Nuñez, Harfield, and Forteza (2016) investigated 70,000 courses from 927 North American institutions, with 3,374,462 unique learners using Blackboard Learn during Spring 2016. In the study, they took Blackboard tool use as a proxy for course design and determined five archetypes:

- Supplemental: Content-heavy archetype with low interaction. LMS is mainly used to augment a traditional face-to-face course and to store digital material as well as grades.
- Complementary: LMS is mainly used for one-way communication from instructors to students through content, announcements, and gradebook.
- Social: LMS is mainly used as a social platform with high peer-to-peer interaction through discussion board.
- Evaluative: LMS is mainly used for evaluation with heavy use of assessments.
- Holistic: High LMS activity with balanced use of assessments, content, and discussion.

It is important to note that these archetypes are not exhaustive, nor are there clear-cut borderlines between them. Moreover, Whitmer et al. (2016) does not provide detailed information as to how the archetypes can intersect or overlap and the tipping points – if any – for each course component. However, one of the main presumptions of learning design is transferability and reuse of good practices, that is, "if good teaching practice in one educational context could be captured in a description, that description could be read, interpreted, and adapted for reuse in another context" (Lockyer et al., 2013, p. 1442). In theory, if instructors know their course archetype, they can use this information to improve their course design. Therefore, it is believed that these five archetypes, while not definitive, provide a helpful starting point for effective learning design.

21.2 Methodology

This study was conducted at an English-medium university in Turkey, where Blackboard LMS has been used in all faculties and courses since September 2015. The university administration encourage the instructors to use the LMS to the maximum extent possible and training sessions are organized by the Teaching and Learning Center on various features of the LMS system on a regular basis. Blackboard Analytics was also implemented, and both course level reports and administrative dashboards have been available since 2017. Since its introduction, an increasing rate of the LMS use in classes has been observed. It can be argued that the initial adoption stage has been completed, and all instructors in the university have a degree of awareness of the affordances of the LMS. The current number of student and instructor users is 16,142 and 1061 respectively.

This study aims to investigate the degree of agreement between instructors' opinion on their course design archetype and the archetype provided by Blackboard Analytics, and to identify any similarities in tool use between the local institution data and the data used in the research by Whitmer et al., 2016. The research is driven by the following research questions:

1. What is the distribution of course archetypes in the institution within the selected semester?
2. Are there any specific patterns of tool use that link the local case (existing study that was carried out in a single institution) with the original study (research by Whitmer et al., 2016)?
3. Are there any discrepancies between instructors' definitions of LMS use patterns and the distribution of the courses according to five pre-defined course design archetypes?

Mixed method sequential explanatory design was used for the analysis. The purpose of this kind of research design is "to use qualitative results to assist in explaining and interpreting the findings of a primarily quantitative study" (Creswell, Plano Clark, Gutmann, & Hanson, 2003).

There were two sequential distinct phases: the quantitative phase in which the Blackboard Analytics data was used to cluster the course archetypes, followed by the qualitative phase, which involved semi-structured interviews with instructors. As Chatti et al. (2014) recommended, "A mixed-method evaluation approach that combines both quantitative and qualitative methods can be very powerful in order to capture when, how often, and why a peculiar behavior happens in the learning environment" (p. 14).

The first phase of the study was the quantitative phase in which the general distribution of all of the courses taught during the 2018–2019 Spring Term were identified according to the five predefined course archetypes of Blackboard LMS (Whitmer et al., 2016). The criteria for clustering course archetypes were average activity by grades, course content, assessment, discussion, announcement, assignments and average enrollment count. The data sample for the quantitative phase includes 1990 undergraduate courses from all faculties, with a total of 51,634 LMS users in the 2018–2019 Spring Semester. The data was anonymized at the individual level, and the data for each course was aggregated for the analysis.

For the qualitative phase, purposeful sampling method was employed based on the following sample selection criteria:

– representation of the whole population with representation of all archetypes
– representation of courses from various disciplines
– convenience of the lecturers of the courses for face-to-face interviews

The distribution of the courses included in the qualitative phase of the research and their archetypes are shown in Fig. 21.1.

