Cognition and Exploratory Learning in the Digital Age

Pedro Isaias
Demetrios G. Sampson
Dirk Ifenthaler *Editors*

Online Teaching and Learning in Higher Education

Springer

Cognition and Exploratory Learning in the Digital Age

This book series focuses on the implications of digital technologies for educators and educational decision makers. Taking an interdisciplinary and visionary perspective on cognition and exploratory learning in the digital age, the series examines how digital technologies can or should be exploited to address the needs and propel the benefits of large-scale teaching, learning and assessment. It includes the newest technical advances and applications, and explicitly addresses digital technologies and educational innovations.
The series incorporates volumes stemming from the Cognition and Exploratory Learning in the Digital Age (CELDA) conference. Since 2004 the CELDA conference has focused on discussing and addressing the challenges pertaining to the evolution of the learning process, the role of pedagogical approaches and the progress of technological innovation, in the context of the digital age. Some of CELDA's main topics include: assessment of exploratory learning approaches and technologies, educational psychology, learning paradigms in academia and the corporate sector, student-centred learning and lifelong learning. In line with and in addition to these CELDA conference volumes, this series publishes monographs and edited volumes covering the following subject areas:

- K-12, Higher Education, Vocational Education, Business Education, Health Education
- Learning Design, Instructional Design
- Change Management, Technology Adoption, Learning Organization
- Data analytics
- Learning, Teaching, Assessment

The book series represents the most recent work in the area where cognitive psychology, information and communications technology and instructional design intersect.

More information about this series at http://www.springer.com/series/16424

Pedro Isaias • Demetrios G. Sampson
Dirk Ifenthaler
Editors

Online Teaching and Learning in Higher Education

Springer

Editors
Pedro Isaias
School of Information Systems &
Technology Management
UNSW Business School
Sydney, NSW, Australia

Demetrios G. Sampson
Department of Digital Systems
University of Piraeus
Piraeus, Greece

Dirk Ifenthaler
Learning, Design and Technology
University of Mannheim
Mannheim, Baden-Württemberg, Germany

ISSN 2662-5628 ISSN 2662-5636 (electronic)
Cognition and Exploratory Learning in the Digital Age
ISBN 978-3-030-48189-6 ISBN 978-3-030-48190-2 (eBook)
https://doi.org/10.1007/978-3-030-48190-2

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

Preface

This edited volume features a collection of extended chapters from the 2017 and 2018 edition of the CELDA (Cognition and Exploratory Learning in the Digital Age) Conference (www.celda-conf.org). In the context of education, the promise of increased flexibility and broader access to educational resources is impelling much of higher education's course offerings to online environments. The twenty-first century learner requires an education that can be pursued anytime and anywhere and that is more aligned with the demands of a digital society. Online education not only assists students to successfully integrate a workforce that is increasingly digital, but it helps them to become more comfortable with the use of technology in general and, hence, more prepared to be prolific digital citizens.

The goal of this book entitled *Online Teaching and Learning in Higher Education* is to explore various facets of online learning environments to understand how learning occurs and succeeds in digital contexts and what teaching strategies and technologies are most suited. The variety of settings that is portrayed in this volume attests to the unlimited opportunities afforded by online learning and serves as valuable evidence of its benefit for students' educational experience. Moreover, these research efforts assist a more comprehensive reflection about the delivery of higher education in the context of online settings. The chapters in this volume were organised into three parts: (a) online higher education; (b) learning analytics in online higher education; and (c) case studies of online higher education.

In Part I, Online Higher Education, the chapters emphasise the importance of the development of adequate skills, learning behaviour and preferences and student empowerment. The chapter "Digital Competence for Online Students", by Da Silva and Behar, focuses on strategies that can be used to assist both online learners and instructors to acquire and perfect their digital skills. The authors focus on a model for digital skills titled MCompDigEAD, for online learners in Brazil, which was founded on theoretical references and the charting of the skills of students in two classes. The skills concerned mainly functional digital literacy, critical digital literacy and digital fluency. In their chapter "Relationship Between Goal Orientation, Conception of Learning and Learning Behavior", Yokoyama and Miwa scrutinise the effect that goal orientation and conception of learning have on learning behaviour. Their study was supported by the distribution of a survey among 340 fourth-grade university students in Japan. The results suggest that interventions that amplify the students' learning goal orientation can be successful in converting their conception of learning into something that fosters adaptive learning behaviour.

"Towards a Model of Learner-Directed Learning – An Approach Based on the Co-construction of the Learning Scenario by the Learner", by Nkwetchoua, Bouchet, Carron and Pernelle, proposes a model that intends to enhance the learning process by assigning the learners with control over two chief elements of the process: on the one hand, the steps that a specific learning scenario should follow, such as learning objective selection, and on the other hand, the type of assessment, by selecting the most appropriate according to own objectives. The model was tested via the students' self-report questionnaires and the data generated by the learning management system. Swanson, Renes and Strange explore in their chapter "The Communication Preferences of Collegiate Students" the preferences of college students concerning communication channels for both academic and non-academic purposes. The authors distributed an online survey among college students to determine the participants' communication preferences and to assess if their technological preferences influence their communication practices and preferences. The results demonstrated that although the respondents reported an intense use of technological devices, they still preferred face-to-face interactions.

In Part II, Learning Analytics in Online Higher Education, the authors portray the benefits of using data to improve the learning process. Ifenthaler, Gibson and Zheng in their chapter "Attributes of Engagement in Challenge-Based Digital Learning Environments" focus on the dynamics and influence of learning engagement in the specific context of challenge-based digital learning settings. The authors conclude that in challenge-based digital learning environments, attributes of learning engagement are positively related to performance, and recommend the development of personalised and adaptive learning settings to address students' individual needs. "Implementation of Adaptive Learning Systems: Current State and Potential", by Imhof, Bergamin and McGarrity, explores the various facets of adaptive learning systems and options available for their design and implementation. The authors posit that these systems emerged more significantly with e-learning and argue that they represent a panoply of benefits to the learning process. They not only offer tailored instructions, guidance and content, but their increasing sophistication holds great potential for enhancing learning processes. The chapter "Sequential Analysis of Online Learning Behaviors According to E-learning Readiness", by Şahin, Keskin and Yurdugül, intends to examine the learners' navigation within e-learning environment according to readiness for e-learning degree. The authors posit that the numerical observations of the students' learning behaviours, allowed by e-learning, can assist the identification of navigation patterns via educational data mining with vital repercussions at a learning and teaching design level.

In Part III, Case Studies of Online Higher Education, different scenarios are presented depicting various facets of online instruction with its associated benefits and shortcomings. "Problem-Based Learning and Computer-Based Scaffolds in Online Learning" by Moallem and Igoe argues that while there is an abundance of research about the importance of scaffolding during problem-solving learning activities, research concerning the effective implementation of problem/project-based learning in the context of online learning is scarcer. The authors describe how an interactive content development tool was used in three self-directed computer based modules, to assist scaffolding in an e-learning course resorting to problem/project-based learning. The chapter titled “Usability Evaluation of Virtual Learning Environments – A University Case Study”, by Vertesi, Dogan, Stefanidis, Ashton and Drake, focuses on the adoption of virtual learning environments from a usability perspective. This chapter describes and scrutinises a case study at a university in two phases. The first phase consisted in the selection of the most appropriate virtual learning environment by examining the usability of the final three environments via the System Usability Scale and collecting feedback from the stakeholders via the Interactive Management methodology. The second phase assessed the selected virtual learning environment 6 months after its implementation.

In their chapter “Reciprocal Learning Assistance Systems in Smart Manufacturing – Transformation from Unidirectional to Bi-Directional Learning Technology in Manufacturing Enterprises”, Ansari and Mayrhofer offer an overview of technology assisted learning and expand on current understandings of Human Machine Reciprocal Learning. The authors contend that the connection between individuals’ digital profiles and machines allows the outline and assessment of learning outcomes via workplace and task sharing. This study examines how contemporary smart factories can be converted into self-learning factories by using the concept model of Autodidact at TU Wien Pilot Factory Industry 4.0.

The delivery of higher education in online environments is far from being a mere transposition of the classroom practices to virtual settings. It demands the restructure of curricula, the evolution of teaching methodologies and the preparation of the students to the particular requirements of online learning. As more technology is created and modified to serve pedagogical purposes, and more higher education institutions embrace them to complement their classroom teaching methodologies, more doubts are created as to the best technologies and strategies. Online learning is an evolving subject and it requires innovative research methods and approaches to be fully explored and harnessed.

Previous editions of the CELDA conference have originated various published volumes. In their first publication, Spector, Ifenthaler, Isaias, Kinshuk, and Sampson (2010) approach the general developments and challenges of learning and instruction in the digital age. More specifically, the editors gathered contributions that examined cognitive approaches to learning and instruction, knowledge representation and mental models technology, facilitated tools and techniques, communications and methods and integrative methods and online learning. In Ifenthaler, Spector, Kinshuk, Isaias & Sampson (2011), the editors compiled research initiatives that emphasise multiple perspectives on problem solving and learning in the context of the digital age by exploring related topics such as pedagogical usability issues in web-based learning objects, automated measurement of critical thinking for discussion forum participants, expanding global awareness with virtual collaboration and simulation games as learning experience.

In Isaias, Ifenthaler, Kinshuk, Sampson & Spector (2012), the editors intended to assess the impact of web 3.0 in learning and instruction, by focusing on student-centred learning, collaborative learning and exploratory technologies, and addressing educational precepts such as just-in-time learning, constructivism and web 3.0's adoption in education. Following the tendency for the adoption of mobile devices in education, Sampson, Isaias, Ifenthaler, & Spector (2013) compiled the most relevant contributions pertaining to ubiquitous and mobile learning in the digital age and all its fundamental ramifications, such as formal and informal learning environments, social web technologies, virtual worlds and game-based learning, and location-based and context-aware environments. On a later publication Sampson, Ifenthaler, Spector & Isaias (2014) emphasized the importance of digital systems for open access in the context of both formal and informal learning and gathered contributions that covered the theoretical and practical aspects of open access, as well as different methods and technologies used to support it. In Isaias, Spector, Ifenthaler, & Sampson (2015) the focus was placed on e-learning systems, which were scrutinized from different perspectives: exploratory learning technologies, e-learning social web design, learner communities through e-learning implementations, and collaborative and student-centred e-learning design.

In the following year, Spector, Ifenthaler, Sampson, & Isaias (2016) gathered contributions about the competencies, challenges, and transformation that stem from the deployment of digital technologies. The publication introduces this subject, reflects about the changes in learning and instructional paradigms, debates assessments and analytics for teachers and decision makers and examines the changing tools and environments teachers and learners must face. In Sampson, Ifenthaler, Spector, & Isaias (2018), digital technologies were explored from the perspective of their role as promoters of sustainable educational innovations for the enhancement of teaching, learning and assessment in all educational levels. The research depicted in this publication addressed the importance of digital technologies in transforming the learning environment, enriching the student learning experiences, measuring and assessing teaching and learning, and cultivating student competences for the digital smart society. In their last publication, Sampson, Spector, Ifenthaler, Isaias & Sergis (20 19) focused on the transformational potential that learning technologies have for large-scale teaching, learning and assessment. The editors gathered the outcomes of research efforts featuring state-of-the-art case studies examining the innovative influence of learning technologies, such as Massive Open Online Courses and educational data analytics.

Sydney, Australia — Pedro Isaías
Mannheim, Germany — Dirk Ifenthaler
Piraeus, Greece — Demetrios G. Sampson

References

Ifenthaler, D., Spector, J. M., Kinshuk, Isaias, P., & Sampson, D. (Eds.). (2011). *Multiple perspectives on problem solving and learning in the digital age*. New York: Springer.

Isaias, P., Ifenthaler, D., Kinshuk, Sampson, D. G., & Spector, J. M. (Eds.). (2012). *Towards learning and instruction in Web 3.0: Advances in cognitive and educational psychology*. New York: Springer.

Isaias, P., Spector, J. M., Ifenthaler, D., & Sampson, D. G. (Eds.). (2015). *E-learning systems, environments and approaches: Theory and implementation*. Cham: Springer International Publishing.

Sampson, D. G., & Ifenthaler, D. (2014). In J. M. Spector & P. Isaias (Eds.), *Digital systems for open access to formal and informal learning*. New York: Springer.

Sampson, D. G., Isaias, P., Ifenthaler, D., & Spector, J. M. (Eds.). (2013). *Ubiquitous and mobile learning in the digital age*. New York: Springer.

Sampson, D. G., Ifenthaler, D., Spector, J. M., & Isaias, P. (Eds.). (2018). *Digital technologies: Sustainable innovations for improving teaching and learning*. New York: Springer.

Sampson, D. G., Spector, J. M., Ifenthaler, D., Isaias, P., & Sergis, S. (Eds.). (2019). *Learning technologies for transforming large-scale teaching, learning and assessment*. New York: Springer.

Spector, M., Ifenthaler, D., & Kinshuk (Eds.). (2010). *Learning and instruction in the digital age*. Boston: Springer.

Spector, J. M., Ifenthaler, D., Sampson, D. G., & Isaias, P. (Eds.). (2016). *Competencies in teaching, learning and educational leadership in the digital age*. New York: Springer.

Acknowledgements

We acknowledge the support of the International Association for Development of the Information Society (http://www.iadisportal.org/) and for its continuing sponsorship of the ***International Conference on Cognition and Exploratory Learning in Digital Age (CELDA)***. In addition, we wish to express our gratitude to all the members of the CELDA 2017 and 2018 international program committees for their timely and thoughtful reviews of all papers submitted to the conferences. We also would like to acknowledge the support of Springer Science + Business Media and Springer's education editor, Melissa James. Springer has been very supportive of CELDA for many years by supporting the publication of an edited volume based on expanded and edited versions of the best CELDA papers. Finally, we would like to acknowledge the support provided by Sandra Santos and Sara Pífano, our editorial assistants, who were instrumental in formatting the papers for electronic presentation and facilitating this edited volume's publication.

Sydney, Australia	Pedro Isaías
Mannheim, Germany	Dirk Ifenthaler
Piraeus, Greece	Demetrios G. Sampson

Contents

Contributors

Fazel Ansari Vienna University of Technology, Vienna, Austria

Patricia Alejandra Behar Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

Per Bergamin Swiss Distance University of Applied Sciences, Brig, Switzerland

François Bouchet Sorbonne University, Paris, France

Thibault Carron Sorbonne University, Paris, France

Huseyin Dogan Bournemouth University, Dorset, UK

David Gibson Curtin University, Perth, WA, Australia

Dirk Ifenthaler Curtin University, Perth, WA, Australia
University of Mannheim, Mannheim, Germany

Elizabeth Igoe Manager of Learning Experience Design, Association of International Certified Professional Accountants, Raleigh, NC, USA

Christof Imhof Swiss Distance University of Applied Sciences, Brig, Switzerland

Sinan Keskin Department of Computer Education and Instructional Technology, Van Yüzüncü Yıl University, Tuşba/Van, Turkey

Walter Mayrhofer Vienna University of Technology, Vienna, Austria

Guy Merlin Mbatchou Nkwetchoua Assane Seck University of Ziguinchor, Ziguinchor, Senegal

Stéphanie McGarrity Swiss Distance University of Applied Sciences, Brig, Switzerland

Kazuhisa Miwa Nagoya University, Nagoya, Japan

Mahnaz Moallem Department of Educational Technology and Literacy, College of Education, Towson University, Towson, MD, USA

Philippe Pernelle Sorbonne University, Paris, France

Susan L. Renes University of Alaska Fsirbanks, Fairbanks, AK, USA

Muhittin Şahin Department of Computer Education and Instructional Technology, Ege University, Bornova, Izmir, Turkey

Ketia Kellen Araújo Da Silva Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

Angelos Stefanidis Bournemouth University, Dorset, UK

Anthony T. Strange Wayland Baptist Universit, Plainview, TX, USA

Joan Ann Swanson Skidmore College, Saratoga Springs, NY, USA

Attila Vertesi Bournemouth University, Dorset, UK

Mai Yokoyama Nagoya University, Nagoya, Japan

Halil Yurdugul Department of Computer Education and Instructional Technology, Hacettepe University, Beytepe, Cankaya , Ankara, Turkey

Longwei Zheng East China Normal University, Shanghai, China

About the Authors

Fazel Ansari (Vienna University of Technology) is assistant professor and deputy head of Research Group of Smart and Knowledge-Based Maintenance at the Institute of Management Science, TU Wien. He is also a senior researcher at Fraunhofer Austria. Fazel obtained his summa cum laude PhD in computer science from the University of Siegen, Germany, in the specialisation of knowledge-based systems and knowledge management. Dr. Ansari's research interests include knowledge-based maintenance, human-centred cyber physical production systems (CPPS) and knowledge management in Industry 4.0. He has published several articles on "Maintenance 4.0", "Reciprocal Learning" and "Ontology-enhanced Human-Machine Collaboration in Smart Factories". In addition, Dr. Ansari teaches courses in "Knowledge Management in CPPS" and "Knowledge-Based Maintenance" at the TU Wien and is a visiting lecturer at the University of Siegen where he teaches "Industry 4.0: From Vision to Reality". Dr. Ansari received a graduate scholar award from 12th Int. Conf. on Knowledge, Culture and Change Management (Chicago, USA), Dean's Award for Excellence in a PhD Thesis (University of Siegen, 2015), 2016 Outstanding Reviewer Award from Journal of Computers and Industrial Engineering, and was the winner of Theta Award 2015 for Person-Job-Fit Innovation.

Patricia Alejandra Behar (Universidade Federal do Rio Grande do Sul) is a Full Professor and Faculty Member of the Education and Postgraduate in Education Department (PPGEdu) and Computer Science in Education (PPGIE) at the Federal University of Rio Grande do Sul (UFRGS). Patricia is a visiting Professor at Columbia University. She obtained her Master's degree and PhD in Computer Science from UFRGS. Patricia is Coordinator of the Nucleus of Digital Technology applied to Education (NUTED/Cnpq) in the Education Department (FACED) and linked to the Interdisciplinary Center for New Technologies in Education (CINTED) since 2000. https://orcid.org/0000-0001-6939-5678.

Per Bergamin (Swiss Distance University of Applied Sciences) is the Head of the Institute for Research in Open, Distance, and e-Learning (www.ifel.ch) at the Swiss Distance University of Applied Sciences (FFHS). Since 2016, he has been Chairman of the UNESCO Chair on Personalised and Adaptive Distance Education. His research focus lies on self-regulated and adaptive learning in technology-based environments as well as on emotions in e-reading and e-learning.

François Bouchet (Sorbonne University) is an assistant professor at Sorbonne Université and a researcher at the Laboratoire d'Informatique de Paris 6 (LIP6). He received his MSc (2006) and PhD (2010) in Computer Science from Université Paris-Sud 11, with a thesis centred on the use of conversational agents for assistance. During his postdoc (2010–2013) at McGill University, he has been the main architect of the Intelligent Tutoring System MetaTutor and focused on applying data mining techniques (e.g., HMM, clustering, sequence mining) across multiple data channels (e.g., logfiles, facial expressions, eyetracking) to identify learners' profiles, in order to conceive a new generation of more adaptive intelligent tutoring systems. His latest research interests revolve around combining numerical and symbolical approaches for learning analytics to analyse multimodal traces produced by e-learning systems and MOOCs, in order to help students learn more efficiently through peer recommendation or by fostering the use metacognitive strategies.

Thibault Carron (Sorbonne University) is an associate professor of computer science at the University Savoie Mont Blanc, accredited research director since 2011. He is a member of the LIP6 laboratory (Mocah team – Sorbonne University). He obtained his PhD in computer science at the "Ecole Nationale Supérieure des Mines de Saint-Etienne" in 2001. His current research interests deal with collaborative activity observation and with serious games.

Huseyin Dogan (Bournemouth University) is a Principal Academic in Computing at Bournemouth University (BU). Dr Dogan's research focuses on Human Factors, Assistive Technology, Digital Health and Systems Engineering. He is the Co-Founder and Co-Chair of the Human Computer Interaction (HCI) research group and previously led the postgraduate courses (2012–2015) and then the undergraduate courses (2015–2017) in Computing at BU, managing over 900 students. He is also the Co-Founder of four MSc programmes: (1) MSc Digital Health, (2) MSc Digital Health and Artificial Intelligence, (3) MSc Cyber Security and Human Factors, (4) and MSc Marketing and User Experience.

Dr Dogan received his Engineering Doctorate (EngD) in Systems Engineering from Loughborough University, MSc in Human Computer Interaction with Ergonomics from University College London, and BSc in Computer Science from Queen Mary University of London.

He was also the General Co-Chair for the 30th International British Computer Society Human Computer Interaction Conference. He has over 100 publications and his research on Assistive Technologies (with Dr Paul Whittington) featured on the BBC South, BBC Radio Solent, The Ergonomist, Auto Express, Bournemouth Echo and The Sunday Times magazine.

David Carroll Gibson (Curtin University) is a Professor, Director of Learning Futures at Curtin University in Australia and UNESCO Chair of Data Science in Higher Education Learning and Teaching, 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 organizational change. He 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 learning platform. Professor Gibson consults with project and system leaders, formulates strategies, and helps people articulate their vision for innovation, then he 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.

Elizabeth Igoe (Manager of Learning Experience Design at Association of International Certified Professional Accountants) works as an instructional designer in Raleigh, NC. She has multiple years of instructional design and curriculum development experience ranging from informal education settings, such as museums and parks, to corporate environments. She earned her MS in Instructional Technology from the University of North Carolina Wilmington, focusing on problem-based learning in online environments.

Christof Imhof (Swiss Distance University of Applied Sciences) is a research associate at the Institute for Research in Open, Distance, and e-Learning (www.ifel.ch) at the Swiss Distance University of Applied Sciences (FFHS). He is also a doctorate student in psychology at the University of Bern. His research focus lies on emotions in e-reading and e-learning. Additional research interests include eye-tracking and procrastination.

Dirk Ifenthaler (Curtin University and University of Mannheim) 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 – see Dirk's website for a full list of scholarly outcomes at www.ifenthaler.info. He is the Editor-in-Chief of the Springer journal *Technology, Knowledge and Learning* (www.springer.com/10758). He received the 2016 Outstanding International Research Collaboration Award from AERA (American Educational Research Association), the 2015 Presidential Award from AECT (Association for Educational Communications and Technology) and the 2012 Outstanding Journal Article Award from AECT, as well as the 2006 Outstanding Dissertation Award by the University of Freiburg, Germany. He published more than 250 journal articles, book chapters and books and has received over 4000 citations resulting in an h-index of 31 (Google Scholar, November 2018).

Sinan Keskin (Van Yüzüncü Yıl University) is assistant professor at Van Yuzuncu Yil University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education at Gazi University in 2010 and worked as a teacher for 1 year. He get his PhD degree in 2019. He has experience in distance education, e- assessment, instructional design and programming teaching. His research interests relate to e-assessment, feedback design, adaptive e-learning, learning analytics and educational data mining.

Walter Mayrhofer (Vienna University of Technology) studied Electrical Engineering and Business Economics at TU Wien as well as Engineering Management at the University of Colorado at Boulder. He also holds a postgraduate degree in business, legal and economic studies from the VUT and an MBA from Danube University Krems and received his PhD in Labour Science at TU Wien. Since 2017, he is a senior researcher at the Research Center for Human Centered Cyber Physical Production and Assembly Systems (bmvit-endowed chair for Industry 4.0). Previously he held positions as Commissioner for Research of the region Burgenland and CEO of FTI-Burgenland GmbH, Head of Research at the University of Applied Science Burgenland and Burgenland Research GmbH as well as Head of Research at Fraunhofer Austria Research GmbH, Division of Production and Logistics and TU Wien, Institute of Management Science. He also held academic and management positions at Danube University Krems and the University of Applied Arts Vienna. Walter has widespread experience with research and industry projects as a researcher, manager and coach. He has taught in numerous undergraduate and graduate programmes and has supervised approximately 100 Master's thesis. Further, he was involved into developing several international co-operations in higher education.

Mahnaz Moallem (Towson University) is a Professor of Instructional Technology and Research and Chair of the Department of Educational Technology and Literacy at Towson University, Towson, Maryland. Previously, she was a Professor of Instructional Technology and Research and Grant Coordinator at the University of North Carolina Wilmington, Watson College of Education. She received her PhD in instructional systems design and her Program Evaluation Certificate from Florida State University. Dr. Moallem's research is focused on applications of various learning and instructional design theories and models for learning and human performance improvement. She has a special interest in the application of PBL and assessment of complex learning outcomes such as problem-solving and critical thinking for STEM fields. Dr. Moallem has coordinated innovative projects funded by National Science Foundation and Department of Education on the integration of PBL with computer modelling and simulation. She serves on the Editorial Board of several prestigious national and international journals and has been the recipient of a number of teaching and research awards. Dr. Moallem has served as a rotating scientist (IPA) for 2 years at the National Science Foundation.

Stéphanie McGarrity (Swiss Distance University of Applied Sciences) is a researcher at the Institute for Research in Open, Distance, and e-Learning (www.ifel.ch) at the Swiss Distance University of Applied Sciences (FFHS). Her research focus lies on how to improve learning or teaching by improving digital competencies or by using physiological sensors.

Kazuhisa Miwa (Nagoya University) received the BS degree in Applied Physics from Nagoya University in 1984. He received Ph D degree in Information Science from Nagoya University in 1989. Kazuhisa stayed in CMU as a visiting scholar from 1991 to 1992. He is currently a professor at Nagoya University. Kazuhisa was the president of Japanese cognitive science society from 2017 to 2018. His research interests include cognitive science and artificial intelligence, with special interest in fundamental studies on higher order cognition, such as creative thinking, insight problem solving, scientific discovery, AI based learning support systems and human factors of automobile driving.

Guy Merlin Mbatchou Nkwetchoua (Assane Seck University of Ziguinchor) is a lecturer in the Department of Computer Science at Assane Seck University in Ziguinchor (UASZ). He conducts his research activities at the Laboratories LI3 (Laboratoire d'Informatique et d'Ingénierie pour L'Innovation) of the UASZ and LIP6 (Laboratoire d'Informatique de Paris 6) of Sorbonne University in the field of Technology Enhanced Learning. His research focuses mainly on the development of educational models for the personalisation and adaptation of learning to each learner. He headed the IT Department from July 2007 to July 2010 and the Distance Training Service from March 2011 to May 2019 at UASZ. He trained the teachers of the UASZ in putting courses online and contributed at the opening of online Legal Sciences academic section at UASZ. He also trained the master degree students in online tutoring and supervised the online legal science training from October 2016 to June 2019.