In the qualitative phase, semi-structured interviews were conducted. The interview protocol was structured and prior to interviews with instructors, it was piloted through an interview with an instructor, and subsequently adjusted based on that session. The protocol consisted of a total of eleven questions to gather as much information about the course design elements as possible. Four questions were phrased so as to include general definitions of the archetypes named *Complementary, Supplemental, Evaluative* and *Social,* provided by Whitmer et al. (2016). Since *Holistic* is defined as a combination of all other archetypes, no separate question was asked for this particular archetype. The rest of the questionnaire consisted of activity-specific questions designed to draw a more comprehensive picture of the LMS usage pattern for each selected course. Sample interview questions are as follows:

- To what extent did the LMS contribute to your teaching as well as achieving the learning outcomes mentioned in your course syllabus?

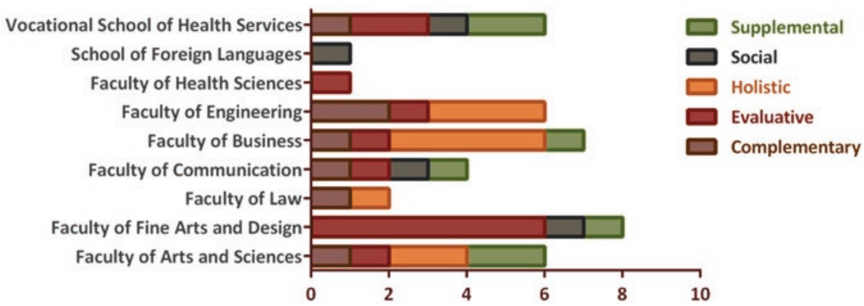

Fig. 21.1 Distribution of the courses and their archetypes included in the qualitative phase

- On this course, how much time do you think your students spent engaging with the content you created?
- Did you make any announcements on this course shell? Do you think they were received; was there any feedback to show this?
- Did you give any assignments? Did you create any rubrics for grading? Did you give any feedback for assignments?
- Did you use interactive tools, such as discussion board and blog? If yes, how engaged were your students?
- Do you think the size of this class was appropriate for interaction among students and the instructor?
- Did you create any groups in this course?

In the second stage of the interviews, each participant was informed about the five archetypes, and were provided with the definitions. Then, they were asked to give an opinion about which archetype best fits their practice. Preferably one answer was required, however; in case of uncertainty, they were allowed to state more than one with sufficient justification. Then, they were informed about the results obtained from Blackboard Analytics platform, and in case of a mismatch between their statement and the Analytics result, they were asked to comment. Finally, they were asked if the information on archetypes provided would be useful in future, especially during the preparation stage of their courses on the LMS.

Each interview was conducted privately in the Teaching Learning Center, and a minimum of two researchers were present in each session; one as the interviewer, and the other as the note-taker. At the beginning of the interview, each participant was briefly informed about the aim of the research. The names of the course archetypes were not mentioned in order to avoid bias towards one particular archetype. Each participant was also asked to sign an informed consent form for their participation, and for the video-recording of the interview. The related course interface was projected on the whiteboard as a reminder to the interviewee. Each interview lasted 15–30 minutes, and interviewees were free to comment and add personal views. Interviews were video-recorded and transcribed. In the analysis of the qualitative data, deductive approach was adopted, i.e. the data was coded according to the predefined archetypes. Following the coding process, the team of researchers came together to discuss individual interpretations and discrepancies in order to ensure the stability and dependability of the construction of interpretation. In the case of discrepancy, the researchers referred to the video recordings. This process enhanced the reliability and trustworthiness of analysis (Creswell, 2009).

21.3 Findings

In the analyses, we focused on three main areas: distribution of archetypes at the university; differences between data from the original study by Whitmer et al. (2016), and the local Analytics data in identifying course archetypes; and consistency between predictions of archetypes extracted from local Analytics data and instructors' predictions.

21.3.1 Distribution of Archetypes at the Local Institution

There was a total of 1990 courses created on the LMS in the 2018–2019 Spring Term at the university. The report retrieved from Analytics platform showed that the most common archetype was *Complementary* (23.66%), and the least is *Social* (1.96%). The distribution of the archetypes is demonstrated in Fig. 21.2a. This finding is not surprising as the courses are conducted face-to-face in classrooms and the LMS is used to assist in course components such as sharing course materials, assignment submissions and announcements. The research by Park, Yu, and Jo (2016) confirmed our finding as they concluded that resources, assignments and announcements were the most frequently used features whereas discussions, wikis, group works were not incorporated much into the courses.

According to the definition provided on Blackboard Analytics, if the courses do not meet the criteria to fit into any of the course archetypes, they are assigned as *Filtered-out*. The archetype of a course is identified in Analytics by the "CustomStage. HelperCourseArchetypeThresholdsSource" stored procedures and released with a general configuration. The ultimate goal is to set up a baseline that accurately identifies as many courses as possible. 36.28% of those courses ($n = 722$) were labeled as *Filtered-out* by Analytics and thus not included in the analysis (Fig. 21.2b).

21.3.2 Comparison Between the Analysis of the Original Data and Local Data

In this part of the study, we focused on the weight of the components constituting each archetype and compared the data in the original study with those in the local context. In this analysis *Average Activity by Tool (Avg. hours/student)* was used.

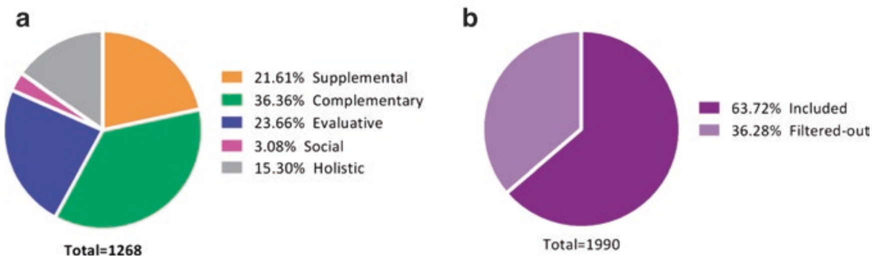

Fig. 21.2 2018–2019 spring term course archetypes distribution

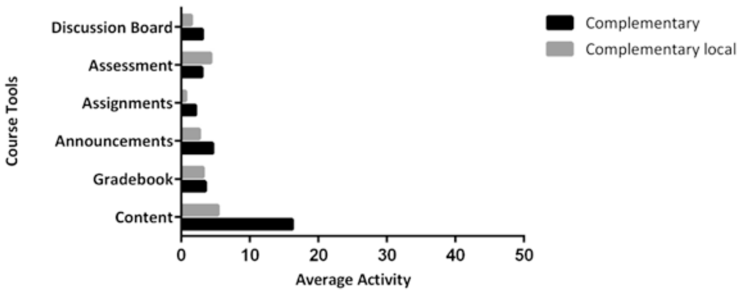

Fig. 21.3 Complementary archetype comparison

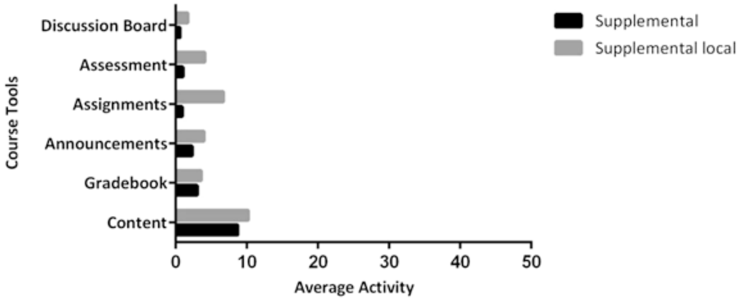

Fig. 21.4 Supplemental archetype comparison

"Tool calculations are averages of individual students, and do not total to 100% or total time at the course level" (Whitmer et al., 2016, p. 8).