Philippe Pernelle (University Claude Bernard Lyon 1) is an associate professor of computer science at the University Claude Bernard Lyon 1.

Susan L. Renes (University of Alaska Fairbanks) is Emeritus Professor at the University of Alaska Fairbanks. Her research focuses on factors related to Indigenous and rural student recruitment and retention in higher education. Dr. Renes presented Expanding Access for Indigenous Students to the Behavioral Health Workforce through Distance Education at the International Congress of Arctic Social Sciences in Akureyri, Iceland, in 2011. In 2013, she received the Elders Award given by Alaska Native Elders to acknowledge those whose deeds and practices promote cultural understanding and balance in all things for a better world community. In 2013, she chaired the roundtable Indigenous Studies in Alaska: Interdisciplinary Initiatives in Research, Service and Pedagogy for the Native American and Indigenous Studies Association (NAISA) in Saskatoon, Saskatchewan. In 2014, Dr. Renes authored *Amplifying Indigenous Voices*. In 2016, she presented Teaching in Higher Education: You Can't Call it an Adventure if You Know How it's Going to Turn Out at the Lilly International Conference on Teaching and Learning in Oxford, Ohio, and served on a panel addressing Reclaiming Indigenous Spaces In Higher Education: Examining Recruitment, Retention, And Mentoring Of Alaska Native Students at the University Of Alaska Fairbanks for the National Indian Education Association in Anchorage, Alaska.

Muhittin Şahin (Ege University) is an academic staff at Ege University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education at Ege University. He completed PhD degree in 2018 at Hacettepe University. His research interests relate with learning analytics, educational data mining, multi-criteria decision making, statistic, e-assessment and intelligent learning management systems.

Ketia Kellen Araújo Da Silva (Universidade Federal do Rio Grande do Sul) is a PhD in Informatics in Education from the Federal University of Rio Grande do Sul (UFRGS), Post-Doctorate in Informatics in Education, UFRGS, and Researcher for the Nucleus of Digital Technology applied to Education (NUTED/Cnpq). https://orcid.org/0000-0003-4722-8072.

Angelos Stefanidis (Bournemouth University) is Associate Dean (Global Engagement) in the Faculty of Science & Technology at Bournemouth University. He received his PhD in Information Systems Education from Loughborough University. Angelos has held various academic roles over the years and has extensive teaching experience in the areas of Computing and Information Management. He also has extensive experience in the design, management and delivery of professionally accredited CPD courses to IT companies and organisations. In addition, he has held various academic management positions and worked externally with numerous universities in the UK and overseas. His current role involves providing leadership, operational development and delivery of the Bournemouth University's Global Engagement plan by supporting recruitment, international partnerships, students and staff mobility, education, research, and professional practice activities on and off-campus.

Anthony T. Strange (Wayland Baptist University) earned his doctorate in Education from the University of Southern California. He has worked in a number of settings including High School Counseling, Assistant and Associate Professor, Chair of Counseling Department and Chair of Graduate Studies at the University of Alaska Fairbanks. He has been invited to present at local, state and national level. He is a Past President of the Alaska School Counseling Association and consultant to school districts. He is currently a Faculty member at Wayland Baptist University. Dr. Strange is a member of the South Carolina Counseling Association and serves on the Executive Governing Board.

Joan Ann Swanson (Skidmore College) has a PhD in Education Psychology and Methodology from the State University of New York, University at Albany. She also has an MS in Educational Counseling from McDaniel College and a BS in Education and Psychology. Dr. Swanson holds New York State teaching certification Nursery through 12th grade and has experience both as a school teacher and college professor. As an Assistant Professor in Education Studies at Skidmore College in Saratoga Springs, she teaches Child and Adolescent Development, Educational Research, Alternative Education and Educational Technology courses. Dr. Swanson's research interests include the study of instruction and learning, with a particular interest in emerging adults and adolescents. Recent research projects analysed emerging adult preferences and patterns for technology use. Her current research examines pedagogical practices involving technology. Additionally, Dr. Swanson has presented her research both nationally and internationally and recently authored a book chapter in which she presented her theory, "Technology as Skin".

Attila Vertesi (Bournemouth University) is a Lecturer at Bournemouth and Poole College (BPC) and an Honorary Lecturer at Bournemouth University (BU) in Computing and Engineering. Attila is a Course Leader of the Access to HE Computing Course at BPC. He received his MSc in Cyber Security and Human Factors from BU, graduated as a Physics Teacher (BSc Hons) at ELTE Budapest and holds Communication Engineering (BSc) and Technical Teacher (BSc) degrees.

Mai Yokoyama (Nagoya University) received the BS degree in System Information Science from Future University Hakodate in 2013. She received the MA degree from Hokkaido University in 2015. She is currently a doctoral student of Nagoya University. Her research interests include educational psychology and educational technology.

Halil Yurdugul (Hacettepe University) is Professor at Hacettepe University, Faculty of Education, Department of Computer Education and Instructional Technology. He completed his undergraduate education at Hacettepe University's statistics department. He completed PhD degree in 2003 at Hacettepe University. His research interests relate with psychology, psychometry, education, measurement and evaluation in education, statistic, assessment, e-assessment, learning analytics, educational data mining and intelligent learning management systems.

Part I
Online Higher Education

Chapter 1
Digital Competences for Online Students

Ketia Kellen Araújo Da Silva and Patricia Alejandra Behar

1.1 Introduction

There has been a considerable increase in distance learning in Brazil in recent years due to new instruments and criteria for using Information and Communication Technologies (ICT). However, using ICT in distance learning requires students to continuously learn about new and varied resources. The concept of digital competences has been used as an alternative in order to provide students a more integrative education using technology. However, there are few studies specifically focused on digital competences for this profile. Thus, this chapter aims to present the construction of a digital competence model for online students. A model is understood as a simplified way of establishing an analogous relationship, a figurative system according to Behar (2009), Anderson et al. (1991), Eppen et al. (1987), Harding and Long (1998), de Lima and Lezana (2005). This proposal focuses on the construction of a model of digital competences for online students called MCompDigEAD.

Existing models of digital competences were analyzed through a bibliographical survey to inform this model, understand the profile of the distance learning student, and to map the competences that appear in the theoretical references. There have been many efforts to define and create standards for digital competences. Yet, research in Brazil has been quite limited and there are no definitions or models focused on the online student. Therefore, international studies are the main theoretical basis for the present study, though they are based on a distinct subject profile and educational level. Thus, the digital competences of the distance learning students had to be mapped in order to build a model focused on this specific subject profile.

This chapter presents the work that was carried out from 2014 to 2018. It begins by mapping these competences based on the theoretical references and then with the online students. Subsequently, it examines the construction of the MCompDigEAD

K. K. A. Da Silva (✉) · P. A. Behar
Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_1

model and its validation, which was done with the support and participation of the Open University of Catalonia (UOC). This work is therefore divided into sections that address digital competences, the profile of the distance learning student, the construction of the digital competence model, and, lastly, final considerations.

1.2 Digital Competences

According to UNESCO reports (2006), digital competence is one of the eight core competences for lifelong development. However, there are few national or international studies available to understand or develop it through education. Moreover, there is little research focused on Distance Learning (DL). Most studies have come from international institutions, such as the EUROPEAN UNION (2006), UNESCO (2006), and OECD (2005), and they generally define a list of digital competences that do not fit the needs of online students.

Digital competences have been defined differently in official and academic documents, which has produced multiple meanings and a range of nomenclatures. Therefore, a vast bibliography can be created conceptualizing the term, generating distinct as well as redundant definitions. Yet, all descriptions refer to how people should deal with ICT in different areas of their lives. Hence, the concept of digital competences has continued to transform as technologies have provoked societal transformations.

This study understands digital competences as presented by Ferrari (2012, p.84), as a "set of knowledge, skills, and attitudes, strategies and awareness that is needed when using ICT and digital media." Therefore, it is the mobilization of knowledge, skills, and attitudes (KSA) in a given context with the support of digital resources and technological tools. However, online students must also know about technology and its possibilities. Palloff and Pratt (2015) argue that there is not one online learner profile, but a range of subjects from youth to adults. Thus, it is necessary to go beyond the characteristics of the new generations and focus on what it means to be an online student. Rather than drawing generalizations based on generational differences, this entails taking into account that there are young people with less ICT skills than others, as well as different cultural, social, and economic contexts.

1.3 The Online Student

Distance learning using ICT resources is continually being redefined through virtual learning environments and new tools, impacting the student profile of this new generation. In Brazil, Law 9.394/96 – Law of National Educational Guidelines and Foundations was introduced in 1996. It proposed DL as a new national educational modality. Years later, guidelines for DL were created, which encouraged public institutions of higher education to create and develop courses. Moreover, the Open

University System (UAB) and the Quality References for Distance Higher Education were also instituted in 2007, making the student the center of the educational process. The concept of DL proposes that all the subjects involved are responsible for their own development, considering their capacity for independent and autonomous learning, through interaction, organized and guided mediation, and clearly defined evaluation criteria (BRASIL 2007). Thus, the use of technologies in education must be supported by a learning philosophy that provides students with opportunities for interaction and the construction of knowledge (BRASIL 2007).

According to the latest 2018 Brazilian DL Census (EAD.Br 2017/2018), there were a total of 7,738,827 online students enrolled in distance learning classes. The student profile was defined as subjects who primarily worked and studied and were between 31 and 40 years of age. In other words, DL students tend to be older than those in traditional classrooms. Hence, it is possible to note the development of DL in Brazil and its potential to democratize and elevate the standard quality of education. Yet, student dropout rates have been one of the main obstacles faced by institutions. In 2018 there was an average dropout rate of 26% to 50% (EAD.Br 2017/2018). According to the survey, the main factors students pointed to were lack of time to study and complete course activities, financial concerns, and the methodology applied by the institutions. Palloff and Pratt 2004, p. 112–113) argue that it is "the very elements that lead students to online education - the reality of restrictive working hours, the possibility of continuing to meet familial demands - that interfere when it comes to staying in the course." Here the discussion of digital competences and their contribution to DL becomes quite apparent. Yet, according to Palloff and Pratt (2015), online learners range from younger students who have grown up with technology to older adults who are returning to college and looking for the convenience of online learning. Behar and Silva (2013) argue that students who seek distance learning need to develop a virtual student identity, which occurs through daily interactions with technology, enabling the students to progressively adopt the tools. Yet, there are three fundamental points that must be taken into consideration: 1. students' strategic performance, such as time management, forms of communication, disposition, motivation related to the subject, etc.; 2. understanding the characteristics of the group, tasks, course objectives, and the overall context; and finally, 3. technological abilities, including the student's Internet connection, use of tools, and familiarity with technology. Students' understanding of these points allows them to better develop their unique way of behaving in the DL context.

According to Gómez and Perez (2015), the daily life of the new generations is mediated by virtual social networks, which have created new lifestyles, processing of information, exchanges, expressions, and actions. Therefore, the characteristics of current students are very different from those of previous decades. According to Esteve et al. (2014), the main terms used to define subjects and their relationship with technology are Digital Natives (Prensky 2001), Generation Net (Tapscott 1998), and Millennials (Howe and Strauss 2000). However, according to Kennedy et al. (2007), although these profiles possess certain ICT skills, these technological skills are often linked to social or leisure activities and cannot necessarily be transferred to the learning context. Therefore, their technological confidence and experience must be developed in terms of learning specific digital competences.

The methodological process carried out to construct the digital competence model used in this research is presented in the next section.

1.4 Methodology

In order to construct the MCompDigEAD model, competences were mapped both using theoretical references and with online students. This chapter presents the six steps that have been implemented thus far.

- **Step 1.** Mapping of digital competencies from the bibliographic study – MAP 1
- **Step 2.** Mapping with online students – MAP 2
- **Step 3**. Cross-referencing the results of MAP 1 with MAP 2, resulting in MAP 3
- **Step 4.** Validation of MAP 3
- **Step 5**. Construction of the MCompDigEAD model based on 4 steps: (1) conception, (2) planning, (3) modeling, and (4) validation
- **Step 6**. Validation of MCompDigEAD

1.4.1 Step 1

The first stage was a bibliographic review related to the relevant areas of knowledge. Competences in education, digital competences, distance learning, and the profile of the online students were developed. A review of the existing models of digital competences at both the national and international level was also carried out. Fourteen models were selected and studied, as shown in Table 1.1.

Each of these steps is explained in detail below.

The diversity and lack of uniformity among the standards made the organization and initial mapping quite difficult. The majority focused solely on knowledge related to digital literacy, limiting the results by excluding skills and attitudes. In addition, the models grouped the competences, but they did so in a myriad ways with different names, such as domains, dimensions, categories, and areas. Proficiency was also analyzed, but was referred to as degrees or stages of development of digital competences. Therefore, the first step was to arrange all of the selected elements in a map and then in a single table, including their domains/categories, resulting in 85 components. Then, similar components were combined and identified as: digital literacy, digital fluency, communication, and teamwork. The following domains were found: digital security, informational literacy, content creation and development. MAP 1 shows this first mapping. The importance of mapping digital competences focused on the DL student profile was made even more clear after the bibliographic study and organization of MAP 1.

Table 1.1 Summary of models studied

Year	Model name	Location
1996	ECDL/ICDL	Spain
2002	ICT – Literacy framework	United States
2002	DeSeCo – Competences	Europe
2004	Digital literacy	Israel
2005	DigEuLit	Europe
2006	E-competences	Europe
2006	Key competences for lifelong learning	Europe
2007	NETs-S	United States
2008	California ICT digital literacy framework	United States
2009	ACTIC e COMPETIC	Catalonia
2011	SIMCE-TIC	Chile
2012	Digital competence	Spain
2013	DIGICOMP	Europe
2013	Basic competences for the digital environment	Catalonia

Source: Created by the authors 2020
Califórnia Emerging Technoogy Fund (2008), Catalunya, Generalitat (2020), Catalunya, Generalitat (n.d.), Chile (2020), Eshet-Alkalai (2004), ETS. Digital Transformation (2002), European Computer Driving Licence – ECDL – Foundation (2020),European E-Competence Framework (e-CF) (2020), European Union (2006), International Society for Technology in Education (ISTE) (2007), La Larraz (2012), Martin and Grudziecki (2006), OECD (2002)

1.4.2 Step 2

In the second step, digital competences with online students were mapped based on Leme (2012) and Torrezzan's (2014) methodologies. Two classes were used: one was a graduate course with 24 students between 25 and 50 years of age from different academic backgrounds, ranging from specialists to postdocs; the other was an undergraduate teaching course with a total of 10 students between 18 and 25 years of age. A learning object (LO) was developed about digital competences for online students. The concept of digital competences and the DL student profile were discussed in both courses in the first module of the LO as well as the challenges proposed in the LO. Then, in the second module, students were taught about mapping digital competences, and they did the required readings and activities in groups. Both were given 20 h to do the mapping, after having already discussed the concepts of DL, competences, and the profiles of DL subjects. The graduate group presented a list with 74 elements based on the activities, divided into knowledge, skills, and digital attitudes. These included basic issues such as turning the computer on and off, saving data, creating folders, knowing how to use e-mail, accessing the virtual learning environment (VLE) on a regular basis, interacting with colleagues, meeting deadlines, responding to requests from professors, as well as time management, as

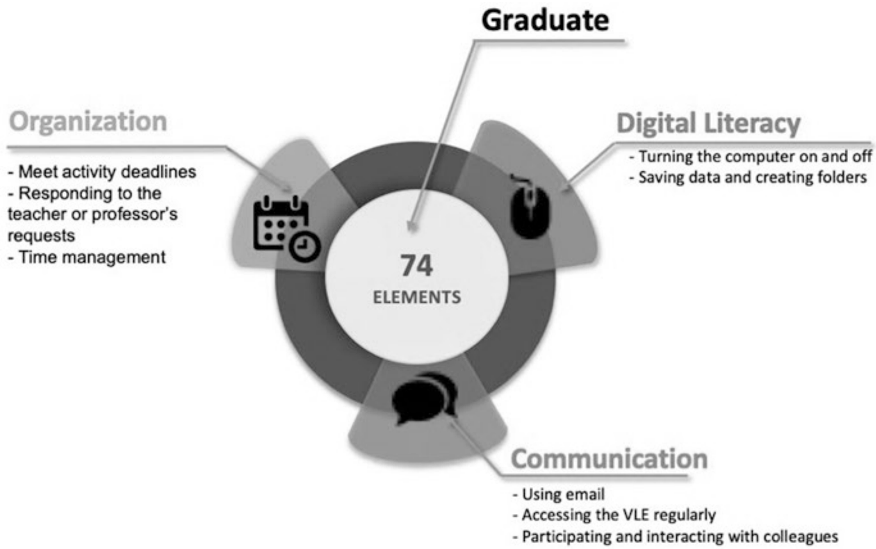


Fig. 1.1 Main competences for graduate students. (Source: Created by the authors 2020)

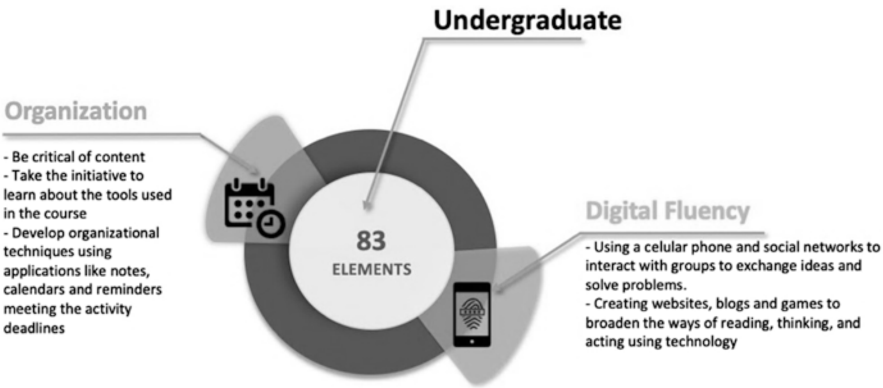


Fig. 1.2 Main competences for undergraduates. (Source: Created by the authors 2020)

can be seen in Fig. 1.1. The undergraduates identified 83 elements, highlighting the use of cellular phones and social networks to interact with groups, exchange ideas, and solve problems. They also proposed creating websites, blogs, and games to broaden ways of reading, thinking, and acting using technology, according to Fig. 1.2.

The elements listed in both groups were related to the competences: digital literacy, digital fluency, organization, communication.

1.4.3 Step 3

The objective of the third step was to compare the competences identified in MAP 1 (theoretical references) with those of MAP 2 (mapping with the online students). This was carried out according to the four steps described below:

1. The results of the digital competences mapping activities from each class were organized in a table.
2. The elements of the graduate and undergraduate mappings were combined separately by skills and attitudes in a new table. This was then refined by combining common elements.
3. After combining them in a single table with skills and attitudes, MAP 2, we searched for similarities with MAP1, inserting knowledge and possible skills.
4. Finally, the elements were arranged by competencies and KSA, removing redundant components and improving the writing. This final table was called MAP 3.

Although almost the same competences have been listed, there are key differences in the elements. While the theoretical framework presented an overview of these competences, the mapping with the online students focused on the student profile in the distance learning modality. Hence, when the elements were combined, the names of those that presented contributions to the subject profile were used, because it is the main objective of this research.

Step 4 is the validation of the mapping of digital competences with online students.

1.4.4 Step 4

This step involves the validation of MAP 3, in order to transform it into a model with competences, KSA, and an evaluation of both focused on the online student, or MCompDigEAD. This step took place in 2016/1 in the graduate class and 2016/2 with specialists. Three classes were used for validation in the course, and the group had already studied the concept of DL, profiles, and competences. The students were then asked to reflect on MAP 3 through activities to provoke ideas about what is needed in a digital competence model focused on distance learning for the student profile. This was also done with experts, however in this case through an online questionnaire. Based on the results, the model was organized as a list of competences directly linked to the student profile and the DL process.

1.4.5 Step 5

The model had competences and KSA related to the technological domain, which were: functional digital literacy, critical digital literacy, digital fluency, communication, information management, online attendance, creation and development of digital content, and virtual profile management.

Table 1.2 Conceptual frameworks

Functional digital literacy	Is the need to functionally master the technologies, reading, and writing to have access to digital and virtual knowledge (Coll and Illera 2010). Functional digital literacy is made up of competences related to the basic use of the computer and the Internet
Critical digital literacy	Is related to research, evaluation, reflection, and critical understanding of the information available on the Internet, as well as the use of digital tools for communication. It is composed of a set of literacies, which are: informational, multimedia, communication, and computational (Ribeiro 2013). Critical digital literacy is composed of competences such as communication and management of information
Digital fluency	Is linked to the use of technology so that the subject feels like a digitally active participant when technology advances. Fluency enables not only use but also the creation and production of content/materials (Behar et al. 2009)

Source: Created by the authors (2020)

According to Behar (2009), the technological domain consists of competences related to the use of technological resources in DL, such as virtual learning environments, learning objects, and tools in general. Thus, an analysis of the mappings carried out with the students was performed in conjunction with the bibliographic survey for each competence. It became clear that online students needed to develop a degree of digital fluency to be digitally proficient. Digital fluency, therefore, is a central concept in this model. According to Machado and Grande (2016), there is a correlation between functional and critical digital literacy and digital fluency. That is, in order for a student to reach digital fluency, they must first be literate.

Each of these levels, functional and critical digital literacy as well as digital fluency, are presented in Table 1.2.

Yet there is also a degree of complexity at each level of the specific competences. Thus, Fig. 1.3 was created.

Hence, there is a nonhierarchical structure for the development of the digital competences, an organization of elements to be constructed by the online students. Many times critical digital literacy is not fully developed, and the subject nonetheless already has a degree of proficiency with respect to the digital fluency competences.

1.4.6 Step 6

The model MCompDigEAD was applied in order to verify its suitability for the public and to identify possible gaps. This was done through three steps: application of the model in the graduate course, application of questionnaire with specialists, and analysis of the final document by experts from Brazil and the Open University of Catalunya (UOC). After the identification and organization of the model, it was validated. It is worth noting that the validation stage was carried out during doctoral

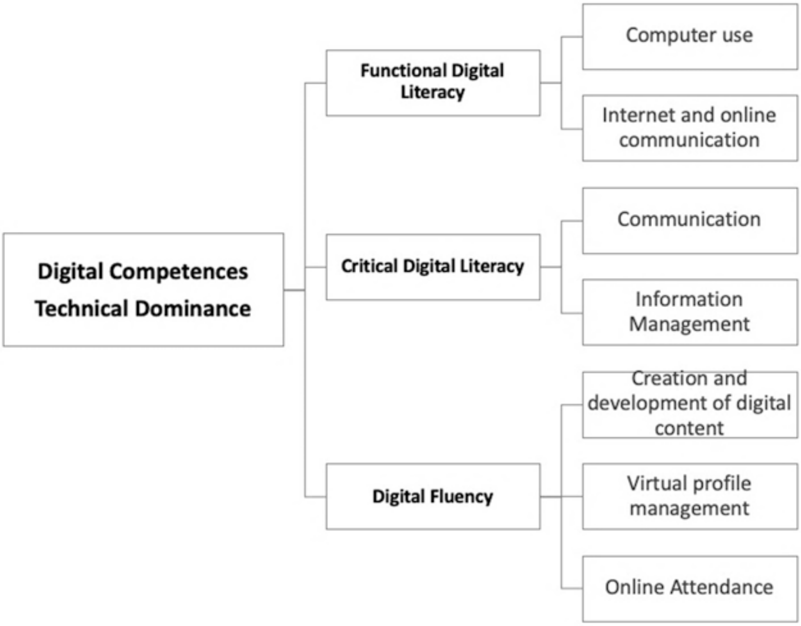


Fig. 1.3 Technical dominance and digital competences. (Source: Created by the authors 2020)

studies abroad at the UOC, which allowed for discussions and adjustments of the model and analysis of the results.

As a result, MCompDigEAD was organized into six areas: introduction of digital technologies, digital communication, network information management, digital health and security, attendance and digital citizenship, and creation and development of digital content. These areas are organized into three levels of digital competences: functional digital literacy, critical digital literacy, and digital fluency, detailed in fourteen specific competences based on knowledge, skills, and attitudes (KSA), totaling 328 elements.[1] Each specific competency has three levels of proficiency: (1) initial, (2) intermediate, and (3) advanced, with example of use cases. We will now describe each element in further detail.

Areas: In MCompDigEAD, the areas are specific to the technology domain and correspond to the areas of action. They were organized based on the analysis of the competences mapped for the student profile compared to the models and references and are divided into six areas, as seen in Table 1.3.

Specific skills: Embedded in the three digital competences, these were organized based on knowledge, skills, and attitudes (KSA), as well as the definition of three levels of proficiency containing examples of use cases. The relationship between the digital competences and specificities can be seen in Table 1.4.