Comparison of the original study (Whitmer et al., 2016) and the local study data sets show some significant inconsistencies. For the *Complementary* archetype, there is a high level of inconsistency in assignment and discussion board tools. Whereas assignment is much lower in the original study, it is significantly high, almost close to the level of content in the local study. In the original study, discussion board usage shows a higher level of activity than in the local case (Fig. 21.3). As for the *Supplemental* archetype, the assessment tool shows a high level of inconsistency between the two studies; it is significantly high in the local case (Fig. 21.4). Figure 21.5 demonstrates the average activity by tool for *Evaluative* archetype. The numbers show a contradiction in assignment and assessment tools, as assessment is seen to be the most frequent tool in the original study, and assignment is the least. This situation is almost completely reversed in the local case, with a much higher level of assignment (although this is not the highest category in the local study), and the lowest level of assessment, which is surprising, especially in an archetype defined as *Evaluative*. As for the *Social* archetype, the average activity in the discussion board tool is the highest in the original study, but considerably lower in the

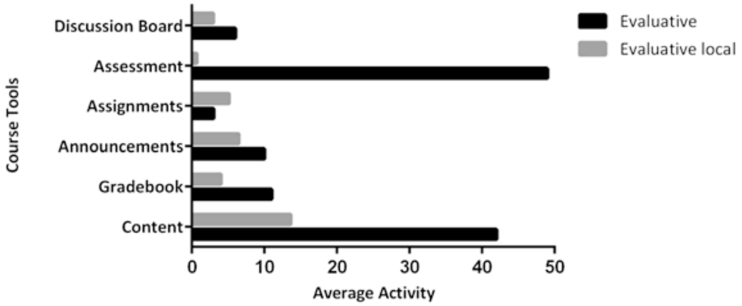

Fig. 21.5 Evaluative archetype comparison

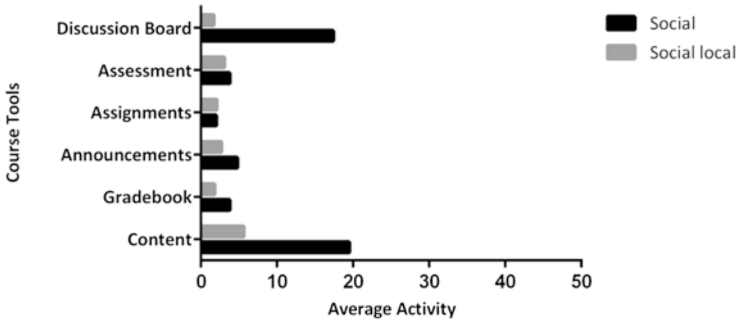

Fig. 21.6 Social archetype comparison

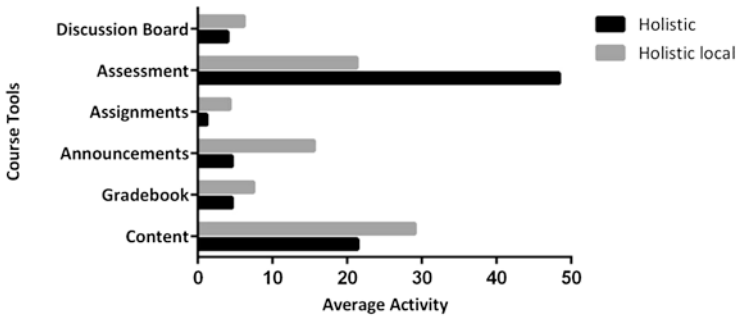

Fig. 21.7 Holistic archetype comparison

local case (Fig. 21.6). The average activity for the assessment tool in the local study is relatively higher for the *Holistic* archetype compared to the other archetypes, yet its level is considerably low, which shows a marked inconsistency with the original study, in which the average activity by assessment is the highest overall for this archetype (Fig. 21.7).

The most significant difference between the current study and the original study is in the *Social* and *Evaluative* archetypes. Despite the low usage of the tools that are critically important for these two archetypes in these courses in the local case, they are still listed under these two archetypes. It is not possible for the researchers to rationalize this discrepancy without knowing the algorithm of the clustering of the archetypes. It is important to note that Whitmer et al. (2016) used k-means cluster analysis to identify these five archetypes, which were then incorporated into Blackboard Analytics platform.