[1] The complete model can be found here: http://nuted.ufrgs.br/MCompDigEAD.pdf

Table 1.3 MCompDigEAD areas

Introducing digital technologies	Using the desktop and mobile functions and applications
Digital communication	Network communication, interaction and collaboration through virtual learning environments, online tools, and applications
Network information management	Develop, search, identify, retrieve, store, evaluate, share, and organize information in a network
Digital health and security	Protect personal data on the network and virtual resilience.
Attendance and digital citizenship	Manage presence and virtual identity in virtual learning environments (VLEs) and social networks through the Internet
Creation and development of digital content	Plan, build, integrate, rework, and deploy digital content

Source: Created by the authors (2020)

Table 1.4 Relationship between digital competences and specific digital competences

Digital competences	Specific digital competences
1. Functional digital literacy	1.1 **Use of desktop and Mobile devices:** This competence is intended to assist the student to use the desktop computer and mobile devices and their applications
	1.2 **Network communication capabilities:** This competence is related to the basic network communication that occurs through different tools and applications. It is aimed at the proper use of different forms of communication. They are the basics necessary in order to adapt the communication formats and strategies according to the students' needs. It includes the use of e-mail, instant messaging such as SMS (via a mobile operator) and WhatsApp (example application), social networks (Facebook, Instagram, LinkedIn), and virtual learning environments (VLEs)
	1.3 **Search and treatment of information:** This competence is linked to accessing and searching for information in networks, allowing the online student to access information. Searching means looking for information through search engines. Processing information is the basic use of word processing applications, spreadsheets, and presentation editors. These applications are used to perform everyday tasks, and they are essential for creating, formatting, and finalizing documents and organizing information in distance learning courses
	1.4 **Ergonomics for the use of desktop computers and mobile devices:** This competence aims to assist in understanding physical health risks related to using technology

(continued)

Table 1.4 (continued)

Digital competences	Specific digital competences
2. Critical digital literacy	2.1 **Network interaction and collaboration tools:** This digital communication competence focuses on network interaction and collaboration based on the clarity and objectivity of oral, body, and written expression. For online students, it is related to the way in which they interact and collaborate with colleagues and teachers. Also their use of netiquette, that is, the behavioral norms on the internet
	2.2 **Evaluation and sharing of information:** a set of strategies that address information needs related to the collection, distribution, and use of information. The student needs to understand, critically evaluate, and judge information on the network and sources according to their needs in order to share appropriately
	2.3 **Organization and planning:** The management of the profile of the virtual student is related to their planning and organization for their autonomy as an online student. Planning is linked to setting priorities, goals, and objectives. In DL, creating situations and applying learning strategies are also considered. Organization is related to the ordering, structuring, and systematization of a student's routine. Therefore, for students to become autonomous in their learning in the virtual space, it is necessary that they engage in planning and organization, as well as establish cooperative relations where mutual respect prevails
	2.4 **Digital profile:** This competence aims to help the online student to understand how their data can be managed and published, both in the VLE and social networks. The focus is on understanding how to securely handle information, with respect and responsibility through different digital profiles. How to build, search, create, adapt, and manage these different profiles, adapting to each environment
	2.5 **Cooperation in virtual learning environments:** Cooperation is related to the processes of understanding common values, the conservation of those values, and reciprocity. Thus, the virtual cooperation competence aims to create cooperative relations needed for the cognitive, affective, social, and technological development of the subjects. This competence is primarily related to the skills of teamwork and digital communication

(continued)

Table 1.4 (continued)

Digital competences	Specific digital competences
3. Digital fluency	3.1 **Content production:** Is related to the creation and development of digital content necessary for learning in different formats, to learn and express oneself creatively through digital formats. It involves the development and/or integration or rewriting of content by modifying, refining, and combining existing resources, as well as the understanding of copyright and licenses applied to the use and construction of network content
	3.2 **Data protection:** This competence is related to the understanding of risks and threats, as well as security measures that can be carried out. The goal is to understand the protection of personal data, so that students knows how to protect themselves from fraud, online threats, and cyberbullying.
	3.3 **Networking relationships:** This competence is related to the student's understanding of safe and responsible use of the network for their learning. Also, behaving based on values such as respect, ethics, and honesty in both VLEs and the network in general. It is necessary to properly choose content, to socialize digitally, and engage with others in the network
	3.4 **Virtual resilience:** This competence is related to how the subject handles unexpected changes, how they adapt and overcome different obstacles and difficulties. Resilience is how the subject reacts in the face of difficulties and has to do with how they deal with adversity, such as when faced with situations of risk, stress, pressure, challenge, obstacle, difficulty, or change of environment. In this sense, resilience is not directly related to the success of actions, but to the process of building these actions and becoming conscious of them
	3.5 **Teamwork:** Teamwork includes intra- and interpersonal relationships, which allow the subject to adequately express and communicate their emotions, desires, opinions, and expectations. In addition, it looks at interpersonal behaviors, the ability to interact with others in a socially acceptable way, and thus, to bring benefits to the participants in moments of interaction. These elements can still be supplemented from the affective point of view, because the complexity of social relationships also requires the ability to perceive and distinguish moods, intentions, motivations, and other people's emotions. It is mainly linked to the competences of cooperation and resilience

Source: Created by the authors (2020)

Levels of proficiency: Levels are gradual for each specific digital competency, as detailed below.

Beginning level: At this level the student shows little familiarity with the use of digital technologies in the process of distance learning. Having mastered the basics, this student is included digitally, but is unaware that they need guidance to increase their knowledge of the DL process. Yet, they are not always able to share their ideas with their colleagues or teachers. In general, this student knows the tools and processes and uses them in a basic way, without questioning or developing different strategies.

Intermediate level: At this level the student already has more experience with technology and uses it in different contexts. Here the student also knows the tools that are used in the process of distance learning. They have a much easier time dealing with other subjects in the learning process and are willing to understand and improve their skills by discovering new strategies, situations, and tools. The students are able to differentiate and choose the best tools for particular situations in order to improve and understand different strategies in each circumstance in the learning process. In general, at this level the student has more autonomy and confidence regarding strategies to be used and is always searching for ways to learn more.

Advanced level: Here students are very familiar with the use of digital technology in the learning process. They have a wide repertoire of strategies for different contexts and various tools. They know how to choose the most appropriate option for any situation or can find an alternative if necessary. They can also share choices, help classmates and even teachers. They are constantly learning, always critical and questioning. In general, this student transforms, creates, and innovates using digital technologies in favor of learning.

A description of these three proficiency levels was created for each specific digital competence. A use case was also built at each level with a situation that seeks to identify the online student and help them to understand their level of competence. The levels of proficiency are expected to be a benchmark and can be adapted to the needs of the group and the institution.

Table 1.5 presented details the first specific competence: 1.1 use of desktop and mobile devices. The chart shows the mapping of the elements (knowledge, skills, and attitudes), the three levels of proficiency, as well as a use case.

Moreover, Fig. 1.4 shows the relationship between the elements of the model. The process of building the competences of the model begins with the competences of functional digital literacy, then critical digital literacy, and finally digital fluency. In this process, the areas are transversal, permeating all competences, as can be seen in Fig. 1.4.

It should be emphasized that digital competences must be constructed gradually over time, taking into account that technology is constantly evolving and provoking changes. Hence, this model is dynamic and must be constantly updated according to the needs of the target audience, in this case online students.

Table 1.5 Elements and levels of proficiency of use of desktop and mobile devices

1.1 Use of desktop computer and mobile devices		
Elements		
Knowledge (Knowing)	Skills (Knowing how to do)	Attitudes (Knowing how to be/ coexist)
Know the basic functions of the desktop computer and mobile devices: turn it on, login with password. Turn it off or put in sleep mode	Know the commands to turn desktop computers and mobile devices on and off	Have the initiative to look for help regarding the different uses of desktop computers and mobile devices
Know the difference between hardware and software	Have skills in using the mouse (one click and double click) and in using the keyboard and touch screen for mobile devices	Be willing to use the desktop computer and its peripherals
Know there are apps for mobile devices	Know how to use the basic configurations on desktop computers and mobile devices	Be willing to effectively use desktop computers and mobile devices to achieve your goals and complete your tasks
Know the desktop computer's input peripherals, such as mouse and keyboard, and output peripherals, such as printer, monitor, speakers, and headphones	Know how to use the desktop computer's input and output peripheral hardware for specific tasks	Have the initiative to explore Internet resources both on desktop computers and mobile devices
Know the data storage devices: internal (HD), removable (CD, DVD,) external (USB flash drive, external HD, Cloud – Google Drive/ One Drive/ Amazon Drive)	Know how to use mobile devices' virtual keyboard	Be alert and attentive when downloading or uploading materials
Know files and folders on the desktop computer: browse, create, open, close, save, delete, and copy	Know how to select and use the different storage devices	
Know the operating system and mobile devices' interface elements, such as buttons, menu, title and scroll bars, tabs, etc.	Know how to identify the different types of files and folders	

(continued)

Table 1.5 (continued)

Know the difference between operating systems for desktop computers (Windows, Mac, Linux etc.) and mobile devices (iOs, Android, etc.)	Know how to find, open, use, and close applications on desktop computers and mobile devices	
Know different browsers for desktop computers and mobile devices and know how to use them	Know how to install and uninstall software on a desktop computer and mobile devices	
Understand the structure of Internet addresses, such as .br, .gov, .edu, .org.	Know how to choose the browser that best suits your desktop computer and mobile device to access the Internet	
Understand the different activities using the Internet, such as using web applications, searching for information, shopping, reading and learning, publishing audio and video materials, accessing bank services, getting entertainment, communicating, etc.	Know how to execute the commands to download and upload files	
Understand the concepts of downloading and uploading		
Proficiency levels		
Beginning	**Intermediate**	**Advanced**
Can use desktop computer and mobile device functions in a basic way based on needs. Can access and browse the Internet	Can configure a desktop computer and mobile devices based on different situations. Can install software and applications. Configures the operating system to more efficiently use digital equipment as needed. Is able to save and exchange data between different data storage devices, as well as over the internet. Chooses the best browser and uses different tabs to organize sites	Optimizes the desktop computer and mobile devices, determining the best way to organize applications and software, as well as archived data. Updates and resolves problems with software and applications

(continued)

Table 1.5 (continued)

Can turn a desktop computer on and off and perform basic tasks. Can open and save files in folders	Can manage and install different software and applications. Recognizes that it is possible to save data on different devices, such as a USB flash drive, HD, in a cloud, etc. Can search for a saved file, open and edit the name, as well as other functions	Can manage, install, and update software and applications. Knows the differences and possibilities of the desktop computer and mobile devices. Knows how to manage files on different devices and keeps copies and backups of what are considered to be the most important files
The same is true with the mobile devices. Can use them, but is unable to configure or install software or applications	Can connect to the Internet using different types of browsers, knows how to access browsers for information and can access the learning environment. Can bookmark pages or other tools for quick access. Knows how to upload and download files	Configures the browser to block pop-ups and cookies and organizes bookmarks by folders with the main visited sites. Can access the Internet using different types of devices and connections
Can open the browser, click on the address bar, and type the address of the website they want to access. Can open another tab and access another website through the same browser at the same time		
Use case		
Setting: Distance learning course		
Situation: Using the desktop computer and mobile devices to access the virtual learning environment (VLE)		
I can turn on my desktop computer, access the browser, and enter the virtual learning environment. I have a little difficulty with mobile devices since the applications are different	I can access the VLE, and I know that a VLE is different from a website, so I need a password and personal login. I can save the VLE address as a favorite in my browser, to make it easier for me to access	I am familiar with using a desktop computers and mobile devices

(continued)

Table 1.5 (continued)

In the virtual learning environment, I open the files that the teacher has made available, but I still don't feel secure. I have technical difficulties, such as trouble downloading the course materials	I know how to find my way around the VLE. I can open the available course materials and download the ones I am most interested in. I save and organize these documents in folders on my desktop computer. If I don't have the right software or application, I know how to install a new one, but I don't always know how to search for the right application. I can save files on different devices, especially when I need to use material on another desktop computer or at another workspace	I can use the Internet skillfully through browsers. I access the VLE from both a desktop computer and mobile devices. I analyze the importance of downloading the files available for the course, according to my Internet connection and need for the material. I know how to submit activities in the VLE, and I keep folders on my desktop computer with all the completed materials and activities, saving them with appropriate names. I keep a copy of the activities on my desktop computer and other storage devices, such as a USB flash drive or in the cloud. In addition, I can solve basic problems that arise on a desktop computer or on mobile devices. Sometimes, it is not possible to access material on mobile devices due to the application, but I can do so on my desktop computer
		I know how to use the browser and its security functions, when necessary. I can successfully take advantage of the resources available on the Internet, such as shopping and checking my bank balance. I access the Internet from my desktop computer through a cable or Wi-Fi and on my cell phone using Wi-Fi or a data plan

Source: Created by the authors (2020)

1.5 Final Considerations

The main objective of this chapter was to present the steps taken to develop the digital competences model for online students. Thus, a discussion of digital competences and the profile of the online student was presented, in order to address the methodology used for the construction of the MCompDigEAD model.

A model of digital competences should be focused on the profile of the online student, requiring specific knowledge of technology and its possibilities. Thus, these were the primary questions. This area is relatively unexplored and therefore poses a challenge for educational and technological research.

Distance learning is fundamental in the current Brazilian context, with thousands of students accessing higher education each year. Therefore, it is one of the prime

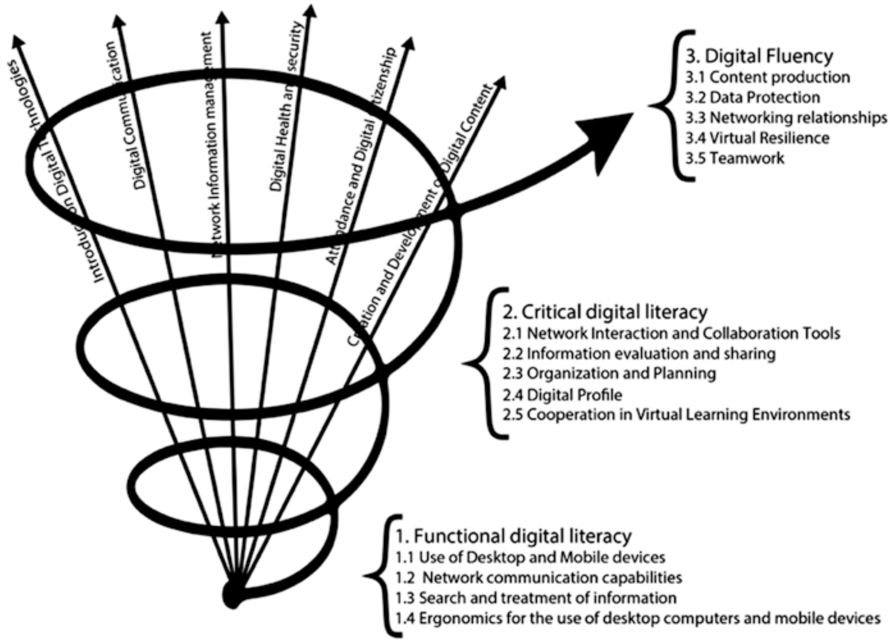


Fig. 1.4 Model of digital competences applied to distance learning source. (Source: Created by the authors 2020)

examples of economic and social development associated with technological advancement.

This continued growth calls for research that can help it improve and expand with quality. DL students' limitations must be recognized and their learning process must be constantly monitored through technologies.

In terms of innovation, this research aimed to demonstrate a model of digital competences for DL students can be built. Though studies in this field are still incipient, there is a clear demand for specific and dynamic solutions. The expectation, therefore, is that the model will become a reference that can be used by different institutions in the distance learning and teaching process, accompanying the student in the identification and construction of their digital competences. It can also be adapted to the needs of particular contexts, which is fundamental because digital technologies are constantly updated.

Various activities are being carried out as a continuation of this project, including the development and application of pedagogical practices for the construction and evaluation of the MCompDigEAD and the development of an app based on the MCompDigEAD. In the future, we would like to extend the digital competences model to teachers and educators and create a database of use cases of digital competences in distance learning.

Finally, the hope is that these results will enable the improvement of online students' digital competences and can be an important resource for professors and students seeking to learn about DL and digital competences.

References

Anderson, D. R., Sweeney, D. J., & Williams, T. A. (1991). *An introduction to management science: Quantitative approaches to decision making* (6th ed.). Saint-Paul: West Publishing.

Behar, P. A. (2009). *Modelos Pedagógicos em Educação à Distância*. Porto Alegre: Artmed.

Behar, P. A., & Silva, K. K. (2013). *Mapeamento de Competências: Um foco no aluno da Educação a Distância*. In: http://www.cinted.ufrgs.br/ciclo20/artigos/5a-ketia.pdf. Acess: 15 de set. 2019.

BRASIL. (2007). *Referenciais de Qualidade para Educação Superior a Distância.* Brasília: Ministério da Educação, Secretaria de Educação a Distância. In: http://portal.mec.gov.br/seed/arquivos/pdf/referenciaisead.pdf. Acess: 10 mar. 2017.

Census EAD BR (2017). Educação a Distância do Brasil 2017. In Associação Brasileira de Educação a Distância. In: http://abed.org.br/arquivos/CENSO_EAD_BR_2018_digital_completo.pdf. Acess: 10 set. 2019.

Catalunya, Generalitat. Departament d'Ensenyament. Acreditación decompetències em tecnologies de la informació i comunicació. (ACTIC). In: http://actic.gencat.cat/es/actic_informacio/actic_documentacio_de_referencia/. Acess: 13 jan. 2020.

Catalunya, Generalitat. Departament d'Ensenyament. Acreditación de competències em tecnologies de la informació i comunicació. (ACTIC). In: http://actic.gencat.cat/es/actic_informacio/actic_documentacio_de_referencia/. Acess: 15 jan. 2020.

Chile, Centro de Educación y Tecnología del Ministerio de Educación de Chile. Sistema de Medici.n de la Calidad de la Educación y Tecnología do Chile (SIMCE-TIC). In: http://www.enlaces.cl/evaluacion-de-habilidadestic/simce-tic/presentacion/. Acess: 15 jan. 2020.

Coll, C., & Illera, J. R. L. (2010). Alfab*etização, novas alfabetizações e alfabetização digital* In: Coll, C.; Monereo, C. (orgs.). Psicologia da educa..o virtual –Aprender e ensinar com as tecnologias da informa..o e da comunica..o. Porto Alegre: Artmed. pp. 289–310.

de Lima, E. P., & Lezana, G. R. (2005). Developing a framework to study organizational action: from competences to the organizational model. Gest.o & Produ..o, v.12, n. 2, pp. 177–190.

Eppen, G. D., Gould, F. J., & Schmidt, C. P. (1987). *Introductory management science* (2nd ed.). Englewood Cliffs: Prentice-Hall.

Eshet-Alkalai, Y. (2004). Digital literacy: A conceptual framework for survival skills in the digital era. *Journal of Educational Multimedia and Hypermedia, 13*(1), 93–106.

Esteve, F. M., Duch, J., & Gisbert, M. (2014). Los aprendices digitales en la literatura científica: diseño y aplicación de una revisión sistemática entre 2001 y 2010. *In. Revista de Medios y Educación.* N° 45.

ETS. Digital Transformation. (2002). *A framework for ICT literacy. A report from the ICT. Literacy panel*. Princeton: Educational Testing Service ETS.

European Computer Driving Licence – ECDL – Foundation. Dispon.vel em: http://ecdl.org/about Acessado em: 1 mar. 2020.

European E-Competence Framework (e-CF). Available in: https://www.ecompetences.eu/. Acess: in 13 jan. 2020.

EUROPEAN UNION. (2006). Recommendation the European Parliament and the Council of 18 December 2006 on Key Competences for Lifelong Learning. Official Journal of the European Union (2006/962/EC), L394/10-18.

Ferrari, A. (2012). *Digital competence in practice: An analysis of frameworks*. Sevilla: JRC IPTS.

Gómez, A. I. Perez. (2015). *Educação na Era Digital: a escola educativa*. Tradução Marisa Guedes. Porto Alegre: Penso.

Harding, S., & Long, T. (1998). *Proven management tools*. Aldershot: Gower.
Howe, N., & Strauss, W. (2000). *Millennials rising: The next great generation*. New York: Vintage Original.
International Society for Technology in Education (ISTE). (2007). National educational technology standards for students. (NETS-s). Acessado em: http://www.iste.org/Content/NavigationMenu/NETS/ForStudents/2007Standards/NETS_for_Students_2007.htm. Acess: 8 jan. 2020.
Kennedy, G. et al. (2007). The net generation are not big users of Web 2.0 technologies: Preliminary findings. En Ascilite 2007. *Universidad Tecnológica de Nanyang, Singapore.* in: http://www.ascilite.org.au/conferences/singapore07/procs/kennedy.pdf. Acess: 20 ago. 2019.
Larraz, V. La competència digital a la universitat. (2012). (Tesis doctoral, Universitatd'Andorra). In: TDX (TD-017-100006/201210).
Leme, R. (2012). *Aplicação prática de gestão de pessoas por competências – mapeamento, treinamento, seleção, avaliação e mensuração de resultados de treinamento* (244 p). Rio de Janeiro: Qualitymark.
Machado, L., & Grande, T. (2016). *Mapeamento de competências Digitais: a inclusão social dos idosos.* In: ETD – Revista de Educação e Temática Digital. Camp. SP, v.18, n.4, pp.903–921.
Martin, A., & Grudziecki. (2006). DigEuLit: Concepts and tools for digital literacy development. *Innovation in Teaching and Learning in Information and Computer Sciences, 5*(4), 1–19.
OECD. (2002). *Definition and selection of competencies (DeSeCo): Theoretical and conceptual foundations (Strategy paper)*. Paris: OECD. Available from: http://www.statistik.admin.ch/stat_ch/ber15/deseco/deseco_strategy_paper_final.pdf. Acess: 06 jan. 2020.
OECD. (2005). *Are students ready for a technology-rich world?* What PISA studies tell us. Paris, 2005a. Available from: http://www.oecd.org/dataoecd/28/4/35995145.pdf. Acess: 10 mai. 2019.
Pallof, R. M., & Pratt, K. (2015). *Lições da sala de aula virtual: As realidades on-line* (2nd ed.). Porto Alegre: Penso.
Palloff, R. M., & Pratt, K. (2004). *O aluno virtual: um guia para trabalhar com estudantes on-line*. Porto Alegre: Artmed.
Panel, I. L. (2002). Digital transformation: A framework for ICT literacy. Educational Testing Service, 1–53.
Prensky, Mark. (2001). *Digital natives, digital immigrants.* On the Horizon. vol 9 5 NCB University Press.
Ribeiro, A. C. R. (2013). *Letramento digital: uma abordagem através das competências na formação docente*. 164 f. Tese (Mestrado em Educação) – Faculdade de Educação, Universidade Federal do Rio Grande do Sul, Porto Alegre.
Tapscott, D. (1998). *Growing up digital: The rise of the net generation*. New York: McGraw-Hill.
Torrezzan, C. A. W. (2014). *ConstruMed: Metodologia para a construção de materiais educacionais digitais baseados no design pedagógico.* 240 f. Tese (Doutorado em Informática na Educação) – Centro de Estudos Interdisciplinares em Novas Tecnologias na Educação, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, 2014. Disponível em: http://goo.gl/lq8B1g. Acess: 05 mai. 2019.
UNESCO. (2006). *Padrões de competência em TIC para professores: módulos de padrão de competências*. Paris: Unesco. In: http://unesdoc.unesco.org/images/0015/001562/156207por.pdf. Acess 17 Abr 2019.

Chapter 2
Relationship Between Goal Orientation, Conception of Learning, and Learning Behavior

Mai Yokoyama and Kazuhisa Miwa

2.1 Goal Orientation

From the 1970s to the 1980s, Dweck studied the difference between helpless students who reported helplessness when they encountered failure and mastery-oriented students who maintained their task persistence even after failure. Diener and Dweck (1978) conducted an experiment in which participants failed to solve the problem and investigated the participants' verbal reports to examine the difference between helpless students and mastery-oriented students. As a result, the mastery-oriented students were more motivated by considering the failure positively and acted to improve their performance. By contrast, helpless students attributed the cause of the failure to their ability deficiencies and predicted further success negatively; in addition, they enjoyed solving the task when they were successful, but after the failure they reported dissatisfaction with the task and anxiety about performing the task. Subsequently, Diener and Dweck conducted the same experiment in 1980 and examined the difference in cognition of success and failure in problem-solving between helpless and mastery-oriented students and observed that mastery-oriented students used success experiences to judge their abilities and recognized them as a predictor of their further success. By contrast, helpless students used failure experiences to judge their abilities and did not recognize success experiences in relation to their further success.

Dweck thought that the difference between being helpless and mastery-oriented was due to the differences in the students' achievement goals. Dweck and Leggett (1988) demonstrated that helpless students were oriented toward performance goals

M. Yokoyama (✉) · K. Miwa
Nagoya University, Nagoya, Japan
e-mail: yokoyama.mai@c.mbox.nagoya-u.ac.jp; miwa@is.nagoya-u.ac.jp

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_2

and mastery-oriented students were oriented toward learning goals. Based on these studies, Dweck (1986) proposed goal achievement theory, which explains that differences in learning behavior depend on the students' goals. According to the theory, students' goals are classified into two categories: learning and performance. The purpose of learning goals is to acquire new knowledge and skills through challenging activities. The purpose of performance goals is to seek positive and avoid negative evaluations. Students oriented toward learning goals tend to select challenging tasks and persevere their motivation even when they encounter failure, regardless of their confidence in their abilities. Performance goal–oriented students behave similarly to students with learning goal orientation, provided they are confident in their abilities; however, if they lack confidence in their abilities, they are less likely to persevere in their motivation and will take passive strategy to complete tasks. Elliott and Dweck (1988) examined differences in behavior after failure due to differences in the students' goals, and their findings supported the theory. They specifically provided instructions to set the learning goal group and the performance goal group. They made the participants recognize that their ability to perform the task was high or low based on the difference in correct and incorrect feedback. As a result, in the performance goal group, students who recognized that their ability was low were unable to cope with the task and made many negative statements such as remarks about anxiety or escape compared with students who recognized that their ability was high. Such differences in learning behavior, which were observed because of differences in ability recognition, were not observed in the learning goal group.

Many studies have investigated the relationship between goal orientation measured by questionnaires and various variables in academic achievement, including Ames and Archer (1987, 1988). Kaplan and Midgley (1997) observed that learning goal orientation has positive effects on adaptive learning behavior, and performance goal orientation has no relationship to or nagative effects on adaptive laerning behavior. Nolen and Haladyna (1990) demonstrated that learning goal orientation has a positive effect on deep-processing behaviors such as monitoring of comprehension and memory and elaboration of ideas. Similar results have been demonstrated in Fenollar et al. (2007) and Liem et al. (2008). Learning goal orientation has also been demonstrated to predict motivational variables such as intrinsic motivation (e.g., Heyman and Dweck 1992; Kavussanu and Harnisch 2000). In subsequent studies, learning goal orientation has been observed to be positively related to adaptive learning, and emphasis has been placed on the superiority of learning goal orientation (e.g., Chea and Shumow 2014; Hudaykulov et al. 2015; Tercanlioglu and Demiröz 2015).

Elliot and Harackiewicz (1996) divided performance goal orientation into performance-approach goal orientation, in which a student attempts to outperform others, and performance-avoidance goal orientation, in which the desire to avoid performing is worse than others. Elliot and colleagues observed that performance-approach goal orientation results in positive effects on various variables in academic achievement, such as endogenous motivation and academic performance, whereas performance-avoidance goal orientation has negative effects on them (e.g., Elliot and Church 1997; Elliot and McGregor 1999; Elliot et al. 1999; Rawsthorne and Elliot 1999). Subsequent studies have shown results consistent with the findings of Elliott and colleagues, demonstrating the importance of distinguishing between approach and avoidance utilities (e.g., Chen and Wong 2014; Li and Shieh 2016; Nasiri et al. 2017).

2.2 Conception of Learning

Conception of learning is defined as learners' ideas and beliefs about learning. In this chapter, we followed the classification of Uesaka (2010), which broadly divided conception of learning into two categories: a broad sense and a narrow sense. The broad sense is a belief regarding "what learning is," and the narrow sense is a belief regarding "what kind of learning is effective." Conception of learning in a broad sense is more abstract than in a narrow sense, which means "effective learning."

2.2.1 Conception of Learning in a Broad Sense

Research on conception of learning in a broad sense began in the late 1970s and early 1980s, primarily in Europe (e.g., Säljö 1979; Van Rossum and Schenk 1984). Säljö (1979) observed the following five conceptions of learning from interview surveys: increase of knowledge; memorizing; the acquisition of facts and procedures, which could be retained and/or utilized in practice; the abstraction of meaning; and an interpretative process aiming at an understanding of reality. Säljö (1979) defined the former three as the passive accumulation of knowledge, obtained externally as the passive accumulation of knowledge obtained from the outside, and the latter two as the active acquisition, interpretation, and application of knowledge, obtained internally. Marton et al. (1993) described the following six categories: as an increase knowledge, as memorizing and reproducing, as applying, as understanding, as seeing something a different way, and changing as a person. Purdie et al. (1996) observed "learning as a duty," "learning as the development of social competence," and "learning as a process not bound by time or place" in addition to the six conceptions of learning. Later, Purdie and Hattie (2002) developed subscales and items for the Concepts of Learning Inventory as a scale to measure the following six conceptions of learning in a broad sense: learning as gaining information; learning as remembering, using, and understanding information; learning as a duty; learning as personal change; learning as a process not bound by time or place; and learning as the development of social competence.

Conception of learning was perceived as hierarchical rather than parallel. Biggs (1994) proposed a quantitative and qualitative conception of learning. The quantitative conception of learning relates to the acquisition and accumulation of content to learn. The qualitative conception of learning emphasizes meaning and understanding by associating new learning content with prior knowledge. Dart et al. (2000) considered the former three conceptions of Marton et al. (1993) as the quantitative conception of learning and the latter three as the qualitative conception of learning. Marton et al. (1996) organized his previous three conceptions as the surface conception of learning and the latter three as the deep conception of learning. Additionally, Ellis et al. (2008) defined the former as fragmentary conception of learning and the latter as cohesive conception of learning.

Conception of learning in a broad sense was demonstrated to be formed by students' cultural values (Purdie and Hattie 2002); hence, Japanese students may have unique Japanese conceptions of learning. Takayama (2000) observed the following nine conceptions of learning from a free description survey completed by Japanese university students: learning as memorizing, learning as an active investigation, learning as lifelong learning, learning as natural acquisition, learning to increase knowledge, learning as growing and improving, learning as applying, learning as acquiring and repetition, and learning as a duty. Learning as lifelong learning, learning as natural acquisition, and learning as acquiring and repetition have not been observed in Marton et al. (1993) and Purdie et al. (1996).

Studies have revealed differences in students' learning behavior depending on their conceptions of learning in a broad sense. For instance, Van Rossum and Schenk (1984) conducted an empirical study on learning behavior in relation to reading materials. Students who perceived learning as memorizing adopted a superficial learning behavior in which they only read a summary, whereas students who perceived learning as the abstraction of meaning or an interpretative process aimed to understand the reality of adopted deep learning behavior and read the sentences while processing the relationship between the paragraphs. Dart et al. (2000) suggested that students who had qualitative conceptions such as personal fulfillment and experiential conceptions such as a process were not bound by time and were more likely to use deep approaches to learning compared with students who had quantitative conceptions such as an increase in knowledge and who were more likely to rely on superficial approaches. Takayama (2002) suggested that "learning as an active investigation," "learning as growing and improving," and "learning as acquiring and repetition" have positive effects on deep learning behavior such as associating new learning with prior knowledge or confirming an individual's understanding; by contrast, learning as a duty has negative effects. In a related assertion, McLean (2001) revealed that students who perceive learning as seeing things differently and changing as a person have good academic performance. Alamdarloo et al. (2013) stated that "learning as the development of social competence" and "learning as a process not bound by time or place" have positive effects on academic achievement. Other previous studies have shown that such qualitative or cohesive conceptions of learning play a positive role in adaptive learning behavior and academic achievement (Norton and Crowley 1995; Cano and Cardelle-Elawar 2004; Ellis et al. 2008).

2.2.2 *Conception of Learning in a Narrow Sense*

Research on conception of learning in a narrow sense has been conducted mainly in the field of educational psychology in Japan. Ueki (2002) examined the structure of conception of learning based on these results and observed three conceptions of learning: strategy oriented, learning-amount oriented, and environment oriented. Later, Uesaka (2010) proposed a structure comprising two superordinate factors and eight subscales: the cognitive conception of learning (thinking process oriented, understanding meaning oriented, strategy oriented, and using failure oriented) and the noncognitive conception of learning (results oriented, learning-amount oriented, rote memorization oriented, and environment oriented). The cognitive conception of learning is an idea that it is critical to remember while thinking about meaning and to understand the intermediate process. By contrast, the noncognitive conception of learning is an idea that it is critical to memorize by rote and to do the amount of learning.

The relationship between conception of learning in a narrow sense and learning behavior has also been studied. Ueki (2002) demonstrated that students who are high strategy oriented take more effective learning behavior than students who are high learning-amount oriented. Shinogaya (2008) clarified that the effects of preparation for classes were dependent on the level of understanding meaning oriented. Suzuki (2016) demonstrated that students who are highly strategy oriented tend to attempt understanding tasks in relation to contexts in real situations, whereas students who are high rote memorization oriented tend to apply contents mechanically and do not fully explain the answering process. As aforementioned, the tendencies of students who have a high cognitive conception of learning (e.g., strategy oriented) take effective learning behavior, whereas students who have a high noncognitive conception of learning (e.g., rote memorization oriented) take ineffective learning behavior.

2.3 Purpose

To promote adaptive learning behavior of students, the factors that define adaptive learning behavior and the relationship between those factors must be understood. As described in Chaps. 1 and 2, goal orientation and conception of learning are critical factors that affect learning behavior. What is the relationship between goal orientation and constructive conception of learning? Nakayama (2005), Yamaguchi (2012), and Akamatu (2017) have examined the relationship between goal orientation and conception of learning in a narrow sense in English learning. Their studies have demonstrated that goal orientation is a predictor of conception of learning in a narrow sense in English learning. Yamamoto and Ueno (2015) demonstrated that goal orientation is a predictor of not only English learning but also a conception of learning in a narrow sense that does not depend on a specific subject. "The constructivist conception of learning" in Yamamoto and Ueno (2015) was defined as a belief that constructivist learning is essential learning. The items of this conception of learning are contents that emphasize the thinking process and understanding of the meaning, corresponding to the cognitive conception of learning in a narrow sense (e.g., “It is more important to think logically than to memorize a lot”; “It is important to know not only the answer but also how to solve it”; and “The constructivist conception of learning”).

In the aforementioned research, what type of goal orientation predicted what type of conception of learning has been also examined. Researchers have demonstrated that learning goal orientation predicts the cognitive conception of learning (e.g., Yamaguchi 2012; Akamatu 2017; Yamamoto and Ueno 2015), whereas performance goal orientation predicts the noncognitive conception of learning (e.g., Nakayama 2005; Akamatu 2017). Yamamoto and Ueno (2015) distinguished performance goal orientation into performance-approach goal orientation and performance-avoidance goal orientation and indicated that performance-approach goal orientation has positive effects on the cognitive conception of learning, whereas performance-avoidance goal orientation has negative effects on it. However, Yamaguchi (2012) demonstrated that performance-avoidance goal orientation has a positive effect on both cognitive conception of learning and noncognitive conception of learning. Consistency has not been demonstrated in the influence of performance-avoidance goal orientation on conception of learning.

Studies have demonstrated that goal orientation is a predictor of conception of learning in a narrow sense, but no studies have examined the relationship between goal orientation and conception of learning in a broad sense. Thus, studying the relationship would be worthwhile. Conception of learning in a broad sense and in a narrow sense represents students’ beliefs about learning. For this reason, goal orientation may predict conception of learning in a broad sense and a relationship with the narrow sense. By contrast, conception of learning in a broad sense is an abstract concept compared with the narrow sense, and it may be a higher belief. Therefore, conception of learning in a broad sense may predict goal orientation. Thus, in this study, we examined the relationship between goal orientation and conception of learning in a broad sense on learning behavior. We focused on conception of learning in a broad sense; hence, we defined conception of learning as conception of learning in a broad sense.

Based on the aforementioned information, this study had two main purposes. The first purpose was to examine three models of goal orientation and conception of learning on learning behavior (Fig. 2.1) and to compare their validities by using

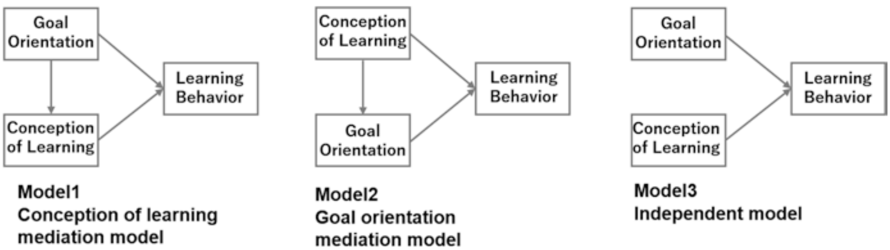


Fig. 2.1 Three models of goal orientation and conception of learning on learning behavior

covariance structure analysis. The second purpose of this study was to focus on the subordinate structures of goal orientation, conception of learning, and learning behavior and to clarify the causal relationship between the three.

We investigated graduation thesis research conducted at a university. Students were required to set their themes and objectives, consider methods for the objectives, conduct literature research or experiments according to those methods, and summarize the results. It was completed over a long-term process, and many opportunities were available for students to make judgments based on their thoughts. Hence, we hypothesized that how the students actively engaged in this type of learning may be greatly influenced by the students' conception of learning.

2.4 Method

Sample

The survey was conducted with fourth-year students from the School of Integrated Arts and Sciences of a Japanese public university in February 2018 and February 2019. The participants answered questionnaires during the presentation session of their graduation thesis. The data of 340 students (2018: 161, 2019: 179) were analyzed.

Instrument

The participants were asked to indicate their agreement or disagreement with each item in the questionnaires on a 5-point Likert scale from do not agree at all to completely agree.

Goal Orientation The questionnaire comprised 18 items, translated from the Achievement Goal Scale, developed by Elliot and Church (1997).

Conception of Learning The questionnaire comprised 24 items, partially modified from Takayama's (2002) scales.

Learning Behavior The questionnaire comprised eight items, modified from scales by Mitsunami (2010) and Hatano and Mizokami (2013). The items were modified to measure students' motivational beliefs and learning outcomes in the context of undertaking graduation work.

Method of Analysis

The first objective of the study, Purpose 1, was to examine three causal models of goal orientation and conception of learning in relation to learning behavior. First, the variables of goal orientation, conception of learning, and learning behavior were clarified by factor analysis. Subsequently, covariance structure analysis was conducted by using the variables clarified by factor analysis. Furthermore, the suitability of the three models was compared. The second objective, Purpose 2, was to clarify the relationship between the subscales of goal orientation, conception of learning, and learning behavior based on the results of covariance structure analysis.

2.5 Structure of the Scales

2.5.1 Goal Orientation Scale

Factor analysis (principal factor with promax rotation) of goal orientation was performed. We observed three factors with eigenvalues 1 or more. The analysis was conducted again; items loaded at 0.40 or less and items loaded at 0.40 or more on two or more factors were excluded. The details of each item and the results of the analysis are presented in Table 2.1. The following three factors emerged: Performance-Avoidance Goal, Learning Goal, and Performance-Approach Goal. An average value of the items was regarded as the respective value of each factor.

2.5.2 Conception of Learning Scale

Factor analysis (principal factor with promax rotation) of conception of learning was conducted. Four factors with eigenvalues 1 or more were observed. The analysis was conducted again; items loaded at 0.40 or less and items loaded at 0.40 or more on two or more factors were excluded. Table 2.2 presents the details of each item and the results of the analysis. The following four factors emerged: Autonomous Development, Duty and Memorizing, Growing as a Person, and Effort. An average value of the items was regarded as the respective value of each factor.

Table 2.1 Goal orientation items and factor loadings

Factors and items	I	II	III
Factor I. Performance-Avoidance Goal (α = 0.87)			
I worry about the possibility of getting a bad grade	**0.86**	0.00	−0.13
I often think to myself, "what if I do badly?"	**0.76**	0.01	0.04
My fear of performing poorly is often what motivates me	**0.73**	−0.10	0.08
I just want to avoid doing poorly	**0.60**	0.02	0.10
I'm afraid that if ask my teachers a "dumb" question, they might think I'm not very smart	**0.43**	−0.08	0.03
Factor II. Learning Goal (α = 0.75)			
I hope my knowledge is broader and deeper when I am done with classes	0.01	**0.83**	−0.03
I want to learn as much as possible from class	0.14	**0.73**	−0.17
I prefer course material that really challenges me so I can learn new things	−0.15	**0.55**	0.07
I prefer course material that arouses my curiosity, even if it is difficult to learn	−0.15	**0.53**	0.28
Factor III. Performance-Approach Goal (α = 0.72)			
I am striving to demonstrate my ability in relation to others	0.11	−0.13	**0.76**
I am motivated by the thought of outperforming my peers	−0.05	0.10	**0.66**
It is important to me to do better than the other students	0.09	0.05	**0.55**

Table 2.2 Conception of learning items and factor loadings

Factors and items	I	II	III	IV
Factor I. Autonomous Development (α = 0.88)				
Learning is something we continue to do as long as we live	**0.97**	0.09	−0.03	−0.12
Learning continues after I become a member of society	**0.88**	−0.04	−0.06	−0.04
Learning is something that will continue throughout life	**0.84**	−0.04	0.00	−0.04
Learning is trying to know what you are deeply interested in	**0.48**	−0.09	0.13	0.21
Learning is actively exploring your interests	**0.45**	−0.07	0.13	0.18
Factor II. Duty and Memorizing (α = 0.84)				
Learning is forced without the freedom	−0.05	**0.78**	−0.08	−0.01
Learning is forced by parents or teachers	0.07	**0.77**	−0.14	0.01
Learning is being forced to do things that you do not want to do	0.10	**0.73**	−0.25	0.05
Learning is accurately memorizing the content of materials	−0.06	**0.67**	0.32	−0.05
Learning is memorizing the textbook contents at a desk	−0.11	**0.63**	0.25	0.08
Factor III. Growing as a Person (α = 0.78)				
Learning means living a life like a human being	0.03	0.04	**0.72**	−0.09
Learning involves human beings' forming a spiritual core	0.12	0.08	**0.71**	−0.09
Learning is not accumulating knowledge but forming an attitude	−0.12	−0.10	**0.67**	−0.10
Learning means absorbing a wide range of knowledge	0.07	0.01	**0.50**	0.20
Factor IV. Effort (α = 0.79)				
Learning is what you acquire with effort	−0.17	−0.04	−0.12	**1.03**
Learning takes much time and effort	0.08	0.16	−0.15	**0.67**
Learning is necessary to become a member of society	0.03	−0.06	0.17	**0.55**
Learning means absorbing more knowledge	0.28	0.04	0.14	**0.44**

2.5.3 Learning Behavior Scale

Factor analysis (principal factor with promax rotation) of learning behavior was performed. The first eigenvalue was sufficiently larger than the second eigenvalue, and subsequently, a one-factor solution was desirable. In Table 2.3, the details of each item and the results of the analysis are presented. An average value of the eight items was regarded as the learning behavior variable.

2.6 Results and Discussion

2.6.1 Structural Equation Modeling

Using structural equation modeling (path analysis), we assessed how well the three models fit the data. In Model 1, goal orientation affects learning behavior directly or through conception of learning. First, we hypothesized that the three variables of goal orientation would predict the relation among the four variables of conception of learning. Second, we hypothesized that the three variables of goal orientation and

Table 2.3 Learning behavior items and factor loadings

Factor and items	I
Factor I. Learning Behavior (α = 0.80)	
I tried to improve the quality of my graduation thesis as much as possible	**0.78**
Although it was difficult, I worked on it without giving up	**0.76**
I studied what I did not know, or I asked my teacher and my friends about it	**0.64**
I set goals and plans	**0.59**
I often tried to read and understand the contents	**0.59**
I was prepared to respond to any questions in the presentation	**0.52**
I worked on the research merely to earn credit	**−0.46**
I often got bored quickly and quit	**−0.40**

Table 2.4 Results of evaluating the models

Model	GFI	AGFI	CFI	RMSEA	AIC
1	0.991	0.969	0.997	0.024	63.105
2	0.990	0.962	0.994	0.038	68.231
3	0.974	0.923	0.965	0.080	87.173

the four variables of conception of learning would predict the learning behavior variable. Subsequently, covariances were added between the variables of goal orientation and the error variables of conception of learning based on the correlation coefficient analysis results. The paths that were not significant, that is, less than the 5% level, were deleted, and the analysis was conducted again. In Model 2, conception of learning affects learning behavior directly or through goal orientation. The same procedure carried out for Model 1 was conducted. In Model 3, goal orientation and conception of learning regulate learning behavior independently. We hypothesized that the three variables of goal orientation and four variables of conception of learning would be related to learning behavior. Based on the results of the correlation analysis, covariances were added between the variables of goal orientation and conception of learning. The paths that were not significant, that is, less than the 5% level, were deleted, and the analysis was conducted again.

Table 2.4 presents the results of the evaluation of the models. The model fit was evaluated by the following indices: the goodness of fit index (GFI), the adjusted goodness of fit index (AGFI), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the Akaike information criterion (AIC). Values above 0.95 for the GFI, AGFI, and CFI, and below 0.77 for the RMSEA were regarded as a sufficient fit (Hooper et al. 2008). The smaller the value of AIC was regarded a sufficient fit (Akaike 1974). The result revealed that Model 1 accommodated the data very well. This result demonstrated that students' conceptions of learning partially mediated the relationship between goal orientation and learning behavior. These results suggest that goal orientation may predict conception of learning in a broad sense.

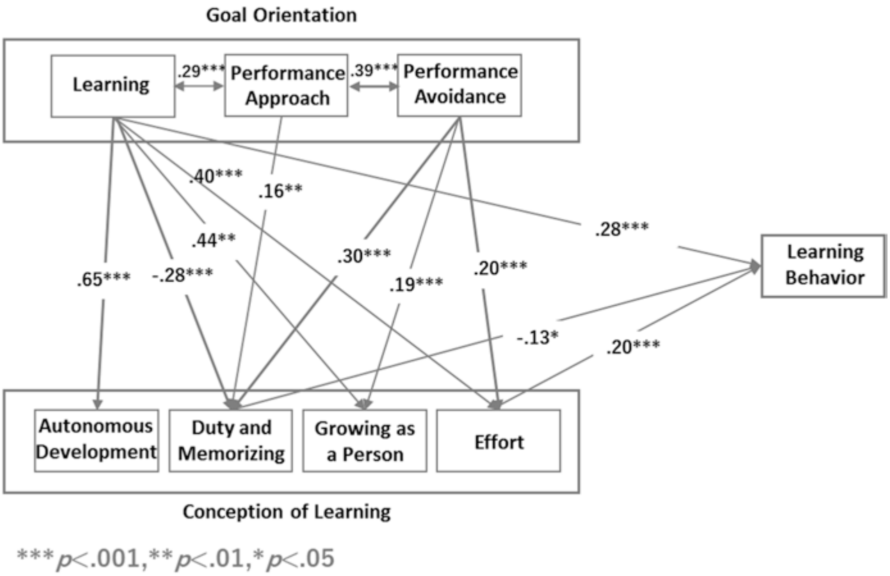


Fig. 2.2 Covariance structure result of model 1

2.6.2 Path Analysis for Causality

We examined the effects of goal orientation and conception of learning on learning behavior with Model 1, which was the most suitable of the three models. The covariance structure analysis result of Model 1 is depicted in Fig. 2.2. The numerical values of the unidirectional arrows are the standardized path coefficients, and the numerical value of the bidirectional arrows are the correlation coefficients.

Effect of Goal Orientation and Conception of Learning on Learning Behavior Learning Goal had a positive effect ($\beta = 0.28$, $p < 0.001$) on Learning Behavior. This result demonstrated that if students are highly oriented toward learning goals, their active learning behavior is promoted. This result is consistent with the results of many studies (e.g., Kaplan and Midgley 1997; Nolen and Haladyna 1990; Fenollar et al. 2007; Liem et al. 2008).

Duty and Memorizing had a negative effect ($\beta = -.13$, $p < 0.05$) on Learning Behavior. This result demonstrated that if students regard learning as a duty, their active learning behavior is suppressed. This result is consistent with the results of Peterson et al. (2010) and Takayama (2002). Effort had a positive effect ($\beta = 0.20$, $p < 0.001$) on Learning Behavior. This result demonstrated that if students regard learning as effort, their active learning behavior is promoted. This result is consistent with the result of Takayama (2002).

Relationship Between Goal Orientation and Conception of Learning

Learning Goal had positive effects on Autonomous Development ($\beta = 0.65$, $p < 0.001$), Growing as a Person ($\beta = 0.44$, $p < 0.01$), and Effort ($\beta = 0.40$, $p < 0.001$) and a negative effect on Duty and Memorizing. ($\beta = -.28$, $p < 0.001$). These results suggest that if students are highly oriented toward learning goals, they do not regard learning as a duty, they regard learning as autonomous, growing as a person, or effort. Takayama (2002) observed that conceptions of learning equivalent to Autonomous Development, Growing as a Person, and Effort had a positive effect on deep learning behavior, and conception of learning equivalent to Duty and Memorizing had a negative effect on it. Based on the results of Takayama (2002) and this study, if students have high learning goal orientation, they tend to have conceptions of learning that promote adaptive learning behavior and do not have conceptions of learning that suppress adaptive learning behavior.

Learning Goal had positive effects on conception of learning that promotes adaptive learning behavior such as Autonomous Development, Growing as a Person, and Effort and had a negative effect on conception of learning that suppresses adaptive learning behavior such as Duty and Memorizing. Based on these results, interventions that increase students' learning goal orientation may be effective at changing into their conception of learning that promotes adaptive learning behavior.

Performance-Approach Goal and Performance-Avoidance Goal had no direct effect on Learning Behavior but had indirect effects through conception of learning. In other words, performance goal orientation has different effects on learning behavior depending on what types of conception of learning are combined.

Performance-Approach Goal ($\beta = 0.16$, $p < 0.01$) and Performance-Avoidance Goal ($\beta = 0.30$, $p < 0.001$) had positive effects on Duty and Memorizing. This result suggests that if students are highly oriented toward performance-approach goals or performance-avoidance goals they tend to regard learning as a duty. Performance-Avoidance Goal had a positive effect on Growing as a Person ($\beta = 0.19$, < 0.001) and Effort ($\beta = 0.20$, < 0.001). Performance-Avoidance Goal had a positive effect on conception of learning that promoted active learning behavior (i.e., Effort) and conception of learning that suppressed active learning behavior (i.e., Duty and Memorizing). This result suggests that performance-avoidance goal orientation has positive and negative effects for learning. Yamaguchi (2012) also demonstrated that performance-avoidance goal orientation is related to a conception of learning that promotes adaptive learning behavior and a conception of learning that suppresses adaptive learning behavior. Fenollar et al. (2007) suggested that performance-avoidance goal orientation has a positive effect on effort. The desire to avoid bad evaluations may lead to the recognition that learning requires effort and might be the impetus for adaptive learning behavior. Compared with learning goal orientation, performance-avoidance goal orientation does not play an absolute positive role in learning, but such factors may exist.

2.7 Conclusion

2.7.1 Summary

We examined three models of goal orientation and conception of learning on learning behavior to compare their validities by using covariance structure analysis. Based on the results, we suggested that goal orientation may predict conception of learning in a broad sense that means “what learning is.”

Focusing on the subordinate structures of goal orientation, conception of learning, and learning behavior, we clarified the causal relationship among the three. Based on the results, we suggested the following three possibilities: (1) learning goal orientation leads to a conception of learning that promotes adaptive learning behavior and does not lead to a conception of learning that suppresses adaptive learning behavior; (2) performance-approach goal orientation leads to a conception of learning that suppresses adaptive learning behavior; and (3) performance-avoidance goal orientation leads to a conception of learning that both promotes and suppresses adaptive learning behavior.

2.7.2 Limitation

The limitations of this study are summarized as follows. First, we examined graduation thesis research conducted at a university as a learning task. Depending on the nature of learning tasks examined, a possibility is that a different result may be reached. Furthermore, we recommend that other learning tasks be examined in further research. Second, although self-evaluation by students was used as a measure of learning behavior, to guarantee objectivity, we recommend adding a more objective viewpoint, such as an evaluation by teachers. Third, we measured students’ goal orientation, conception of learning, and learning behavior by a single time point survey. A two-point study would be more suitable to clarify the influence on learning behavior from goal orientation and conception of learning as the students’ characteristics and/or beliefs, namely, a measurement of goal orientation and conception of learning before starting graduation research and learning behavior at the end of graduation research.

2.7.3 Future Work

In this study, we examined the relationship between goal orientation and conception of learning in a broad sense. Because Model 1 was more suitable than Model 2, the results and discussions were written to focus on the effect of goal orientation on conception of learning based on the result from Model 1. However, Model 2 was also an acceptable model with good model fit. Based on this result, we infer the possibility that goal orientation and conception of learning may influence each other. We would also like to measure students' goal orientation and conception of learning several times and postulate on and examine an interactive model between goal orientation and conception of learning.

As described in the results and discussion, interventions that increase students' learning goal orientation may be effective in changing their conception of learning into something that promotes adaptive learning behavior. Notably, few intervention studies on goal orientation have been performed. For example, Geitz et al. (2015) intervened in students' goal orientation by using the method to increase the involvement of students in their feedback and examined the effects on goal orientation and learning behavior. However, the intervention did not influence goal orientation directly. Thus, the intervention method for goal orientation has not been established. Ames (1992) proposed teachers' involvement from the three dimensions of "task," "authority," and "evaluation/cognition" to create a classroom environment that increases students' learning goal orientation. However, no empirical study has investigated this proposal. Further research could develop an intervention method that increases learning goal orientation to change into students' conceptions of learning that promote adaptive learning behavior.

Acknowledgements This work was partially supported by JSPS KAKENHI Grant Number 18H05320.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705.

Akamatu, D. (2017). Relation between high school students' beliefs and learning strategies, and their academic achievement in learning English. *Japanese Journal of Educational Psychology, 65*(2), 265–280. https://doi.org/10.5926/jjep.65.265.