A key finding of the study is the level of similarity between the courses in the *Holistic* archetype and the *Filtered-out* courses. As can be seen in Fig. 21.8, in the local data, the activity levels in both courses in terms of all tools show a similar pattern. For instance, the activity in discussions is about 7%, and in announcements it is about 18% in both categories.

Another parameter involved in the archetype analysis is the number of students enrolled in courses. The analysis of the data showed a lower average number of students in the local institution compared with the original study for all archetypes except for the *Holistic* one (Fig. 21.9).

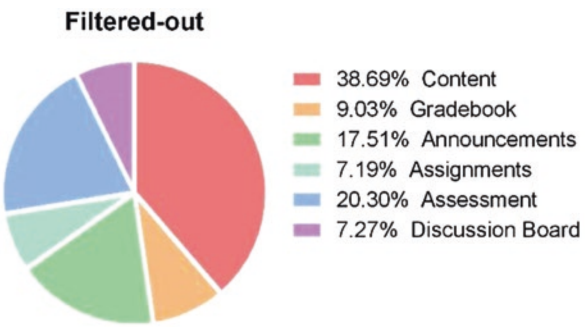

Fig. 21.8 Analysis of filtered-out courses

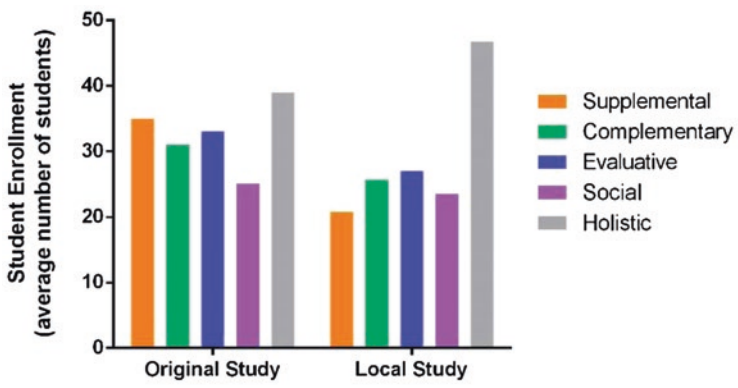

Fig. 21.9 Comparison between the original study and the local study in terms of student enrollment

The sample size of the current research is significantly lower; however, the distribution ratios between the five archetypes and *filtered-out* classification are consistent with the original study. Similarly, as with the original study, *Complementary* and *Supplemental* archetypes are the most popular in the local case. This finding is relevant, since Blackboard LMS is mainly used for accessing the course content involving a rather limited amount of student activity.

21.3.3 Consistency Between Archetypes Extracted from Analytics and Instructors' Predictions

For the qualitative phase of the study, we identified 41 courses for the detailed analysis of archetypes. Purposeful sampling was employed in order to ensure that cases were distributed across archetypes (based on distribution of archetypes extracted from local Analytics data as presented in Fig. 21.10) and information-rich cases (Patton, 2002).

Based on the analysis of the semi-structured interviews, a low level of consistency was found between the identified course archetypes in the local data and the participants' opinion about the archetype of the courses in the sample. None of the courses labeled by Blackboard Analytics as *Social* were identified as such by the instructors (see Fig. 21.10 and Fig. 21.11). The results were similarly divergent for the other four archetypes but the highest level of agreement was observed for the *Complementary* courses.

Each archetype in the sample was further analyzed in order to identify the direction of divergence in instructors' predictions. The archetypes *Supplemental* and *Evaluative* were often selected by instructors in lieu of the *Complementary* archetype, with 42.86% and 46.15% being predicted respectively. On the other hand, only 10% of the instructors predicted their *Holistic* course archetype, consistent with the Analytics findings.

According to the findings, the two most common answers by the participants were *Complementary* and *Supplemental*; however only in *Complementary* was there a high level of match between the assigned archetype for the course and instructor's prediction (>80% agreement). For all others, the agreement was less than 20%. The *Social* archetype was the least prevalent (9.76%) in the local case; however, none of the instructors used this definition for their courses. This disagreement is an outstanding finding because of the relative lack of use of interactive tools which are essential criteria for the *Social* archetype. It is also considered as an interesting finding, because the pattern of tool use in these courses are significantly different from the *Social* courses in the original study.

During the interviews, the instructors were informed about the archetypes and their features. In the case of inconsistency, the instructors were asked the reason for the inconsistency between the course archetype identified by Blackboard Analytics and their predictions. One instructor commented:

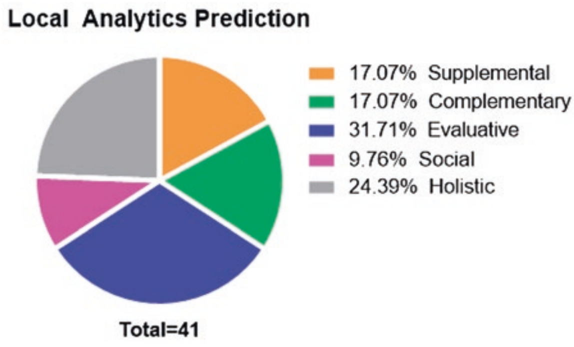

Fig. 21.10 Archetypes extracted from Analytics data

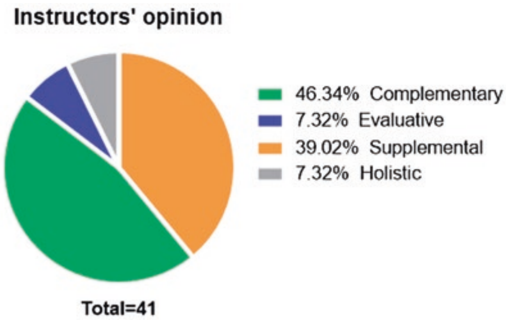

Fig. 21.11 Instructors' predictions

> I did not assign any exams or tests in this course, so I thought it would be a Supplemental course. But, it turned out to be Evaluative. On second thoughts, it might be right as I created assignments and graded them on Blackboard.

Another instructor who assumed her course would be *Supplemental* was surprised when she learned that it was a *Holistic* one commenting:

> I did not use the assignment and assessment tool; I did not give any assignments on this course but I made some announcements and used the discussion board. The students who took this course were very keen and hardworking. This could be the reason.

Another unexpected finding was that one of the instructors predicted the course to be either *Supplemental* or *Evaluative*, but the Analytics data classified it as *Social*. The instructor speculated:

> There were about 40 students in this class so it was impossible for me to use the discussion board. I did not create any group assignments or tests either. Could it be [Social] because I graded the individual assignments and gave feedback? I am not sure.

The last question in the interview protocol probed whether knowing the course archetype would be useful in helping instructors design their courses in the following semesters. 26 out of 41 instructors responded positively. Some stated that they