Alamdarloo, G., Moradi, S., & Dehshiri, G. (2013). The relationship between students' conceptions of learning and their academic achievement. *Psychology, 4*(1), 44–49. https://doi.org/10.4236/psych.2013.41006.

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology, 84*(3), 261–271. https://doi.org/10.1037/0022-0663.84.3.261.

Ames, C., & Archer, J. (1987). Mothers' beliefs about the role of ability and effort in school learning. *Journal of Educational Psychology, 79*(4), 409–414. https://doi.org/10.1037/0022-0663.79.4.409.

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80*(3), 260–267. https://doi.org/10.1037/0022-0663.80.3.260.

Biggs, J. (1994). Student learning theory and research. Where do we currently stand? In G. Gibbs (Ed.), *Improving student learning: theory and practice* (pp. 1–19). Oxford: Oxford Brookes University: Oxford Centre for Staff Development.

Cano, F., & Cardelle-Elawar, M. (2004). An integrated analysis of secondary school students' conceptions and beliefs about learning. *European Journal of Psychology of Education, 19*(2), 167–187. https://doi.org/10.1007/BF03173230.

Chea, S., & Shumow, L. (2014). The relationships among writing self-efficacy, writing goal orientation, and writing achievement. *Language Education in Asia, 5*(2), 253–269. https://doi.org/10.5746/LEiA/14/V5/I2/A07/Chea_Shumow.

Chen, W., & Wong, Y. (2014). Chinese mindset: Theories of intelligence, goal orientation and academic achievement in Hong Kong students. *An International Journal of Experimental Educational Psychology, 35*(6), 714–725. https://doi.org/10.1080/01443410.2014.893559.

Dart, B. C., Burnett, P. C., Purdie, N., Boulton-Lewis, G., Campbell, J., & Smith, D. (2000). Students' conceptions of learning, the classroom environment and approaches to learning. *The Journal of Educational Research, 93*(4), 262–270. https://doi.org/10.1080/00220670009598715.

Diener, C. I., & Dweck, C. S. (1978). An analysis of learned helplessness: Continuous changes performance, strategy, and achievement cognitions following failure. *Journal of Personality and Social Psychology, 36*(5), 451–462. https://doi.org/10.1037/0022-3514.36.5.451.

Diener, C. I., & Dweck, C. S. (1980). An analysis of learned helplessness: II. The processing of success. *Journal of Personality and Social Psychology, 39*(5), 940–952. https://doi.org/10.1037/0022-3514.39.5.940.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41*(10), 1040–1048. https://doi.org/10.1037/0003-066X.41.10.1040.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256–273. https://doi.org/10.1037/0033-295X.95.2.256.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72*(1), 218–232. https://doi.org/10.1037/0022-3514.72.1.218.

Elliot, A. J., & Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis. *Journal of Personality and Social Psychology, 70*(3), 461–475. https://doi.org/10.1037/0022-3514.70.3.46.

Elliot, A. J., & McGregor, H. A. (1999). Test anxiety and the hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 76*(4), 628–644. https://doi.org/10.1037/0022-3514.76.4.628.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91*(3), 549–563. https://doi.org/10.1037/0022-0663.91.3.549.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology, 54*(1), 5–12. https://doi.org/10.1037/0022-3514.54.1.5.

Ellis, R. A., Goodyear, P., Calvo, R. A., & Prosser, M. (2008). Engineering students' conceptions of and approaches to learning through discussions in face-to-face and online contexts. *Learning and Instruction, 18*(3), 267–282. https://doi.org/10.1016/j.learninstruc.2007.06.001.

Fenollar, P., Román, S., & Cuestas, P. J. (2007). University students' academic performance: An integrative conceptual framework and empirical analysis. *British Journal of Educational Psychology, 77*(4), 873–891. https://doi.org/10.1348/000709907X189118.

Geitz, G., Joosten-Ten Brinke, D., & Kirschner, P. (2015). Goal orientation, deep learning, and sustainable feedback in higher business education. *Journal of Teaching in International Business, 26*(4), 273–292. https://doi.org/10.1080/08975930.2015.1128375.

Hatano, K., & Mizokami, S. (2013). The examination of student' type based on active class attitude and learning time in university students. *Japan Journal of Educational Technology, 37*(1), 13–21. https://doi.org/10.15077/jjet.KJ00008721374.

Heyman, G. D., & Dweck, C. S. (1992). Achievement goals and intrinsic motivation: Their relation and their role in adaptive motivation. *Motivation and Emotion, 16*(3), 231–247. https://doi.org/10.1007/BF00991653.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53–60. https://doi.org/10.21427/D7CF7R.

Hudaykulov, A., Hongyi, X., & Galib, M. A. (2015). Impact of goal orientation theory on social capital: The implications for effective team cooperation in Uzbekistan textile industry. *The International Journal of Management Science and Business Administration, 1*(6), 58–71. https://doi.org/10.18775/ijmsba.1849-5664-5419.2014.16.1005.

Kaplan, A., & Midgley, C. (1997). The effect of achievement goals: Does level of perceived academic-competence make a difference? *Contemporary Educational Psychology, 22*(4), 415–435. https://doi.org/10.1006/ceps.1997.0943.

Kavussanu, M., & Harnisch, D. L. (2000). Self-esteem in children: Do goal orientations matter? *British Journal of Educational Psychology, 70*(2), 229–242. https://doi.org/10.1348/000709900158074.

Li, J., & Shieh, C. (2016). A study on the effects of multiple goal orientation on learning motivation and learning behaviors. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(1), 161–172. https://doi.org/10.12973/eurasia.2016.1221a.

Liem, A. D., Lau, S., & Nie, Y. (2008). The role of self-efficacy, task value, and achievement goals in predicting learning strategies, task disengagement, peer relationship, and achievement outcome. *Contemporary Educational Psychology, 33*(4), 486–512. https://doi.org/10.1016/j.cedpsych.2007.08.001.

Marton, F., Dall'Alba, G., & Beaty, E. (1993). Conceptions of learning. *International Journal of Educational Research, 19*(1), 227–300.

Marton, F., Wen, Q., & Nagle, A. (1996). Views on learning in different cultures. Comparing patterns in China and Uruguay. *Anales de Psicologia, 12*(2), 123–132.

McLean, M. (2001). Can we relate conceptions of learning to student academic achievement? *Teaching in Higher Education, 6*(1), 399–413. https://doi.org/10.1080/13562510120061241.

Mitsunami, M. (2010). Influence of achievement motive and goal orientation on learning behavior: Different in cognitive strategies. *Japanese Journal of Educational Psychology, 58*(3), 348–360. https://doi.org/10.5926/jjep.58.348.

Nakayama, N. (2005). Testing a hypothesized model of English language learning: Japanese university students' goal orientation, beliefs, and learning strategies. *Japanese Journal of Educational Psychology, 53*(3), 320–330. https://doi.org/10.5926/jjep1953.53.3_320.

Nasiri, E., Pour-Safar, A., Taheri, M., Pashaky, A. S., & Louyeh, A. A. (2017). Presenting the students' academic achievement causal model based on goal orientation. *Journal of Advances in Medical Education & Professionalism, 5*(4), 195–202.

Nolen, S. B., & Haladyna, T. M. (1990). Motivation and studying in high school science. *Journal of Research in Science Teaching, 27*(2), 115–126. https://doi.org/10.1002/tea.3660270204.

Norton, L. S., & Crowley, C. M. (1995). Can students be helped to learn how to learn? An evaluation of an approaches to learning programme for first year degree students. *Higher Education, 29*(3), 307–328. https://doi.org/10.1007/BF01384496.

Peterson, E. R., Brown, G. T. L., & Irving, S. E. (2010). Secondary school students' conceptions of learning and their relationship to achievement. *Learning and Individual Differences, 20*, 167–176. https://doi.org/10.1016/j.lindif.2009.12.004.

Purdie, N., & Hattie, J. (2002). Assessing Students' conceptions of learning. *Australian Journal of Educational and Developmental Psychology, 2*, 17–32.

Purdie, N., Hattie, J., & Douglas, G. (1996). Student conceptions of learning and their use of self-regulated learning strategies: A cross-cultural comparison. *Journal of Educational Psychology, 88*(1), 87–100. https://doi.org/10.1037/0022-0663.88.1.87.

Rawsthorne, L. J., & Elliot, A. J. (1999). Achievement goals and intrinsic motivation: A meta-analytic review. *Personality and Social Psychology Review, 3*(4), 326–344. https://doi.org/10.1207/s15327957pspr0304_3.

Säljö, R. (1979). *Learning in the learner's perspective. I. Some common-sense conceptions* (Reports from the Institute of Education, 76). Göteborg: University of Göteborg.

Shinogaya, K. (2008). Effects of preparation on learning: Interaction with beliefs about learning. *Japanese Journal of Educational Psychology, 56*(2), 256–267. https://doi.org/10.5926/jjep1953.56.2_256.

Suzuki, G. (2016). Relation between fifth and sixth graders' conception of learning and mathematical problem solving. *Japanese Journal of Educational Psychology, 46*(3), 327–339. https://doi.org/10.5926/jjep.64.327.

Takayama, S. (2000). Characteristics and structure of student conception of learning. *Memoirs of the Faculty of Education, Shimane University, 34*, 1–10.

Takayama, S. (2002). The relationship between learning conception, it's determinants and learning strategies. *Memoirs of the Faculty of Education, Shimane University, 37*, 19–26.

Tercanlioglu, L., & Demiröz, H. (2015). Goal orientation and reading strategy use of Turkish students of an English language teaching department. *The Qualitative Report, 20*(3), 286–311.

Ueki, E. (2002). Structure of high-school students' beliefs about learning. *Japanese Journal of Educational Psychology, 50*(3), 301–310. https://doi.org/10.5926/jjep1953.50.3_301.

Uesaka, Y. (2010). Meta cognition, conception of learning, learning strategy. In S. Ichikawa (Ed.), *Development and learning* (pp. 172–200). Kyoto: Kitaooji Shobo Publishing.

Van Rossum, E. J., & Schenk, S. M. (1984). The relationship between learning conception, study strategy and learning outcome. *British Journal of Educational Psychology, 54*(1), 73–83. https://doi.org/10.1111/j.2044-8279.1984.tb00846.x.

Yamaguchi, T. (2012). Learning strategy use and cognitive and motivational factors in high School students: Individual differences in predicted test scores with a focus on effects of perceived utility. *Japanese Journal of Educational Psychology, 60*(4), 380–391. https://doi.org/10.5926/jjep.60.380.

Yamamoto, M., & Ueno, M. (2015). Analysis of the effects of using rubric in constructivist learning: Focusing on goal orientation, conception of learning, motivation, learning strategy, and learning task performance. *Japan Journal of Educational Technology, 39*(2), 67–81. https://doi.org/10.15077/jjet.39007.

Chapter 3
Towards a Model of Learner-Directed Learning: An Approach Based on the Co-construction of the Learning Scenario by the Learner

Guy Merlin Mbatchou Nkwetchoua, François Bouchet, Thibault Carron, and Philippe Pernelle

3.1 Introduction

According to the pedagogical triangle, learning is a process involving three components: the knowledge, the learner and the teacher (Friesen and Osguthorpe 2018). The integration of the social dimension, with the notion of learners group, makes this process even more complex (Ruthven 2012). At best, the teacher creates a knowledge-based course with well-defined learning goals. The course is then organized in a scenario which is used to guide both the teaching and the learning (Mbatchou 2016). However, this standard scenario, as envisioned by the teacher, can be inappropriate or at least suboptimal for some learners, because the learning also depends on their personal characteristics (e.g. pace of work, cognitive styles, emotional factors, prior knowledge, …). To improve the learning process, it is therefore ideal for each learner to have their own personalized scenario. Moreover, while learning, some characteristics of the learner may change (e.g. more motivation to learn about a topic than another, less time because of personal issues), making the initially defined scenario less and less appropriate. It would be difficult and time-consuming for the teacher, particularly in an online context, to detect the change in the learners' characteristics in order to propose a new better suited scenario. However, this detection may be more achievable by using computer-based methods relying on the use of learning traces, learner modeling (Greer and McCalla 2013) and intelligent tutoring systems (Ma et al. 2014). A limit of these methods though, is that they usually require a large volume of traces (which can be challenging for

G. M. Mbatchou Nkwetchoua (✉)
Assane Seck University of Ziguinchor, Ziguinchor, Senegal
e-mail: guy.mbatchou@univ-zig.sn

F. Bouchet · T. Carron · P. Pernelle
Sorbonne Université, CNRS, LIP6, Paris F-75005, France
e-mail: francois.bouchet@lip6.fr; thibault.carron@lip6.fr; philippe.pernelle@univ-lyon1.fr

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_3

courses with only a few students enrolled), and when new profiles are detected the system may need reengineering or a refinement of some parameters to take them into account. Thus, there can be issues relative to the real-time detection of changes in learner profiles to assign them an appropriate scenario. Involving the learner in the construction of their learning scenario can be a way to tackle this issue. Moreover, more fundamentally, various works on metacognition and self-regulation show that involving the learner, for instance by making them choose their learning goals, can lead to deeper learning and increased motivation (Harley et al. 2018), compared to a linear more passive way predefined by the teacher. This approach forces the learners to re-evaluate their decision if they realize they have chosen an activity for which they do not master yet all the required skills. Therefore, it seems that involving the learner in the choice of their learning scenario is not only a solution to a technical issue, but also a pedagogical choice that can have additional benefits for their learning.

Following these observations, this paper focuses on the co-construction of the learning scenario by the learners, as they learn, to make the learning process or acquisition of knowledge more efficient. We use the term “co-construction” because although the next learning goal depends on the learner, the range of their choice is constrained by the teacher, to prevent them from making illogical choices (e.g. trying to acquire a competence before its prerequisite). In this context, our research questions are: (RQ1) Can we set up a model allowing each learner to co-construct his or her scenario during the learning process? (RQ2) Is such a model understandable and acceptable to learners? (RQ3) How do learners use the possibilities of co-construction made available to them? Our contribution is to provide learners with conceptual and technological tools to build their learning scenario in a learning context imposed by the teacher and supported by technology.

The remainder of this paper is organized as follows. In Sect. 3.2, we present a brief overview of related works on personalization and adaptation of learning. Section 3.3 presents the core concepts of our model. Section 3.4 presents our model of co-construction of the learning scenario. Section 3.5 presents our implementation of the model in a LMS. Finally, Sect. 3.6 presents results of an evaluation of our approach in terms of acceptability of the model by learners, but also an evaluation of the system usability through an analysis of data collected in a preliminary experiment conducted in real situation with a class of students.

3.2 Related Work

The description of a learning scenario can be formalized with the Educational Modeling Language (EML) (Koper and Manderveld 2004) which offers the modeling of reusable, interoperable, rich and customizable learning units. Through personalization and reuse, it is possible to design several scenarios, but the EML language does not provide ways to switch from one scenario to another during the learning. This is because the scenario design is generally based on the intentions of teachers (Emin et al. 2010) (teacher-centered pedagogy) and on pedagogical goals (Dalziel 2008) (content-centered pedagogy). Some works have tried to be closer to a learner-centered pedagogy, for instance by taking into account teachers' intentions, activities to follow by learners and learner interactions (Mariais et al. 2010).

To design a pedagogical scenario, (Esnault and Daele 2003) defined 17 dimensions of question, taking into account learners' individual differences. However, to take this personalization into account, the scenario designer must know the learners' profiles in advance. Even if new scenarios can be designed by reuse and adaptation of existing ones (Riad et al. 2012), profiles can evolve during the learning process and no personalized path corresponds to the new profile. Marne and Labat (2014) proposed a scenario based on activities with several input and output states. The links between activities based on prerequisite relationships among them makes it possible to have several learning paths. However, their model, defined in the context of serious games, does not give the learner the possibility to choose the scenario to follow.

The Competence-based Knowledge Space Theory (CbKST) offers a model for structuring competences-based learning for personalization (Heller et al. 2006). From the relationship of prerequisite among competences, the model constructs several recommended learning paths (Kopeinik et al. 2012). Each path is composed of knowledge states (set of competences acquired in a particular field). From a knowledge state, the learner progresses in their learning by choosing a competence to acquire that will bring them into a new higher knowledge state. The learning is complete when the learner is in the terminal knowledge state (state with all acquired competences). Although the CbKST offers several learning paths, it does not consider learning constraints (temporal and qualitative related to satisfaction threshold of activities) in choices of paths, nor multi-goal activities (e.g. case studies), nor the conditions to change paths (e.g. a change can take place after a certain number of failures or the incapability to reach a fixed goal or a temporal constraint non-respected).

3.3 Core Concepts of the Model

There is not a single path to knowledge acquisition: there are many ways to do it, depending on the learning goal. But to build multiple scenarios, the course design model must allow it. We proposed a multi-scenario model of learning relying on five concepts (cf. Fig. 3.1):

1. *Decomposition of knowledge by learning goal to be achieved*

The learning or teaching is decomposed by learning goals where each of them is defined by the tuple of 5 elements detailed below.

Considering a course with **N** learning goals, a learning goal $\mathbf{G_i}$ ($\mathbf{i \in [1, N]}$) is defined by the following elements:

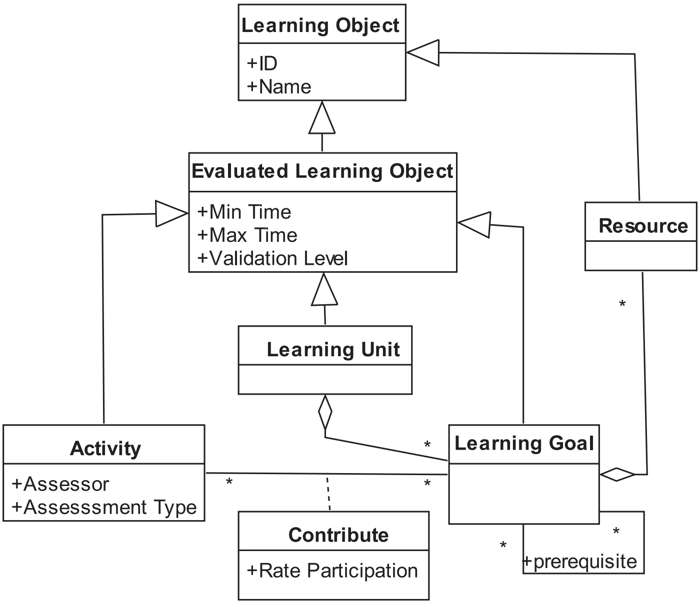


Fig. 3.1 Class diagram of learning objects for course design

- A minimum duration ($\mathbf{T_i^{Min}}$) to achieve a goal; it is a recommended minimum deadline.
- A maximum duration ($\mathbf{T_i^{Max}}$) to achieve a goal; it is a recommended maximum deadline.
- A satisfaction thresholds ($\mathbf{S_i}$) that determines the minimum expected achievement of the goal.
- A set of $\mathbf{M_i}$ learning resources ($\mathbf{R_i^j}$; $1 \leq j \leq M_i$) for knowledge acquisition.
- A set of $\mathbf{N_i}$ learning activities ($\mathbf{A_i^j}$; $1 \leq j \leq N_i$) for validating acquired knowledge.

To achieve a goal, we have a time range [$\mathbf{T_i^{Min} - T_i^{Max}}$] for the following reasons:

Definition of Learning Goal

- $\mathbf{G_i = \{T_i^{Min}, T_i^{Max}, S_i, \{R_i^1, R_i^2, \ldots, R_i^{Mi}\}, \{A_i^1, A_i^2, \ldots, A_i^{Ni}\}\}}$
- $(M_i, N_i) \in \mathrm{IN}^2 - \{(0, 0)\}$ are respectively the number of learning resources and the number of learning activities.

- There are learners qualified as "last minute" who only work intensively towards the end of allocated time to be on time. To allow them to work frequently, the system will propose them a minimal duration (T_i^{Min}) to achieve a learning goal. If a learner is not able to achieve the goal in a time inferior to T_i^{Min}, the system will give him gradually an extra time up to the maximum duration (T_i^{Max}).

- There are learners who are not able to reach their goal in the time initially defined or chosen, for instance if they have had exterior events reducing their expected availability. The system will allow them to go beyond the maximum duration if their progress to achieve goal are satisfactory. Otherwise, the system recommends changing this learning goal.
- A learner who achieves a goal with a grade not satisfactory for him, has the possibility to keep on improving it until the maximum duration (T_i^{Max}).
- Before the end of course duration, a learner who finished his learning can come back on the aspects he wants to improve.

2. *Prerequisite relationship between knowledge component.*

There can be many ways to learn a course, but there are nevertheless order constraints, taken into account in our model by a prerequisites graph between the goals. Let G_1 and G_2 be 2 goals. If G_1 is a prerequisite to G_2, it is represented by $G_1 \rightarrow G_2$ and means that: to master the goal G_2, it is necessary to master the goal G_1. Conversely, if a learner has the mastery of goal G_2, it means that they must already have the mastery of goal G_1. The prerequisite relations must be transitive and asymmetric.

3. *Encapsulation of knowledge in learning resources for learning goals.*

This encapsulation guarantees modularity in a course since a resource is reusable in another course without modification. The resource can be a file, a video, a web site, …

4. *Assessment of acquired knowledge.*

We define activities to assess the learning. To prevent assessment from depending on only a single activity, we define for each activity ($\mathbf{A_i^j}$) a percentage of participation ($\mathbf{P_i^j}$) in knowledge validation. Each activity ($\mathbf{A_i^j}$) contributes to the validation of goal G_i with the rate $\mathbf{P_i^j}$ where $\sum_{N^i}^{j=1} \mathbf{P_j^i} \geq \mathbf{100\%}$. The sum of the percentages must be greater than or equal to 100 so that the learner has a flexibility in the choice of activities to achieve his goal. An activity can also contribute to the validation of several knowledge components.

When a learner performs an activity A_i^j, he obtains a grade $\mathbf{V_i^j}$. A_i^j has also a satisfaction threshold $\mathbf{S_i^j}$ which determinates if it is validated or not.

Acquisition Conditions of Knowledge

- An activity A_i^j is validated if $\mathbf{V_i^j \geq S_i^j}$
- An goal G_i is validated if $\sum_{N^i}^{j=1} \mathbf{P_i^j V_i^j} \geq \mathbf{S_i}$

To prevent a learner from validating all activities N_i of goal G_i and not to be able to validate the associated goal, the rates participation (P_i^j) of activities (A_i^j, $1 \leq j \leq N_i$) at the achievement of a goal ($\mathbf{G_i}$) will respect this condition $\sum_{\mathbf{N^i}}^{\mathbf{j=1}} \mathbf{P_i^j V_i^j} \geq \mathrm{Si}$.

5. *Grouping learning goals into learning units*. To be close to the teachers' practice, the goals are grouped into learning units (generally parts, chapters, sections, …).

Our model allows to create several learning scenarios by articulating the learning objects.

3.4 Co-construction Model of Learning Scenario by Learners

3.4.1 Hypothesis, Goal and Theoretical Grounding

Our approach of co-constructing knowledge with learners, relies on two observations and one hypothesis.

The first observation is that we do not have a priori learner profiles due to lack of appropriated data for profiling. The second one is without necessarily being able to choose the adapted scenario for learners, giving them the choice in scenario building involves them more as an actor of their training than when there is a linear sequence of activities predefined by the teacher. This approach forces the learners to make decisions and eventually to re-evaluate them if they realize that they have been too ambitious either in their level of requirement for an activity or in their choice of an activity for which they do not yet master all the required competences.

The hypothesis of our work is that each learner is aware of the new skills they acquired and able to detect their behavioural changes. This is a strong hypothesis, as it basically means that the learner is able to properly self-regulate their learning, which is certainly not the case of every learner. There are nonetheless dedicated tools based on trace analysis that can help in raising students' self-awareness (Sambe et al. 2018), which could be used complementarily with our work to ensure this hypothesis is realistic. Under this assumption, we believe the learner is able to define or construct the adapted scenario.

The model is meant to provide learners with an environment allowing them to learn the way they want while respecting the rules and constraints of learning. This should enable them to make the learning process or acquisition of knowledge more effective. Thus, the learning scenario to be followed by learners has to be built by them.

The pedagogical reasons behind of our model rely on various works on metacognition and self-regulation that show that involving learner in his learning (for example by giving him a choice of his learning goals or competences to acquire) can lead to deep learning and increased motivation (Harley et al. 2018), compared to a linear and passive method predefined by the teacher.

The model is based on knowledge states to enable each learner to situate themselves in their learning and to progress. A knowledge state is a state that describes acquired and validated knowledge by a learner; it is composed by achieved learning goals (Mbatchou et al. 2018a). The knowledge states are produced and associated according to the Knowledge Spaces Theory to obtain different learning paths (Falmagne et al. 2013).

3.4.2 Learning Process

The co-construction of the learning scenario is based on the notion of knowledge state. At each stage of learning, the learner chooses the goal to achieve. The system provides learning resources to acquire knowledge and learning activities to evaluate the knowledge acquired. The learning process is to guide the learner from initial state to final state. The learning constraints defined by the teacher when designing learning objects is an implicit guidance contributing to co-construction. Learning is supervised by a human tutor as a learning facilitator (role not detailed in this chapter) (Fig. 3.2).

3.4.3 Decision During Co-construction

To allow co-construction to happen, there needs to be moment during the learning process in which the learner is asked to take decisions about his learning, i.e. to enter into a more metacognitive mode. During the learning, the system determines

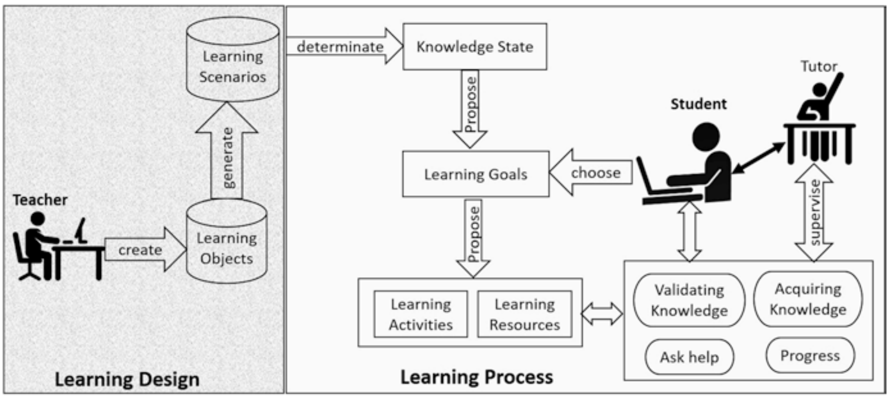


Fig. 3.2 Learning process

the learner's knowledge state and offers them a set of goals to achieve. Then for the chosen goal, the system proposes a set of resources and activities that will allow them to reach it. After an assessment that the knowledge is acquired, the system determines their new knowledge state. If they are unable to perform a given activity (resp. progress in a chosen scenario), the learner can abandon it and choose another activity (resp. scenario) offered by the system in the same scenario (resp. according to the learning goals) (Fig. 3.3).