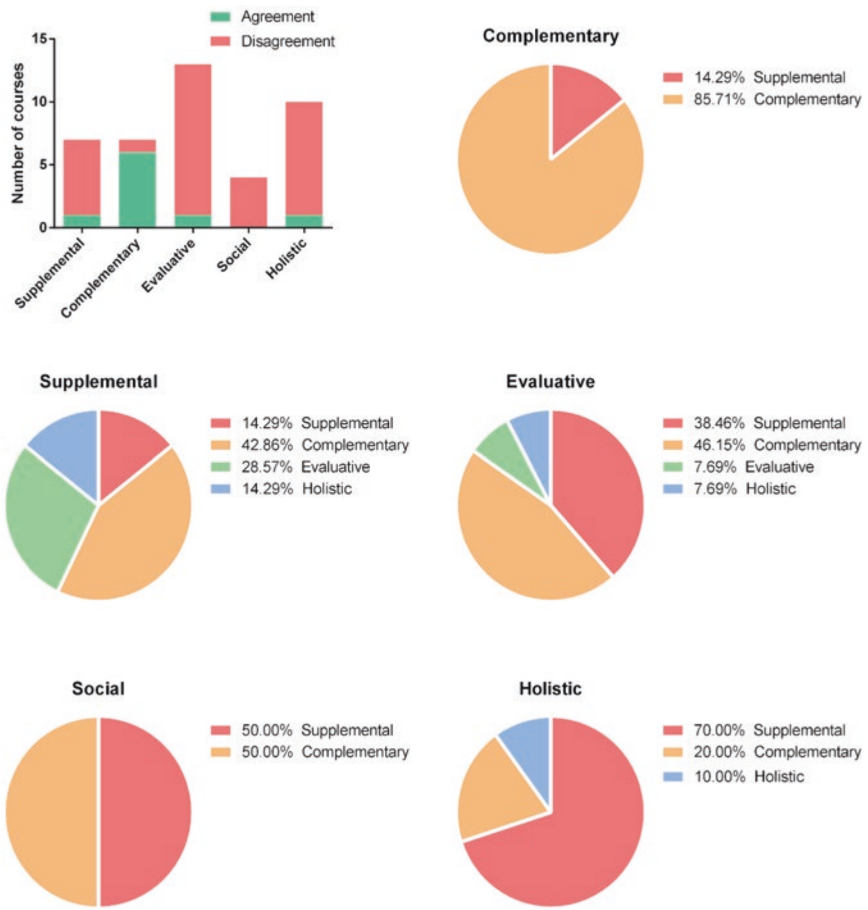

Fig. 21.12 Analysis of consistency between instructors' predictions and local analytics archetype classification

would benefit more from the social tools, such as discussion boards or blogs if they had more time and/or fewer students in their class. One instructor said: "*I want to use more tools to increase my students' engagement and interaction with the course*". In another instructor's words:

> This made me think more about my course. It is all about your past experiences, I mean, what worked well last year… Because of time constraints, you just rush it and do what you did in the same course in the previous year… I can assign tests and perhaps try an online discussion next term. Why not?

Naturally, the instructors whose predictions corresponded with the results of Analytics expressed their contentment, while the others took note of the tool usage patterns of their predicted archetype in order to re-structure and upgrade their course design to align with their expected/preferred archetype, which for these instructors was generally *Social* and/or *Holistic*. These instructors emphasized their intention to consider and carefully study the characteristics of these archetypes while re-structuring their course in the following semesters. This finding is consistent with that of Rienties et al. (2015), who suggest that academics generally lack awareness of the pedagogical principles employed in LMS course design and simply structure their courses "with an invisible blueprint in mind" (p. 318). It also suggests the need for more guidance for instructors on mapping the planned learning design activities such as assignments, assessments, and collaborative tasks with LMS usage. In order to refine and redesign learning activities, instructors would benefit from explicit guidance on how to utilize, interpret and reflect learning analytics results (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015).

21.4 Discussion

Although it is still undergoing its initial stages of development, LA has received considerable attention in higher education, as emphasized in the 2011 Horizon Report (Johnson, Smith, Willis, Levine, & Haywood, 2011) and is gaining momentum. Among the benefits of LA are the capacity to predict and improve student success, increase engagement and retention, and facilitate proactive intervention (e.g., Macfadyen & Dawson, 2010; Olmos & Corrin, 2012; Smith, Lange, & Huston, 2012). LA also helps teaching staff and administrators understand and improve course quality, monitor and analyze trends to enact or validate curriculum and pedagogical change based on data-driven decisions. Instead of relying merely on previous experiences and their notes, student surveys and subjective recalls, instructors can now make use of LA data collected during their course to shape the design of their courses for the future student cohorts (Lockyer et al., 2013; Hung, Hsu, & Rice, 2012).

However, a major challenge in this domain is how LA might actually be implemented. Dringus (2012) identified the minimal requirements for LA to be beneficial: collect relevant data with efficient algorithms, inform users about the processes and practices, and provide transparency. However, as LA data is context specific, the meaning attributed to selected variables and their implications may vary across institutions (Ifenthaler & Widanapathirana, 2014). Choosing the most relevant data to analyze, identifying the most appropriate courses and individual characteristics, careful consideration of the student and teacher profiles as well as their learning and teaching styles are some of the issues that need to be addressed. However, there is still no consensus over how these issues can be resolved (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014).