3.4.4 Quality of the Co-constructed Scenario

The model integrates knowledge assessment modes to progress in learning. The choice of the mode depends on the challenge that the learner sets for themselves at any moment. Since the learner is situated in learning by their knowledge state, suppose a state with N goals $\{G_1, G_2, \ldots, G_N\}$. Each G_i has a set of learning activities $\{A^1{}_i, A^2{}_i, \ldots, A^{Ni}{}_i\}$ for validating the acquired knowledge. Each activity $A^j{}_i$ has a percentage of participation $P^j{}_i$ to achieve the goal G_i. When a learner chooses to perform the activity $A^j{}_i$ we keep the obtained value $V^j{}_i$ to compute the score obtained for this goal. The validation of each goal (G_i) is constrained by a threshold (S_i). To validate his state with N goals, the learner has the following modes:

Assessment Mode by Flexible Compensation The state is validated if $\sum_{N}^{\mathbf{i=1}} \sum_{Ni}^{\mathbf{j=1}} P_i^j V_i^j \geq \sum_{N}^{\mathbf{i=1}} S_i$. So, learner can progress without validating certain goals because he can obtain them by compensation.

Assessment Mode by Restrictive Compensation With the previous mode, a learner can validate a state even with one goal with a very low level of satisfaction. To avoid this case, in compensation mode, the learner must make minimum efforts for each goal. The state is validated if $\prod_{N}^{\mathbf{i=1}} \sum_{Ni}^{\mathbf{j=1}} P_i^j V_i^j \geq \prod_{N}^{\mathbf{i=1}} S_i$.

Strict Assessment Mode This mode allows challengers learners to master all goals of a state before progressing. The state is validated if $\boldsymbol{\forall\, i, 1 \leq i \leq N,}\ \sum_{Ni}^{\mathbf{j=1}} P_i^j V_i^j \geq \mathbf{S_i}$.

The quality of the built scenario is better if the strict mode is used throughout the learning.

3.4.5 Progression in Learning

During the co-construction of the scenario, it is necessary to ensure the progression of the learner and to be able to anticipate failure (non-progression). To progress in learning is to move from the current knowledge state to one of higher knowledge

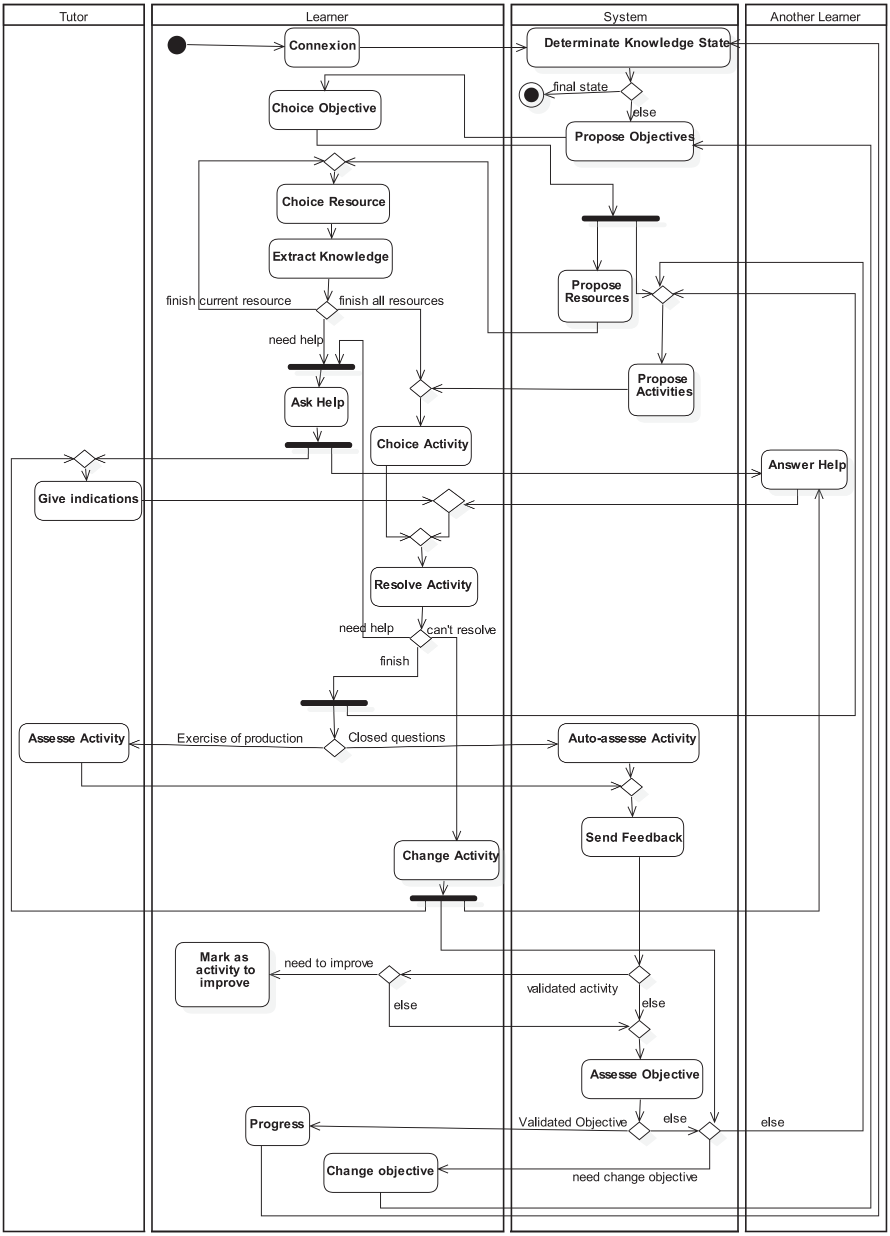


Fig. 3.3 Activities diagram of learning

states. Progression can be sequential or not. In our model, to allow non-sequential progressions, we introduced the notion of fast progression. To anticipate failure, we have also introduced the notion of blocked progression when the learner is blocked in a knowledge state.

Sequential Progression A progression is sequential when the learner moves from a current knowledge state to a knowledge state immediately superior. This progression is made by mastering only one goal not in the current knowledge state.

Fast Progression A progression is fast when the learner uses an augmented link (Mbatchou et al. 2018a) to progress. An augmented link allows the learner to skip some intermediates states. It is possible when the learner chooses an activity with multiples goals without master all goals of activity. This possibility allows to take into account learners who have knowledge about the goals of course.

Blocked Progression (No-progression) A blocked progression is the inability of learner to move from a current knowledge state to a higher knowledge state at the given time. A goal of our model is to help each learner to achieve their goals by anticipating failure and offering appropriate suggestions.

Example: Considering a learner in a knowledge state where he has 3 goals A, B and C to achieve. The precedence relationships between these goals are A → B and B → C. In sequential progression, the learner must achieve the goal A, then B and finally C. In fast progression (if there is an activity with multiple goals aiming to achieve both the goals A, B and C), the learner can attempt to achieve goal C. If he succeeds, then goals A and B are also achieved since they are prerequisites for C. In case of blocking situation, the system suggests sequential progression. If it is blocked in a sequential progression, the system will propose to him to change goal. In a blocking situation, the system sends an alert to the human tutor who can help the learner.

In conclusion, from the previous points, we answered positively to our first research question (RQ1) by proposing a theoretical model which embeds several features that we think would help learners in co-constructing their learning scenario.

3.5 System Overview

We chose to implement our model as a plugin in MOODLE (Modular-Object Oriented Dynamic Learning Environment), which is the LMS used in our test university (the model being platform-independent). The plugin, named EGbKST (Educational Goal based Knowledge Space Theory), provides a dynamic interface to be used while learning (cf. Fig. 3.4) as well as an on-demand interface allowing the learner to see a summary of their results so far (not presented here). The learning interface is organized in several dynamic blocks (Communication, Statistics, Resource, Goal and Activities) which content and visibility depend on each learner and their knowledge state.

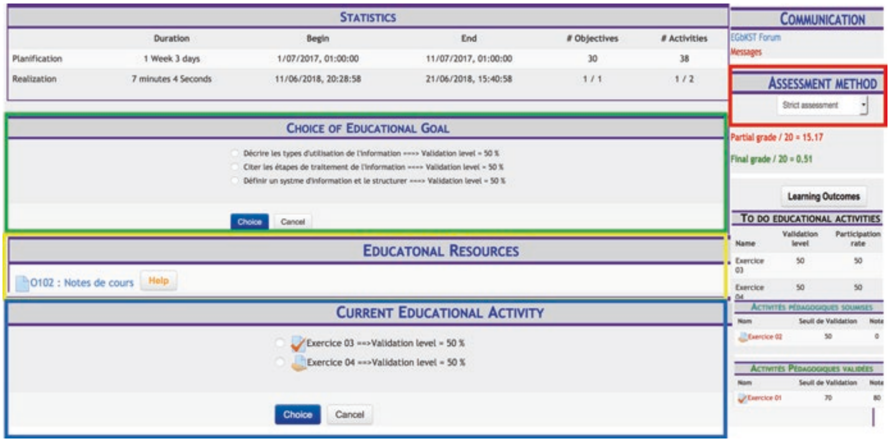


Fig. 3.4 Learning interface

3.5.1 System Used for the First Experiment

The learner initially chooses a goal to achieve (block in green). As soon as it is reached, the system offers them a new set of goals they can achieve and so on. During the procedure of achievement of the current goal, the system shows the relevant resources (block in yellow) that allows to acquire the necessary knowledge. The assessment of acquired knowledge is done by choosing activities to do (block in blue). The learning ends when the learner has achieved all the goals. The goals and the order in which they are chosen represent the scenario built by learner. The system allows to change current goal to choose another one if necessary. To progress in learning, the learner has a list of assessment modes (block in red) to choose from to express their desired degree of challenge. The efforts made and the chosen mode allow them to progress at a higher knowledge state.

The acceptability of our model by the learners is made during the first experiment. The results presented in (Mbatchou et al. 2018b) reveal that our model is understandable and acceptable by learners. This result allows us to be optimistic that our model will improve the learning process of each learner. But this experiment revealed some bias during the learning process which were related to some system weaknesses that need to be corrected not to misinterpret the learners' behaviours. Some recommendations were thus made during the analysis, and adaptation of the model as well as system reengineering were necessary.

In a previous work, we have also assessed our model acceptability (https://goo.gl/forms/ne1Uua4UeYPW3EeO2) from the teacher's point of view (Mbatchou et al. 2018a), showing their willingness to use it. An experiment with 16 teachers from 8 specialties also allowed us to (1) detect and correct the inconsistencies in their educational productions; (2) find that certain goals of their course are not related to others; (3) find that there is little prerequisite relationship between goals; and (4) note the multiplicity of scenarios in their course.

3.5.2 Reengineering for the Second Experiment

At the end of the first experiment, we revealed system weaknesses to correct in order to avoid bias in the analysis of learners' behaviors. For example, a bias during the construction of a scenario due to the presentation of goals with numbers which could suggest an order between the goals.

Before the second experiment, we made the reengineering of our model and system. We added to the model (1) strategies to ensure learning progression and (2) the guarantee of learning to be sure that learner acquired knowledge during its progression.

3.5.2.1 Strategies to Ensure Learning Progression

Each goal (G_i) has minimal (T_i^{Min}) and maximal (T_i^{Max}) durations recommended by teacher to achieve a satisfaction threshold (S_i). To ensure the learners' progression, retroactions (feedbacks) are proposed to guide him (cf. Table 3.1). The retroactions are based on duration (T_i) and grade (V_i) obtained at goal (G_i). To encourage learner to achieve the current learning goal, extra-time are granted, defined according to the following formula:

$$\text{ExtraTime} = \left(T_i^{max} - T_i^{min}\right) / 2$$

3.5.2.2 Guarantee of Learning

To be sure that learners acquire knowledge during their progression, it can seem reasonable to impose to learners the sequential progression because at least it is a path that is known to help in acquiring knowledge progressively. However, by not proposing the fast progression, we penalize some learners (challengers, learners with acquired knowledge before, …), preventing them from choosing activities with multiples goals where several of them are not yet acquired. To find a right balance, we chose to suggest to learners who uses fast progression, the strict mode acquisition of knowledge. Additionally, for a learner who uses the sequential progression, when he is in a knowledge state greater than an augmented knowledge state, the activities with multiples goals of that augmented knowledge state will be systematically proposed. The success of these activities helps in strengthening the competence level of learner in the different goals of the activities. In case of failure, the learner is free to progress but, these non-validated activities will be notified to them as weak points to work on. They then have opportunity to redo each of them when he wants. Once an activity has been validated, it is no longer considered as a weak point.

Table 3.1 Table of suggestions to ensure the progression and to anticipate failure

Condition on T_i	Condition on V_i	Action
$T_i \geq 50\%$ of T_i^{Min}	$V_i \leq 10\%$ of S_i	Be careful!
		You have consumed more than 50% of allocated time for educational goal.
		Your grade for this goal is very poor because it does not exceed 10% of the required score
$T_i \geq 75\%$ of T_i^{Min}	$V_i \leq 20\%$ of S_i	We suggest that you change the educational goal because you have consumed more than 75% of allocated time to educational goal while your grade is less than 20% of required score
$T_i \geq 75\%$ of T_i^{Min}	$V_i \leq 50\%$ of S_i	Be careful!
		You have consumed more than 75% of allocated time for educational goal.
		Your grade for this goal is insufficient because it does not exceed 50% of the required score
$T_i \geq T_i^{Min}$	$V_i \leq 25\%$ of S_i	We suggest that you change the educational goal because you have consumed more than 100% of allocated time to educational goal while your grade is less than 25% of required score
$T_i \geq T_i^{Min}$	$V_i \leq S_i$	To offer you opportunity to validate this educational goal, we offer you an extra-time.
$T_i \geq T_i^{Min}$ + ExtraTime	$V_i \leq S_i$	Despite the extra-time, you could not validate the educational goal.
		We give you a last extra-time.
		On the other hand, we advise you to change your educational goal if you can't progress.
$T_i \geq T_i^{Max}$	$V_i \leq S_i$	Your grade does not allow you to validate the educational goal.
		Change your assessment method which allow you to progress in your learning.
		If no method allows you, change immediately your educational goal.

3.5.2.3 Reengineering of System

During the first experiment, we have strict mode as default assessment mode. To avoid this bias, we designed an interface (Fig. 3.5) allowing learners to explicitly choose its initial assessment mode. This mode can be changed at any time during the learning.

Another bias of previous system was the numbering of goals, which indirectly reflected the original sequential approach followed by the teacher. Instead, in the reengineered version, we decide to show each goal with its metadata like satisfaction threshold, recommended time, number of resources and activities (Fig. 3.6).

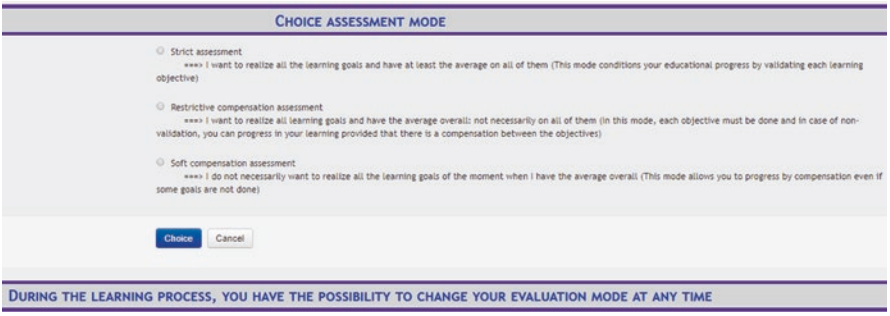


Fig. 3.5 Interface to choose the assessment mode at the beginning of learning

To help a learner to choose an activity, we present the activities with their satisfaction threshold, number of targeted goals and a message to prevent the learner if they do not yet have all the skills to complete it (Fig. 3.7). We randomized the order of activities to prevent a learner from having the same list in the same order every time.

The other interfaces can be found in (Mbatchou 2019).

3.6 Assessing Co-construction of Scenario by Learners

3.6.1 Methodology

3.6.1.1 Experimental Protocol

The experiment was realized in 3 phases in a public university in sub-Saharan Africa, with nearly 3500 students enrolled in 21 academic sections and 120 teachers in 15 specialties (from bachelor to doctorate).

Phase 1: Assessing the Acceptability of the Model by the Learners To answer our second research question, we submitted a survey[1] to students. The survey questions are in affirmative form with responses on a 4-point Likert scale extending from “strongly disagree” to “strongly agree”. The survey collected student opinion on the following aspects: (1) Current educational model: the question is to find if they find that (a) the courses have clearly defined and identifiable educational goals, (b) for the defined goals, do they have learning resources and activities to evaluate them? (c) can the learning be done in a different order than the teacher’s? (2) Interests for a goal-based educational model: the question is to know if they think that a such model would facilitate their learning and success. The questionnaire was sent to all

[1] https://goo.gl/forms/EgiVdEgE1z8mfFQr1

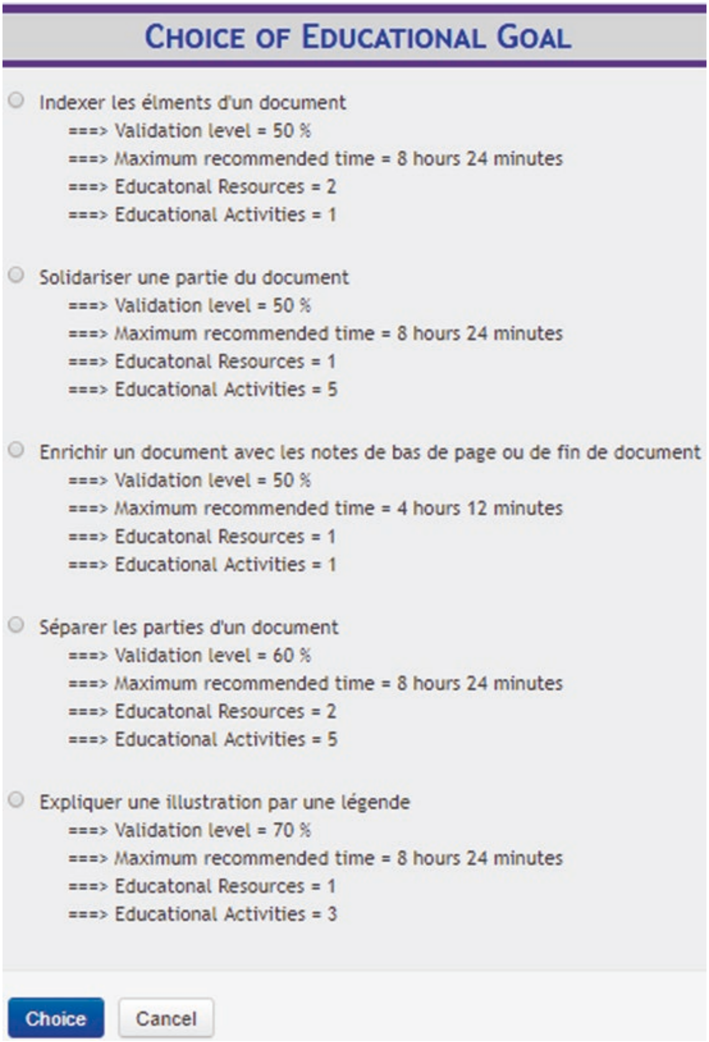


Fig. 3.6 Interface to choose learning goal

3500 students, but we received only 85 responses.[2] This can be explained by the fact very few students are trained to take online courses (around 250 students have access to online training platform). Participants come from 14 academic sections and 3 teaching cycles. Their age varying between under 18 years to over 45 ($M = 21.60$, SD = 6.46). Eighty percent of survey responses are from learners who have been trained in the use of online learning platform.

[2] Consulted at 11-24-2017.

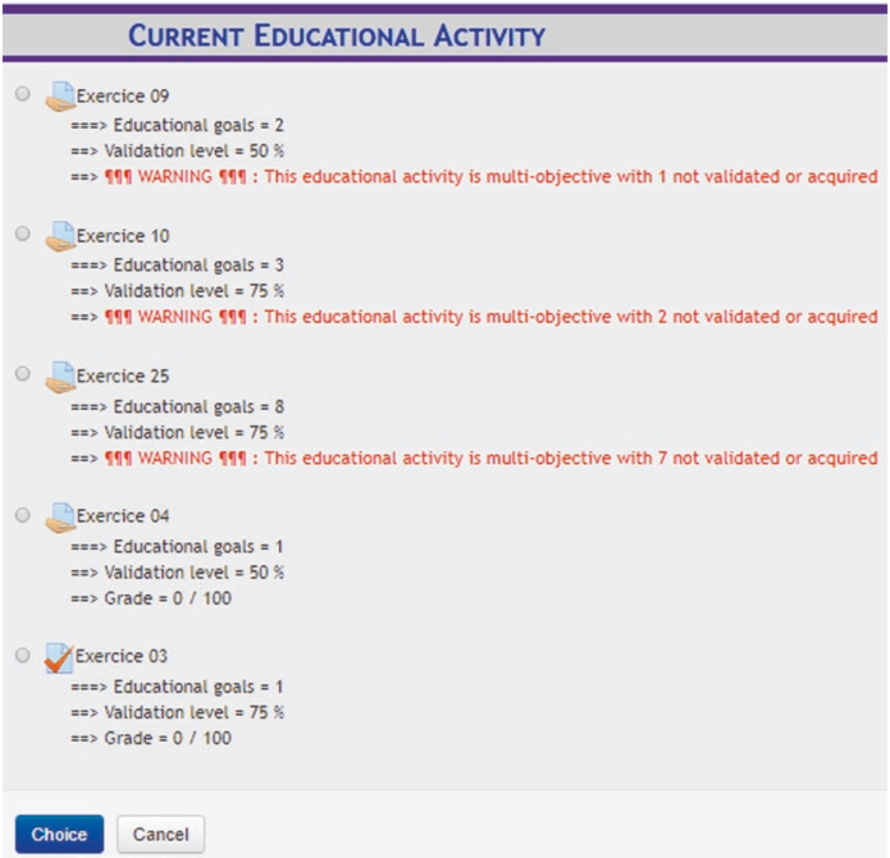


Fig. 3.7 Interface to choose learning activity

In view of the response rate, these results should be taken with caution, because it probably over represents certain categories of students (e.g. motivated, technophiles). To counter this potential bias, we also asked those questions[3] to the 11 students who tested the system (cf. below) in the first experiment.

Phase 2: Assessing the Usability of the System The first experiment conducted on the "General Political Economy 1" teaching unit with 11 learners (Mbatchou et al. 2018b) revealed weaknesses in the system that must be corrected to avoid bias in the analysis of the results. After having done a reengineering of the model and the system (cf. Sect. 3.5.2), we carried out a second experiment on a different computer science course in continuing training with the students of the professional license in Renewable Energies. This course has 20 objectives, 32 resources, 25 activities, and a known predefined scenario recommended by the teacher. The resources are a mix of files, webpages and videos. The activities are of the production type (open-ended

[3] http://foad.uasz.gouv.sn/mod/questionnaire/view.php?id=5273

questions) and quizzes (true/false, yes/no, matching, single choice and multiple choice). The students ($N = 16$) are those of the initial training who have chosen to continue Renewable Energies in continuing training with a level of license 2 in physics. The learning lasted 2 months and was performed in blended learning alternating online sessions and face-to-face sessions. Learning was done more online because work instructions, resources and learning activities are available online. A forum has been created for discussions among students on the one hand and between students and the teacher on the other. To break the isolation effect of students, face-to-face sessions were organized to allow students to meet in a classroom once a week to discuss the difficulties encountered. A face-to-face session lasted an average of 1 h and is led by the teacher. Forum questions with unsatisfactory answers are processed again. New questions about resources and activities are addressed and guidance is provided for successful learning activities.

3.6.1.2 Data Collection Protocol

Assessment of the model acceptability (phase 1) is done with the Google Forms tool, with data saved in a CSV (Comma-Separated Values) file. During learning (phase 2), learner interactions with the system are recorded in a plain text log file in which each line contains a 7-uplets (date, action, grade, type of learning object, learning object, learner identification on Moodle, learner identification on EGbKST plugin), corresponding to the action done by a learner on a learning object.

3.6.1.3 Data Analysis Protocol

To validate our third research question, we considered 2 indicators: diversity of scenarios and of assessment modes. We considered only 14 students because 2 of them did not participate in the training.

The diversity of scenarios allows to determine if co-constructed scenarios are different. For each learner, we extract successive learning goals followed in chronological order. For those who have not completed their learning, we compare their learning sequence with the corresponding sequence in the reference teacher-recommended scenario (e.g. the first 5 steps for a learner who dropped out after 5 steps). The diversity of scenarios is represented by the number of different scenarios and the distance between alternative scenarios (distance based on the Levenshtein distance – when computing distances between scenarios, we only consider sequences of identical length).

The diversity of assessment modes allows to determine the willingness of each learner to progress according to the mode chosen at each learning stage. This indicator is broken down into 2 sub-indicators: the percentage of time that each assessment mode is used to progress, and for each mode, the number of learners who used it and the number of times used.

3.6.2 Results and Discussion

3.6.2.1 Acceptability of the Model by the Learners

The acceptance of the model is assessed in the general framework with all 85 respondents. We present below the results and then contrast them with the results obtained with the 11 students involved in the experiment.

Current Educational Model The survey shows that the courses are organized mainly in chapters (81.2%) and often in parts (32.9%). 27% of participants estimate that certain learning goals do not have learning resources clearly associated to them. 3.5% of participants believe that in some courses, goals are not announced. Results are more concerning for exercises, for which 50.7% learners estimate that educational goals are not assessed. This finding justifies our approach to associate resources and exercises with each goal to better structure and facilitate learning. 70.6% of participants' estimate that the course could be better learned with a different scenario than the one imposed by the teacher. We conclude that current educational model contains weaknesses identified by learners and their wish reinforces our approach of co-construction.

Interests of Pedagogical Model Based on Goals 81.2% of learners estimate that learning would be easier if it is organized and presented by goals and not by chapter. 91.8% of them believe they would obtain better results if they were assessed by goal. The results obtained from the 11 students of our first experiment are similar to those obtained on the larger sample. The only difference is the availability (online) of resources and activities for the goals. This difference is justified by the fact that online course procedure requires the availability of resources and activities for each learning sequence.

We thus can respond positively to our RQ2: our approach seems in agreement with learners' expectations.

3.6.2.2 Scenarios Diversity

To visualize different scenarios followed by the learners, we represented each stage of the scenario of each learner with a different color (cf. Fig. 3.8). We can see each student has built its own scenario.

By computing the Levenshtein distance between the scenarios, we see that the scenarios are different from each other (cf. Table 3.2). The maximum distance is 20 and we find that the majority of the scenarios have a distance of more than 10 of the others. Despite the possible interactions between students and weekly meetings, each student has chosen different goals to achieve.

We wanted to know if the scenarios were also as distant from the one recommended by the teacher. This, we calculated the distance between each scenario and

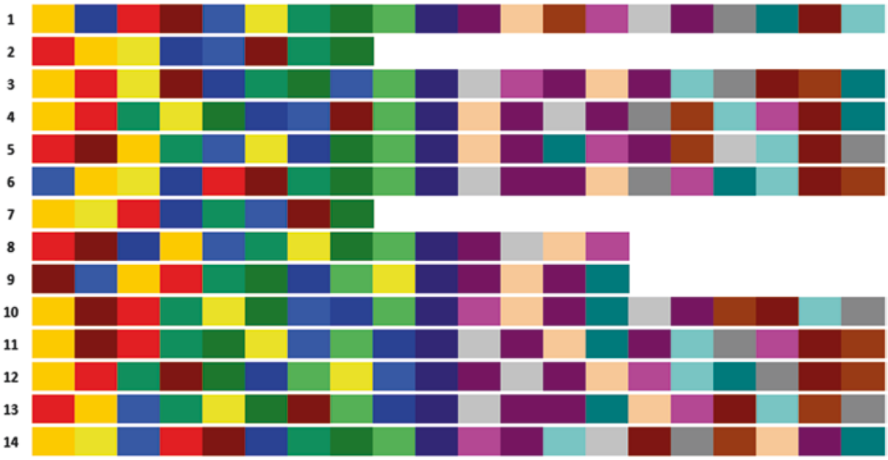


Fig. 3.8 Visualization of 14 scenarios built by learners

Table 3.2 Levenshtein distance between different scenarios

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	0	5	14	15	13	12	5	8	9	13	14	14	16	13
2	5	0	6	5	5	2	4	5	8	7	8	8	6	4
3	14	6	0	12	15	12	5	10	11	13	11	11	14	11
4	15	5	12	0	13	14	5	11	9	10	12	12	13	13
5	13	5	15	13	0	14	6	7	9	10	13	16	13	15
6	12	2	12	14	14	0	5	10	10	16	12	13	13	13
7	5	4	5	5	6	5	0	6	7	6	6	6	7	4
8	8	5	10	11	7	10	6	0	9	10	10	10	8	10
9	9	8	11	9	9	10	7	9	0	7	9	6	9	11
10	13	7	13	10	10	16	6	10	7	0	13	14	13	15
11	14	8	11	12	13	12	6	10	9	13	0	11	12	17
12	14	8	11	12	16	13	6	10	6	14	11	0	13	17
13	16	6	14	13	13	13	7	8	9	13	12	13	0	17
14	13	4	11	13	15	13	4	10	11	15	17	17	17	0

the recommended one. We realized that no scenario is similar or close to that recommended by the teacher (cf. Fig. 3.9) except for scenarios 2 and 7 where students only completed 8 steps out of 20.

These results show that when giving choice to the learners to build their own scenario, they can build a variety of logical scenarios while respecting to pedagogical constraints.

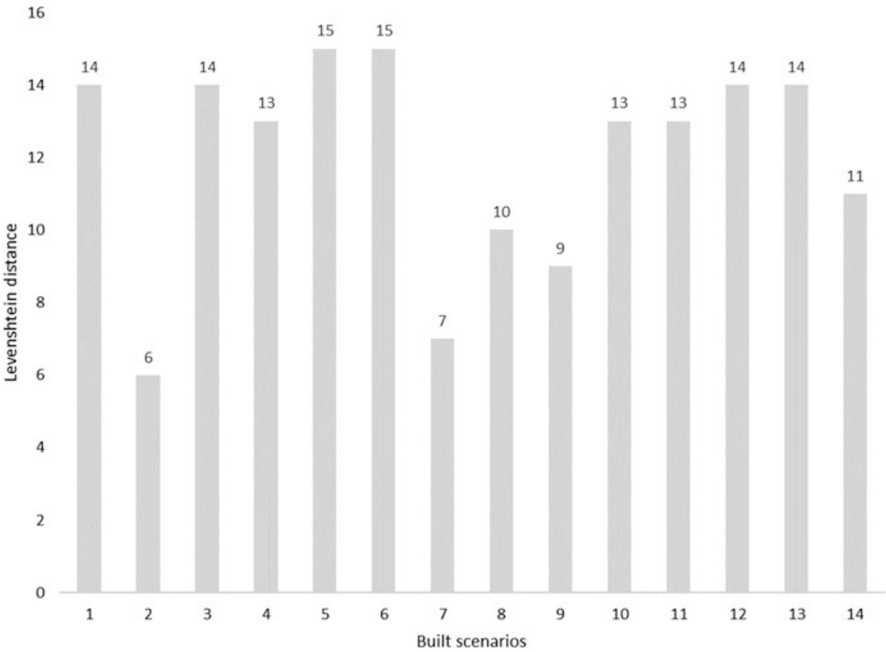


Fig. 3.9 Levenshtein distance between students' scenarios and the teacher's recommended scenario

3.6.2.3 Assessment Modes Diversity

At the beginning of the learning, the assessment mode is chosen by each learner and we note (except learner L07) that all the learners started with the strict mode (cf. Fig. 3.10). Unlike the first experiment, the percentage of use of the strict mode decreased from 75% to 29.1% (cf. Fig. 3.11) because the system (cf. Table 3.1) suggested to learners the appropriate mode of evaluation for each learning stage (cf. Sect. 3.5.2.1). Nevertheless, we observe some learners (L12 and L13 in Fig. 3.10) who decided not to follow the suggestions of the system because they wanted to keep on using the strict mode. There are learners (L10 and L12 in Fig. 3.10) who have chosen to improve certain learning activities to return to the strict mode. We think that once the learners have changed the assessment mode, they want to progress quickly and therefore preferred the flexible mode over the restrictive one. We find that all learners who prematurely stopped learning changed their assessment mode for the flexible mode. This could mean that changing to flexible mode indicates future dropout, and that could be brought to the teacher's attention.

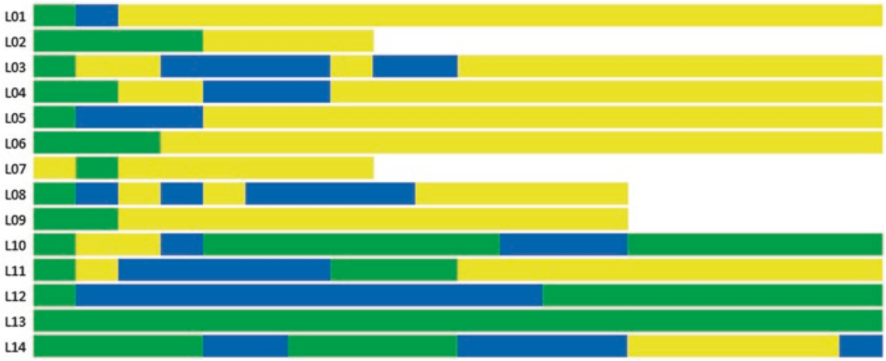


Fig. 3.10 Scenario representation of each learner by assessment mode (Strict mode in green; Restrictive mode in blue; Flexible mode in yellow)

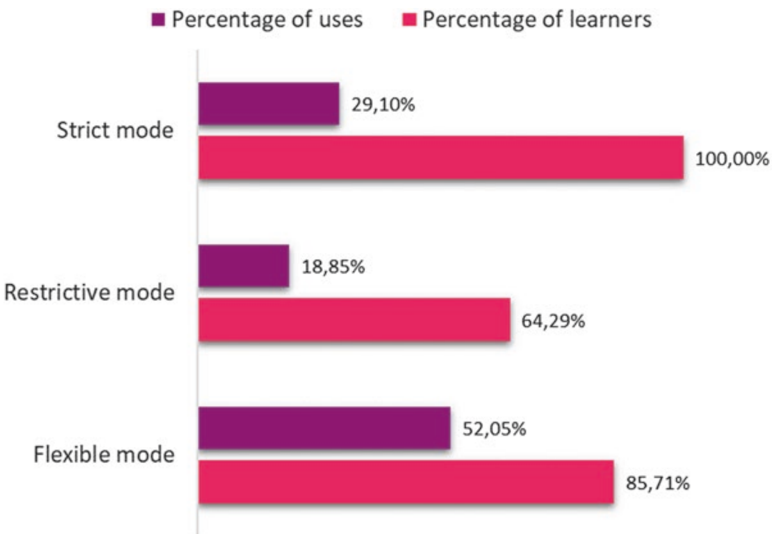


Fig. 3.11 Representation of learners and progress number by assessment mode

3.7 Conclusion

Giving learners the opportunity to build their scenario while learning, making them a main actor of its co-construction, is not really considered in recent research in TEL. Our model shows that it is possible, and that the built scenarios respect educational constraints defined by the teacher. Experiments led with teachers and learners show their satisfaction and the ability of the model to improve both the learning and teaching processes. The diversity of scenarios built by learners revealed that some learners seem to prefer a different approach than the teacher's default one. Moreover, the model offers learners to modify their assessment mode at any time. Their desire to be challenged is a sign that our model offers a motivating framework to better acquire competences. This is confirmed by the fact some learners returned on previous activities to improve their score to remain in a strict assessment mode.

Among the limits of this work, the context of our experimentation (few online learners in sub-Saharan Africa) does not allow us to fully validate our approach – integration to a MOOC could help reaching a more reliable conclusion. Moreover, our model is only applicable for learning by competences or educational goals.

In future work, we will integrate into the model the analysis of the chosen scenario and present it to the learner. When they face difficulties while diverging from the reference scenario, we may redirect them towards the reference scenario. Moreover, traces analysis over several courses could help in identifying patterns and thus learner profiles and learning indicators that will help us to guide or redirect future learners.

References

Dalziel, J. (2008). Using LAMS version 2 for a game-based learning design. *Journal of Interactive Media in Education, 2008*(2). Retrieved from http://www-jime.open.ac.uk/jime/article/view/2008-24.

Emin, V., Pernin, J.-P., & Aguirre, J. L. (2010). ScenEdit: An intention-oriented authoring environment to design learning scenarios. In M. Wolpers, P. A. Kirschner, M. Scheffel, S. Lindstaedt, & V. Dimitrova (Eds.), *Sustaining TEL: From innovation to learning and practice* (pp. 626–631). Berlin/Heidelberg: Springer. https://doi.org/10.1007/978-3-642-16020-2_65.

Esnault, L., & Daele, A. (2003). *Higher education and ICT: Questions to design successful pedagogical scenarios to improve the learning process* (pp. 944–951). Retrieved from https://www.learntechlib.org/primary/p/12506/

Falmagne, J.-C., Albert, D., Doble, C., Eppstein, D., & Hu, X. (Eds.). (2013). *Knowledge spaces: Applications in education*. Berlin/Heidelberg: Springer. Retrieved from http://link.springer.com/10.1007/978-3-642-35329-1.

Friesen, N., & Osguthorpe, R. (2018). Tact and the pedagogical triangle: The authenticity of teachers in relation. *Teaching and Teacher Education, 70*, 255–264. https://doi.org/10.1016/j.tate.2017.11.023.

Greer, J. E., & McCalla, G. I. (2013). *Student modelling: The key to individualized knowledge-based instruction*. Berlin/Heidelberg: Springer.

Harley, J. M., Taub, M., Azevedo, R., & Bouchet, F. (2018). "Let's set up some subgoals": Understanding human-pedagogical agent collaborations and their implications for learning and prompt and feedback compliance. *IEEE Transactions on Learning Technologies, 11*(1), 54–66. https://doi.org/10.1109/TLT.2017.2756629.

Heller, J., Steiner, C., Hockemeyer, C., & Albert, D. (2006). Competence-based knowledge structures for personalised learning. *International Journal on E-Learning, 5*(1), 75–88.

Kopeinik, S., Nussbaumer, A., Bedek, M., & Alber, D. (2012). *Using CbKST for learning path recommendation in game-based learning*. In Proceedings of the 20th international conference on Computers in Education, pp. 26–30. Retrieved from http://www.researchgate.net/publication/274256220_Using_CbKST_for_Learning_Path_Recommendation_in_Game-based_Learning

Koper, R., & Manderveld, J. (2004). Educational modelling language: Modelling reusable, interoperable, rich and personalised units of learning. *British Journal of*

Educational Technology, 35(5), 537–551. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.0007-1013.2004.00412.x/full.

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

Mariais, C., Michau, F., & Pernin, J.-P. (2010). *The use of game principles in the design of learning role-playing game scenarios*. In Proceedings of the 4th European conference on Games Based Learning, pp. 462–469. Retrieved from https://hal.inria.fr/hal-00948755

Marne, B., & Labat, J. M. (2014). Model and authoring tool to help teachers adapt serious games to their educational contexts. *International Journal of Learning Technology, 9*(2), 161–180. https://doi.org/10.1504/IJLT.2014.064491.

Mbatchou, G. M. (2016). Accompagnement de l'apprentissage/formation: Modélisation du scénario pédagogique. In S. Iksal, C. Michel, & C. Pelissier (Eds.), *6èmes Rencontres Jeunes Chercheurs en Environnements Informatiques pour l'Apprentissage Humain* (pp. 95–100). Retrieved from https://hal.archives-ouvertes.fr/hal-01337569.

Mbatchou, G. M. (2019). *Towards a model to support the learning in learning management systems: An approach based on the multi-scenario modelling of a course and the co-construction of the learning scenario by the learners*. Theses, Sorbonne Université/Université Pierre et Marie Curie – Paris VI. Retrieved from https://hal.archives-ouvertes.fr/tel-02170783

Mbatchou, G. M., Bouchet, F., & Carron, T. (2018a). Multi-scenario modelling of learning. In C. M. F. Kebe, A. Gueye, A. Ndiaye, & A. Garba (Eds.), *InterSol: Innovations and interdisciplinary solutions for underserved areas* (pp. 199–211). Cham: Springer. https://doi.org/10.1007/978-3-319-98878-8_19.

Mbatchou, G. M., Bouchet, F., Carron, T., & Pernelle, P. (2018b). Proposing and evaluating a model of co-construction of the learning scenario by the learner. In D. G. Sampson, D. Ifenthaler, P. Isaías, & L. Rodrigues (Eds.), *Proceedings of the 15th international conference on Cognition and Exploratory Learning in Digital Age* (pp. 208–214). Retrieved from http://celda-conf.org/.

Riad, B., Mourad, H., Nourredine, G., & Hamid, S. (2012). The scenarization: A new task for teachers. *Procedia – Social and Behavioral Sciences, 31*, 732–737. https://doi.org/10.1016/j.sbspro.2011.12.132.

Ruthven, K. (2012). The didactical tetrahedron as a heuristic for analysing the incorporation of digital technologies into classroom practice in support of investigative approaches to teaching mathematics. *ZDM, 44*(5), 627–640. https://doi.org/10.1007/s11858-011-0376-8.

Sambe, G., Bouchet, F., & Labat, J.-M. (2018). Towards a conceptual framework to scaffold self-regulation in a MOOC. In C. M. F. Kebe, A. Gueye, & A. Ndiaye (Eds.), *Innovation and interdisciplinary solutions for underserved areas* (Vol. 204, pp. 245–256). Cham: Springer. https://doi.org/10.1007/978-3-319-72965-7_23.

Chapter 4
The Communication Preferences of Collegiate Students

Joan Ann Swanson, Susan L. Renes, and Anthony T. Strange

4.1 Introduction

An estimated 22.2 million students will enrolled in degree-granting postsecondary institutions in the United States in the fall of 2018 (National Center for Education Statistics 2017; Duffin 2019). Each of these individuals will communicate in some fashion for academic-related purposes with educational administrators, faculty, and students and communicate with others for personal purposes. A majority of students in institutions of higher education today were born into a generation immersed in technology and thus are referred to as digital natives, digital learners, and digital residents (Gutiérrez-Porlán et al. 2018; White and Le-Cornu 2011; Prensky 2001).

Today's technological environment has not only influenced how society communicates; technology has also redefined learning and educational opportunities in many ways. In the academic realm, it is essential to recognize and reconcile college student communication needs and preferences and how they are likely to impact corresponding educational practices.

For the purposes of this chapter, communication is defined as the collaborative transmission of information between individuals through a common verbal or non-verbal system based upon an understanding of their strengths and limitations (Munodawafa 2008). This collaborative process can be accomplished in a multitude

J. A. Swanson (✉)
Skidmore College, Saratoga Springs, NY, USA
e-mail: jswanson@skidmore.edu

S. L. Renes
University of Alaska Fsirbanks, Fairbanks, AK, USA
e-mail: slrenes@alaska.edu

A. T. Strange
Wayland Baptist University, Plainview, TX, USA
e-mail: stranget@wbu.edu

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_4

of ways and may be enhanced through the use of technological tools. In learning situations, communication is the key venue with which messages are disseminated, whether written, spoken, or through nonverbal means. With the rapid proliferation of technological communication tools, colleges and instructors can potentially connect with students anytime and anywhere. The quality of a college's ability to effectively communicate internally and externally impacts their ability to survive in a world where many college doors are being closed (Boyer 2016). Colleges need to stay abreast of the most effective ways to communicate.

Following this introduction, the literature review describes the nature of communication and the significance it has in the academic realm. The literature review delineates the significant role of student communication preferences and patterns. The chapter then discusses technology's impact upon communication in light of continued technological advancements. The importance of competence with and purposes for communication is then addressed. Additionally, theory for understanding the role of preferences and choices in communication is highlighted. As illustrated in the literature review, academic and nonacademic settings reveal differing preferences and patterns for communication. The method section details the descriptive comparative methodology utilized for this study including information about the research tool and participant demographics. Finally, the chapter concludes with the results and a discussion explaining the significance of the revealed patterns of preferred college student communication and how those preferences affect communication practices.

4.2 Literature Review

With the onslaught of potential ways to communicate, administrators and instructors struggle to know the most effective means by which to relay messages and important details to collegiate students. The famous playwright, George Bernard Shaw, said "The single biggest problem in communication is the illusion that it has taken place." The key element in communication is not only disseminating information but knowing it has been received. Boyer (2016) notes effective communication is more than sending a message; it must also foster dialogue. Collegiate students represent individuals who most likely own and use mobile devices, yet utilize a multitude of platforms from which messages could potentially be disseminated, and may or may not receive those messages. Collegiate communication specialists state that relying on only one method of communication to college students can result in messages not being received; thus a growing trend now is to additionally utilize Facebook, Twitter, Pinterest, and other forms of social media (Mangan 2012). Some studies have taken on the task of researching collegiate students' communication preferences (Cassidy et al. 2011; Kvavik 2005; Lightfoot 2009; Robinson and

Stubberud 2012); however, considering the rapid pace at which technological advances are occurring, Robinson and Stubberud (2012) recommend periodically revisiting the moving target of collegiate communication preferences.

Not only do preferences and patterns for use of communication devices vary a great deal among college students and additionally; it is possible that collegiate communication preferences may change over time. Even though most have grown up in a digital age, their competencies may vary. As this study seeks to understand communication preferences and patterns of college students, it also acknowledges that not all students are the same, and adjustments may be needed for varied levels of competence related to communication tools and methods, as well as students' locations.

4.2.1 Communication and Technology

The history of communication methods reaches back to clay tablets and smoke signals and then fast forwards to today to the use of smart phones and virtual realities. Technology has not only influenced communication; it has also redefined learning and educational opportunities. The use of technological tools has become so widespread that these tools permeate daily functioning. Technological communication tools not only impact our daily functioning but also our perceptions and preferences. "Neuroscientist now tell us that we constantly integrate what we are stimulated by and it changes our brain: we then perceive the world differently because of how our brains have changed" (Levy-Warren 2012, p. 1164). The Pew Research Center reports (2018) that 95% of American adults own a cellphone and 77% own a smartphone. This trend of mobile device ownership has become a key factor in communication modes today, not only for simple conversation but as a means to access the Internet and its accompanying vast variety of communication avenues including social media outlets. Perrin and Duggan (2015) report 96% of 18–29 year olds use the Internet daily. Additionally, Pew reports three quarters of adults in the United States own desktop or laptop computers. With the increase in technological devices with which to communicate, there are continuous shifts in how communication is taking place. Knowing these technological tools are at our fingertips affects how and what we think. Farber et al. (2012) suggest technology-enhanced communication has become convenient, resulting in both advantages and disadvantages that vacillate with technological trends. Such emerging technology trends were investigated by Cassidy et al. (2011, 2014), who also indicate an increasing variety of student usage related to technological tools in higher education as well as the dependence on technology. These technologies then expand the options for choosing modes of communication.

4.2.2 Communication Competence and Purpose

Communication often occurs in contexts that may overlap. Lightfoot's (2009) research indicated students choose technology with which to communicate that best carries the message in the particular context. There are also ramifications when communication is unsuccessful, such as embarrassment, disruption in a relationship, and misunderstandings. When technological tools enter the communication equation, Conole et al. (2008) found students select technologies they feel comfortable with to meet their learning needs and rely upon those technologies for their interactions as well. This supports the concept that personalization and a sense of control build communication competence while using familiar tools for communication purposes. Some researchers suggest comfort level with technology, which in turn impacts preference and use of technology, is closely associated with student age as well as their familiarity with the technology (Oblinger and Oblinger 2005; Prensky 2001; Waycott et al. 2010).

Often communication choices, even if they are influenced by available tools, are also dependent upon the purpose for such communication. In an educational setting, the way a course is delivered (face to face, blended, or online) happens through some form of communication (speaking in a classroom, online with live videos or chat, or through information disseminated via a computer). In each of these instructional situations, communication between the instructor and the students is key in the learning process. While patterns develop for communication between the instructor and students, additional patterns of communication also develop for communication between student to student within the context of the academic course. Conole et al. (2008) remark about the extent to which students are now capitalizing on the social affordances of technology to communicate and build peer support. Students will have some opportunity to choose how to interact and communicate, but it may be also be dictated to them by the instructor for course purposes.

4.2.2.1 Academic Situations

Recent technological developments provide students with a rich variety of alternatives for interaction and communication in relation to learning and a flexibility of use which enables them to take control of their learning (Conole et al. 2008). However, the purpose of the communication may impact the preferred method of communicating. When examining communication preferences of students involved in massive open online courses (MOOCs), Zhang et al. (2016) found students overwhelmingly preferred asynchronous text-based posts (45%) to text-based chats which were synchronous (38%) or video- and audio-based conversations (15%). Chang et al. (2015) additionally sought to understand student preferences related to instructor communication in online courses in light of new technological developments. They found 97% of their study participants preferred communication through email and secondly (77%) through a course learning management system. These studies demonstrate students preferred communication in computer-mediated courses to be more distant, and they especially valued communication with the instructor the most. However, these studies reflect investigation involving online course delivery. There seems to be a lack of such investigation for blended and traditional course formats.

4.2.2.2 Nonacademic Situations

After completing a systematic review of communication technology, Hessel and Dworkin (2017) note research gaps in the manner in which emerging adults communicate. However, there is no argument or lack of evidence that today's college student is operating in a fast-paced, media-saturated environment with unlimited options for communication. Research conducted by Chang et al. (2015) revealed that many collegiate students do communicate frequently via social media but more frequently check email. Regardless of the mode, one outstanding finding concerning college students is that staying connected is central (Robinson and Stubberud 2012). Mobile devices are a key part of that connection; however, the mode for the communication may vary (e.g., texting, messaging, talking, chat, social networking, emailing). Communication methods have now been found to be influenced by immediacy and mobility (Baskin and Barker 2004; Robinson 2011) with the most preference given to modes where communication can be accomplished quickly. Despite being in a technologically rich environment, when surveyed, researchers report many college students indicate a preference for face-to-face communication especially involving personal relationships (Morreale et al. 2015).

4.2.3 Theory for Communication Preferences and Choices

The construction of communication preferences and communication choices can be viewed from several theoretical lenses. According to Hoeffler and Ariely (1999), two aspects of experience impact preferences – their intensiveness and extensiveness. As college students have an increased amount and breadth of experience with any given mode of communication, they will naturally have a propensity to prefer that mode. However, Glasser (1999) contends that our behavioral choices are based upon meeting certain needs (power, love and belonging, freedom, fun, and survival). In this sense, students will choose to communicate in manners that will accomplish what they need given that particular situation. Often times this looks differently in academic and nonacademic situations because the purpose for the communication differs. Learning is often socially mediated (Vygotsky et al. 1980). Communication is a key part of social interactions and occurs within multiple cultural contexts. Communication is additionally influenced by opportunities afforded by choice (Glasser 1999) such as a technological tool. Individuals can then choose how they communicate in any given situation. In summary, preferences for communication will be chosen because they align with a particular purpose within a

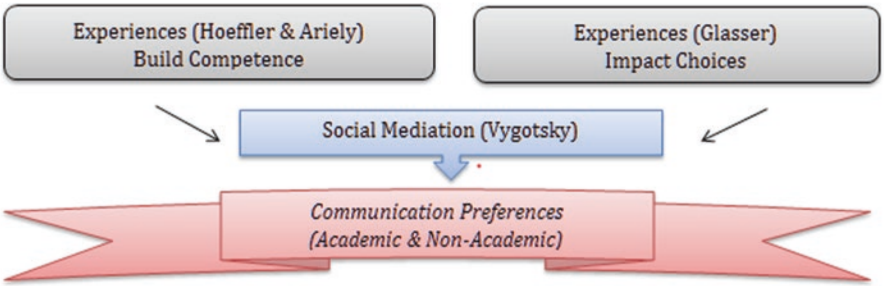


Fig. 4.1 Theoretical lenses for communication preferences

given context and will be based upon experiences and needs, as well as involve social mediation (Fig. 4.1).