At its early stages of implementation in education, it is not surprising why there is scant empirical work on LA. The large amount of data from LMSs and student information systems (SIS) are currently difficult to extract, organize, analyze and interpret. The global variation in context, with differences in education systems, teaching contexts, and culture also make it difficult to offer more global interpretations and generalizations (Machajewski, Steffen, Fuerte, & Rivera, 2019). However, as a starting point, it is possible and useful to conduct research on local cases and compare findings in order to attain a more global perspective. The current study was conducted using the data obtained from one single institution, with a particularly homogeneous user profile, and compared it with the findings of a previous research that addresses the course design archetypes.

Although LA has emerged as a promising area of research with its significant potential to support learning at scale, and optimize instruction, there are dangers in relying solely on the quantitative results. Categorization of courses and learners, alignment and modification of engagement and performance against statistical benchmarks may hinder creativity, experimentation and personalization unless diversions and variations are carefully analyzed (Greller & Drachsler, 2012). In order to reap its benefits; therefore, LA should be supported with input from instructors themselves. As designers of course content and determinants of learning outcomes and level of engagement, instructors potentially have the best understanding of their own teaching contexts (Wilson, Watson, Thompson, Drew, & Doyle, 2017).

Identifying course archetypes and informing learning design may help effective use of LMSs and potentially promote student engagement through better learning design and effective interactions between instructors and learners, and therefore boost student achievement. However, it is restrictive to cluster and label courses based on statistical measures as proxies. Well-articulated learning designs should reflect instructors' pedagogical approaches (Lockyer et al., 2013). As such, course design indexes and archetypes should be built taking into consideration instructors' views and the instructional context, and cross-cultural validation of the quantitative data should be sought. Research aiming to identify to what extent the analytics data are indicative of student engagement and guidance for instructors about which variables are pedagogically meaningful is limited. The interplay of human and non-human agents, which is, in our case, instructors' intended course structure and the structure read by the LMS based on usage statistics, seems to be of utmost importance for the successful integration of instructional technologies in the teaching and learning process. The harmony between the two is expected to result in better outcomes on all fronts. Researchers, instructional technologists and managers should consider combining research data with local institutional data to reveal how student learning is impacted by the context, learner characteristics and learning design activities (Arbaugh, 2005).

LA complements learning design initiatives and has the potential to facilitate data-driven learning design decisions and optimize the learning process as long as it involves multiple data sources, and is readily accessible for educators (Mangaroska & Giannakos, 2018). Following Ifenthaler, Gibson, and Dobozy (2017), there is a "synergistic relationship" between LA and learning design (p. 1); the latter provides the theoretical foundations for planning instructional activities whereas the former serves as a source of information for validating the effectiveness of particular learning designs. All in all, the ultimate aim of both is to enhance teaching quality and to support the integration of technology into learning and teaching.

In order to help instructors to adopt the learning design mindset and to implement their pedagogy in course design, professional development programs should be introduced in higher education institutions. Teaching and Learning Centers, which aim to promote improvement of teaching skills and better understanding of student learning, are in a unique position to assist academics to employ pedagogy in their course design (Schumann, Peters, & Olsen, 2013; Sorcinelli, 2002).

Although great caution is needed in making generalizations based on course design applications in various learning environments, the researchers contend that this study will contribute to learning design research, guide practitioners and analysts on the effective use of analytics in educational contexts, and offer an empirical basis for future research in this emerging field of learning analytics, which has potential to provide constructive and objective feedback to the instructors regarding their design if interpreted accurately. It is also important to note that the geographic and cultural idiosyncrasy of each educational institution should be taken into consideration in the identification or comparison of course archetypes. Customizing archetype structures and benchmarks, for example, is possible in Blackboard in determining which courses should be labeled as "filtered-out". Such institutional intervention can allow more informed decisions for learning design at the macro level. Therefore, this research can be further developed by investigating the course archetypes in different higher education contexts, which may help enhance ecological validity over time.

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