The purpose of this study is to better understand the communication-related preferences of collegiate students and how those preferences and use patterns are affected by student interactions with technological tools. The importance of this understanding of student communication is to then provide awareness to educators of preferred and enhanced communication and learning opportunities. The following research questions guided this study:

1. What are the patterns of preferred communication for college students?
2. Do the technological preferences of college students affect their communication preferences and practices?

4.3 Method

This study was descriptive comparative and utilized survey methodology in which a sampling of the college student population in the United States was gathered through a cross-sectional design (Shaughnessy et al. 2011) to study the prevalence of college student communication patterns and preferences. This chapter is part of a larger study that expanded upon previous work comparing college students' academic and nonacademic technology use (Swanson and Walker 2015). The study follows survey methodology suggestions of Busha and Harter (1980) seeking representative samples of collegiate experiences but also had the goal of increased demographic data enhancing comparative analysis.

4.3.1 Participants

Participants in this study included a cross section of college students (N = 1986) from four coeducational institutions in the northeastern, southeastern, southwestern, and northwestern regions of the United States (Table 4.1). One of the institutions

Table 4.1 Comparison of survey respondents' enrollment by percent

Institution	Gender		International	Emer. adult	Coursework			
	M	F			Traditional	Blended	Online	Other
A – private	25.5	72.8	[a]	100	99	1	0	0
B – public	21.1	75.7	2[b]	74	73.9	30.9	14.1	5.9
C – private	40.7	58.7	2[b]	22	31.5	40.4	35.4	0.6
D – public	32.2	65.7	5[b]	48	48.4	28.7	31.9	4.8
Total	31	65	≥9	53	63.2	25.3	81.4	2.8

Note: [a]Citizenship was not asked for at this institution
[b]Estimate as some preferred not to answer this

was a private college only serving undergraduates with the other three institutions enrolling students in undergraduate through doctoral programs. Of the latter three institutions, one was private and the other two public. Males in this study represented 31% of the total participants, while females made up 65%, and another 4% indicated other or preferred not to answer. The participant age range in years varied from students under 18 years (1%), 18–26 years (53%) to over 27 years (44%), and an additional 2% preferred not to answer. While most traditional undergraduate institutions target emerging adults who are considered to be 18–26 years of age, many institutions serve students well beyond the defined emerging adult age range.

The cultural and ethnic diversity of these participants was broadly composed of African American (8%), Asian (5%), European American (68%), Hispanic (11%), American Indian/Alaskan Native (8%), other (4%), and 6% preferring not to answer. Students reported citizenship representing 40 difference countries; however, 89% were from the United States, 3% international, 2% of dual citizenship, and 5% preferring not to answer. Lastly, students identified 33 languages as their first language, in addition to English, but 54 students, 3% of the total respondents, did not choose to share their first language.

4.3.2 Survey

The data collection instrument for this project was a self-report, anonymous Internet survey administered using Survey Monkey (Survey Monkey 1999) following approval of Internal Review Boards from all four institutions. Email invitations to participate in the survey were sent to students at all four institutions with a 9% return, providing a yield of 1986 participants. The survey was comprised of 21 questions which sought both demographic information about the students and their technological preferences and use patterns. Students were asked to indicate time spent using technological devices and for what purpose. They were also asked specifically to rank their preferences for academic and nonacademic communication. The format of these questions included check-off boxes, ranking for Likert-type scale responses, and open-ended response boxes.

4.4 Results

Based upon the survey results of a cross-sectional sample of college students in the United States, the following research questions were addressed regarding communication preferences and patterns. A more precise analysis was achieved by collecting data about communication preferences separately from technological tool use. These are related but different points of analysis.

4.4.1 What Are the Patterns of Preferred Communication for College Students?

The survey results indicated that collegiate students preferred the following technological devices: the mobile/cell phone, the personal computer, an institutional computer, and an iPad/tablet (Fig. 4.2). The use of these devices was then broken down into segments and analyzed for frequency of use: daily, weekly, and never used. Additionally, presentation and storage or sharing tools were used almost exclusively for academics. YouTube, online news, and TED talks were frequently used both academically and nonacademically. Social media, blogs, Google Maps, and games were utilized mostly for nonacademic purposes.

One factor that impacts both academic and nonacademic-related communication is the comfort level students have using technology. When experiences increase in breadth with a particular technological tool, their comfort level and competence are likely to increase. The more students use a tool, which meets a particular need, the more likely they are to utilize that same tool for other purposes. For example, they will be more likely to transfer communication skills utilizing particular technology for both nonacademic and academic situations. Students completing the survey reported up to 75% of nonacademic time involved technology, and their technology

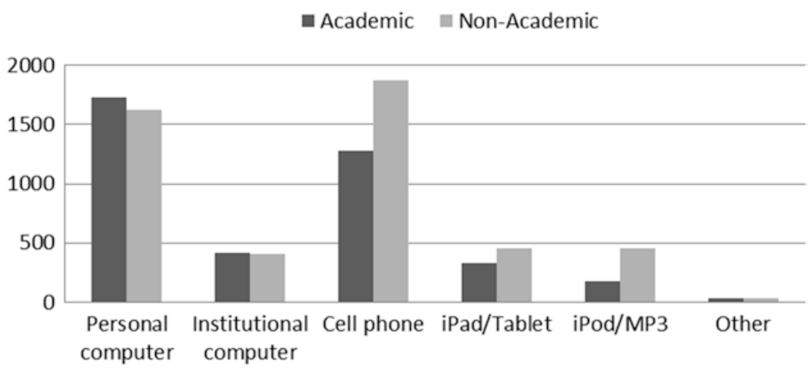


Fig. 4.2 Preferred technological tools by collegiate students

use for academic purposes ranged from 50 to 100% of their time. These students claim at least 50% of their current academic work is connected to technology in some way.

4.4.2 Do the Technological Preferences of College Students Affect Their Communication Preferences and Practices?

Academic and nonacademic communication preferences patterns in college students can first be understood by analyzing the modes of communication most frequently utilized by this population. Individuals in this study who rated traditional landline phone use high for academic communication were 64% more likely to rate landline use high for nonacademic communication, 40% less likely to refrain from texting for nonacademic communication, 25% less likely to use social media for academic communication, 15% less likely to use social media personally, and 24% more likely to use postal communication. The use of a traditional landline phone likely reflects the varied demographic of the ages of today's college students. Increased numbers of students are beyond the traditional 18–21 years of age demographic and may have experiences with technologies rarely used today (i.e., landline phones).

Most participants in this study indicated daily use of a personal computer as well as a mobile phone for both academic and nonacademic use. A large number of students report using institutional-owned computers on a weekly basis for academic use, while half of the respondents never reported using an iPad or tablet. Communication involving a computer or mobile phone would then be supported most naturally as a communication preference for either academic or nonacademic use because of the depth and breadth that comes from using that tool daily, and it can serve to fulfill both academic and nonacademic needs. Communication then utilizing these devices supports email as the most preferred academic mode of communication, likely because it can be accessed with these commonly owned devices.

However, as indicated in the survey results, students across all four institutions and regions of the United States highly prefer in-person communication for both academic and nonacademic purposes (Fig. 4.3). This supports findings from previous research indicating preference for in-person communication for complex, formal and personal messages (Lightfoot 2009). It should be noted, however, that student preferences do not always reflect their practices, which was also noted in a similar study by Robinson and Stubberud (2012). The collegiate student demographics did have some additional impact on communication choices. For example, emerging adults were 13.8% less likely to want to use a landline for communicating academic purposes. Modes of communication involving the digital technology may be assumed to be preferred or favored by digital natives, yet, emerging adults who were 18–25 years of age, had a positive correlation with preference for in-person communication $r(1893) = 0.227$, $p < 0.01$, $R^2 = 0.052$.

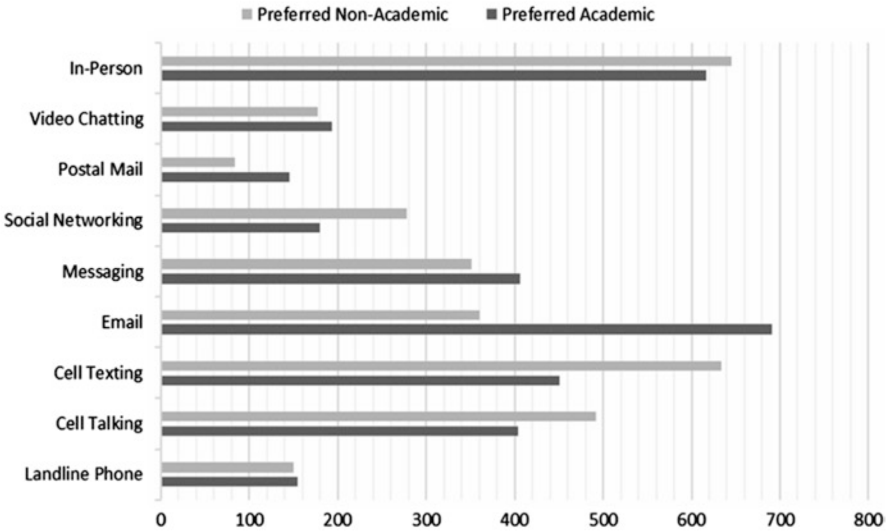


Fig. 4.3 Most frequently used collegiate communication disaggregated by academic and nonacademic purposes

4.5 Discussion and Conclusion

These results support previous work which found that collegiate students prefer face-to-face communication in most situations (Morreale et al. 2015). However, most college students heavily use technological tools to communicate. For example, academic communication is most preferred via email (Fig. 4.3), followed by cell texting and messaging. Although many campuses are using Facebook, Twitter, and other modes of social media, these are not as highly preferred modes to receive message for academic purposes. The communication modes involving email, texting, talking, messaging, and social networking can all be accomplished via a mobile phone and often personal computer if it is a laptop, which allows for mobility. This explains why the computer, personal and institutional, ranked in the top three for most used technological devices. Another important aspect of these favored communication modes is that they allow for information sharing but also are able to solicit feedback, an aspect noted as very important for effective communication (Boyer 2016).

The purpose of this study was to investigate college student communication preferences, and one significant and unexpected finding relates to the hesitancy of students in sharing information that communicates ethnicity and country of origin. This finding may reflect a hesitancy to communicate for fear of repercussions surrounding the current political state in the United States relating to immigration. This finding reinforces the sociocultural role in interactions impacting student communication preferences and the role that the purpose for such communication may hold. A potential way to clarify communications may be to setup systems in which differing types of communication, which have differing purposes, are consistently disseminated by particular mediums. For example, it would be useful for colleges and universities to establish their own app or website from which core communications would emanate. The next level down could involve emails and text messages to both groups and individuals for general housekeeping communications (announcements, reminders about assignments, sending brief updates, etc.). Additionally, videos could be created for tutorials, explanations, etc. and accessed via emails or texts.

With the understanding of how heavily mobile phones and mobile devices are being utilized by college students, it makes sense to consider more innovative ways to communicate and instruct using these tools. Instructors can help establish communication patterns that fit the flow of the technological use patterns of their students. However, it also makes sense to establish an understanding that there are preferred types of communication associated with such tools in which some academic activities are less productive when using mobile devices.

The reported lack of innovative academic uses of varied technological resources may relate to collegiate instructor's lack of incorporation of such technology into their courses. Similarly, students may not indicate a preference for certain tools or modes of communication in academic realms simply because of not having experienced the use of such tools for academic communication.

Students across all four institutions and regions of the United States who participated in this survey overwhelmingly indicated a preference for face-to-face communication. While there are some advantages of electronic communication, such as being able to correspond from a distance, and the communication being immediate, accessible, and affordable, there are also communicative disadvantages such as missing face-to-face cues like body language and voice tone (Carter and Werts 2015).

Many factors need to be considered when choosing communication modes involving college students. Traditional educational settings, where students and instructors are face to face, are not always feasible or optimal. However, because of technological developments, there are alternatives and possibilities involving bringing face-to-face types of experiences to academic communication. Students and instructors can communicate via a screen and still view the other person they are speaking with. This can be accomplished by web conferencing types of communication or even using applications that provide face time with a mobile device. Understanding the importance of this type of communication to learners should influence how courses, including online courses, incorporate elements where face-to-face conversation can occur.

Understanding that communication is an essential, socially mediated process for collegiate students should provide the impetus for instructors to seek to explore and understand communication preferences within the context of academic and nonacademic realms. Students indicate daily and weekly use for online resources yet still highly value face-to-face communication. Technology is here to stay and is continuously evolving. Educators and researchers need to value the importance of accessing and disseminating information yet understand the significance and role of in-person communications. Additionally, educators need to choose modes of communication with students and technology that best meets the educational skills, competencies, and needs of their student's preferences for both academic and non-academic communications will be impacted by those students' breadth of experience, the competence they have built with particular modes of communication, and additionally the purposes for specific communications. Student communication preferences will continue to develop thus making continued investigation significant.

Even though there is a cross section of varied participants geographically, one limitation for this current study is the methodology. The particular methodology used in this study limits the ability to generalize the findings to the entire population of college students as the participants were not randomly selected nor was there a depth of international representation. Future investigations of collegiate communication might be enhanced by additionally utilizing a mixed method design that includes interviews which would provide more in-depth information. Further research may seek an even more diverse population by expanding the participant pool to include international representation from colleges across the globe. Lastly, future communication studies should reflect technological advancements.

References

Baskin, C., & Barker, M. (2004). Scoping social presence and social context cues to support knowledge construction in an ICT rich environment. *Proceedings of 2004 AARE conference*. Melbourne, VIC, Australia. Retrieved from http://www.aare.edu.au/04pap/bas04434.pdf

Boyer, R. K. (2016). Achieving a culture of communication on campus. *The Chronicle of Higher Education*. Retrieved from https://www.chronicle.com/article/Achieving-a-Culture-of/237120

Busha, C. H., & Harter, S. P. (1980). *Research methods in librarianship: Techniques and interpretation*. Orlando: Academic Press.

Carter, L. C., & Werts, N. (2015). Intimacy in the electronic age. *Journal of Health Education Teaching Techniques, 2*(1), 16–24.

Cassidy, E. D., Britsch, J., Griffin, G., Manolovitz, T., Shen, L., & Turney, L. (2011). Higher education and emerging technologies: Student usage, preferences, and lessons for library services. *Reference & User Services Quarterly, 50*(4), 380–391.

Cassidy, E. D., Colmenares, A., Jones, G., Manolovitz, T., Shen, L., & Vieira, S. (2014). Higher education and emerging technologies: Shifting trends in student usage. *The Journal of Academic Librarianship, 40*, 124–133. https://doi.org/10.1080/03634523.2014.978799.

Chang, C., Hurst, B., & McLean, A. (2015). You've got mail: Student preferences of instructor communication in online courses in an age of advancing technologies. *Journal of Educational Technology Development and Exchange, 8*(1), 39–37. https://doi.org/10.18785/jetde.0801.03.

Conole, G., DeLaat, M., Dillon, T., & Darby, J. (2008). 'Disruptive technologies', 'pedagogical innovation': What's new? Findings from an in-depth study of students' use and perception of technology. *Computers & Education, 50*, 511–524.

Duffin, E. (2019). *Undergraduate enrollment in U.S. colleges and universities from 2007/2008 to 2017/2018 (in millions)*. Statista. Retrieved from https://www.statista.com/statistics/235406/undergraduate-enrollment-in-us-universities/

Farber, B. A., Shafron, G., Hamadani, J., Wald, E., & Nitzburg, G. (2012). Children, technology, problems, and preferences. *Journal of Clinical Psychology: In Session, 68*(11), 1225–1229.

Glasser, W. (1999). *Choice theory: A new psychology of personal freedom*. New York: HarperPerennial.

Gutiérrez-Porlán, I., Román-García, M., & Sánchez-Vera, M. (2018). Strategies for the communication and collaborative online work by university students. *Comunicar: Media Research Journal, 26*(54), 91–99. https://doi.org/10.3916/C54-2018-09.

Hessel, H., & Dworkin, J. (2017). Emerging adults' use of communication technology with family members: A systematic review. *Adolescent Research Review*. https://doi.org/10.1007/s40894-017-0064-1.

Hoeffler, S., & Ariely, D. (1999). Constructing stable preferences: A look into dimensions of experience and their impact on preference stability. *Journal of Consumer Psychology, 8*(2), 113–139. https://doi.org/10.1207/s15327663jcp0802_01.

Kvavik, R. B. (2005). Convenience, communications, and control: How students use technology. In D. Oblinger & J. Oblinger (Eds.), *Educating the net generation* (pp. 7.1–7.20). Educause. Retrieved from https://www.educause.edu/ir/library/PDF/pub7101.PDF

Levy-Warren, M. H. (2012). Press pause before send: A case in point. *Journal of Clinical Psychology: In Session, 68*(11), 1164–1174.

Lightfoot, J. M. (2009). Student communication preferences in a technology-enhanced learning environment. *International Journal of Instructional Media, 36*(1), 9–19.

Mangan, K. (2012). As students scatter online, colleges try to keep up. *The Chronicle of Higher Education*. Retrieved from: https://www.chronicle.com/article/Digitally-Savvy-Students-Play/134224

Morreale, S., Staley, C., Stavrositu, C., & Krakowiak, M. (2015). First-year college students' attitudes toward communication technologies and their perceptions of communication competence in the 21st century. *Communication Education, 64*(1), 107–131. https://doi.org/10.1080/03634523.2014.978799.

Munodawafa, D. (2008). Communication: Concepts, practice and challenges. *Health Education Research, 23*(1), 369–370. https://doi.org/10.1093/her/cyn024.

National Center for Education Statistics. (2017). Enrollment in elementary, secondary, and degree-granting postsecondary institutions, by level and control of institution, enrollment level, and attendance status and sex of student: Selected years, fall 1990 through fall 2026. *Digest of Education Statistics, Table 105.20.* Retrieved from https://nces.ed.gov/programs/digest/d16/tables/dt16_105.20.asp?current=yes

Oblinger, D., & Oblinger, J. (2005). Is it age or IT: First steps toward understanding the net generation. *Educating the net generation.* Educause. Retrieved from https://www.educause.edu/ir/library/PDF/pub7101.PDF

Perrin, A., & Duggan, M. (2015). *Americans' internet access: 2000–2015*. Pew Research Center. Retrieved from http://www.pewinternet.org/files/2015/06/2015-06-26_internet-usage-across-demographics-discover_FINAL.pdf

Pew Research Center. (2018). *Mobile fact sheet*. Retrieved from http://www.pewinternet.org/fact-sheet/mobile/

Prensky, M. (2001). Digital natives, digital immigrants. *On the Horizon, 9*(5), 1–6. https://doi.org/10.1108/10748120110424816.

Robinson, S. (2011). *MAT2R model*. Retrieved from https://blogs.psu.edu/mt4/mt.cgi?mode=view& type=entry&id=357413&blog id=l1032

Robinson, S., & Stubberud, H. A. (2012). Communication preferences among university students. *Academy of Educational Leadership Journal, 16*(2), 105–113. Retrieved from https://search.proquest.com/docview/1037692095?accountid=13894

Shaughnessy, J., Zechmeister, E. B., & Zechmeister, J. S. (2011). *Research methods in psychology* (9th ed., pp. 161–175). New York: McGraw Hill.

Survey Monkey Inc. (1999). Retrieved from www.surveymonkey.com

Swanson, J. A., & Walker, E. (2015). Academic versus non-academic emerging adult college student technology use. *Technology, Knowledge, and Learning, 20*(2), 147–158.

Vygotsky, L. S., Cole, M., John-Steiner, V., Scribner, S., & Souberman, E. (1980). *Mind in society: Development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Waycott, J., Bennett, S., Kennedy, G., Dalgarno, B., & Gray, K. (2010). Digital divides? Student and staff perceptions of information and communication technologies. *Computers & Education, 54*(4), 1202–2011.

White, D., & Le-Cornu, A. (2011). Visitors and residents: A new typology for online engagement. *First Monday, 16*(9). https://doi.org/10.5210/fm.v16i9.3171.

Zhang, Q., Peck, K. L., Hristova, A., Jablokow, K. W., Hoffman, V., & Park, E. (2016). Exploring the communication preferences of MOOC learners and the value of preference-based groups: Is grouping enough? *Educational Technology Research & Development, 64*(4), 809–837.

Part II
Learning Analytics in Online Higher Education

Chapter 5
Attributes of Engagement in Challenge-Based Digital Learning Environments

Dirk Ifenthaler, David Gibson, and Longwei Zheng

5.1 Introduction

Learners differ in their reasons for engaging in learning tasks, and these inter-individual differences require personalised support while learning (Schunk and Zimmerman 1994). In addition, research also reports intra-individual differences in engagement, i.e. during a learning-dependent progression, engagement changes over time and requires adaptive support to cater for the learners' needs (Ifenthaler and Seel 2005).

Learning engagement is generally regarded as the time and effort an individual invests on a specific learning activity (Kuh 2009). Several studies focussing on learning engagement support the assumption that higher engagement of a learner corresponds with higher learning outcomes (Carini 2012). However, most of these studies have been conducted in face-to-face learning environments. Accordingly, a confirmation of these findings in digital learning environments is still lacking.

This study seeks to close this gap by investigating the dynamics of learning engagement in a challenge-based digital learning environment using a data analytics approach. The context of the presented study is set in the Curtin Challenge which is a mobile-ready interactive learning delivery platform that illustrates several

D. Ifenthaler (✉)
Curtin University, Perth, WA, Australia

University of Mannheim, Mannheim, Germany
e-mail: dirk.ifenthaler@curtin.edu.au

D. Gibson
Curtin University, Perth, WA, Australia
e-mail: d.c.gibson@curtin.edu.au

L. Zheng
East China Normal University, Shanghai, China
e-mail: lwzheng@dec.ecnu.edu.cn

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*,
Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_5

features of game-inspired challenge-based learning while adding a layer of big data collection to enable research into teaching and learning. A learner interacts with Curtin Challenge content by pointing, clicking, sliding items, vocalising, taking pictures and drawing as well as watching, listening, reading and writing as in typical digital learning environments.

5.2 Learning Engagement

Learning engagement is a multidimensional concept and understood as the individual's ability to behaviourally, cognitively, emotionally and motivationally interact with learning artefacts in an on-going learning process (Wolters and Taylor 2012). A generally accepted assumption is that the more students engage with a subject matter or phenomenon in question, the more they tend to learn (Carini et al. 2006). This assumption is consistent with the theory of self-regulated learning (Zimmerman 2002) and concepts of engagement (Fredricks and McColskey 2012). Accordingly, learning engagement is positively linked to desirable learning outcomes or learning performance (Klein et al. 2005).

While learning performance is linked closely with behaviours (Bandura 1993), several assumptions are associated to the relationship between the performance of an individual and learning engagement. For example, Chen (2017) investigated the relationship between learning engagement and learning performance of students of ten schools based in Taiwan. Findings of the multilevel analysis indicate a significant positive relationship between learning engagement and learning performance. Recent findings also document that serious games drive learning engagement (Peng et al. 2017). Similar implications focussing on learning engagement and learning performance have been reported in other contexts (Flowerday and Shell 2015; Lin et al. 2016; Pourbarkhordari et al. 2016).

An impressive number of research studies have been conducted in the field of cognitive load with links to task characteristics and learning engagement (Kirschner et al. 2011; van Merriënboer and Sweller 2005). This line of research assumes an active role of the learner in learning processes, i.e. learners select tasks relevant to them (Corbalan et al. 2011) and are actively engaged while interacting with the learning environment (Schwamborn et al. 2011).

In addition, research on reading utilises reading time measurements in order to identify learning engagement and linking those to learning performance (Graesser et al. 1997). The general assumption is that the intensity of mental effort aimed at achieving a greater understanding, i.e. time spent on reading task, is critical during learning. Findings indicate that increased reading times as a sign of greater learning engagement are positively related to learning performance measured as comprehension scores (Miller 2015; Miller et al. 2014).

5.3 Challenge-Based Learning Environment

The Curtin Challenge platform (http://challenge.curtin.edu.au) is being developed to support both individual and team-based learning in primarily open-ended ill-structured problem-solving and project-based learning contexts (Eseryel et al. 2014). The platform can also support self-guided learning, automated feedback, branching story lines, self-organising teams and distributed processes of mentoring, learning support and assessment (Gibson 2018; Gibson and Ifenthaler 2018). The Curtin Challenge digital learning platform supports gamified, challenge-based, open-ended, inquiry-based learning experiences that integrate automated feedback and rubric-driven assessment capabilities. A challenge is regarded as a collection of information and corresponding tasks linked to specific learning outcomes. Currently, there are three *challenges* offered by Curtin University: *Careers Illuminate Challenge*, *Leadership Challenge* and *English Challenge* (see Fig. 5.1). This study includes analysis from the initial challenges available, Career and Leadership Challenges, which both require approximately up to 1 h of learning time. Career Challenge includes 14 modules, while Leadership Challenge includes 11 modules (see Fig. 5.2 for individual modules).

The design features of each module contain up to five activities including one to three different learner interactions or tasks. For example, the module *Who am I* in the Career Challenge is a collection of five activities containing learning interactions, such as choosing from among options; writing a short response to a prompt; spinning a wheel to create random prompts; creating, organising and listing ideas; or matching items. Each page can contain one or several such interactions, and the learner does not have to submit the page in order for the data to be captured.

Data is constantly being captured, which creates information about the timing, sequence and completeness as well as the content of the interactions (i.e. navigation event and sequences). The data record is thus highly granular, providing an opportunity to examine the dynamics of the activity as well as the contents of the artefacts created by the learner for every click on every activity or module page.

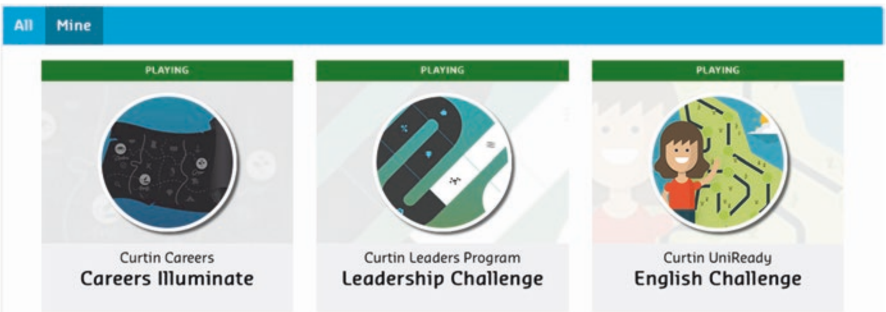


Fig. 5.1 Selection of available challenges

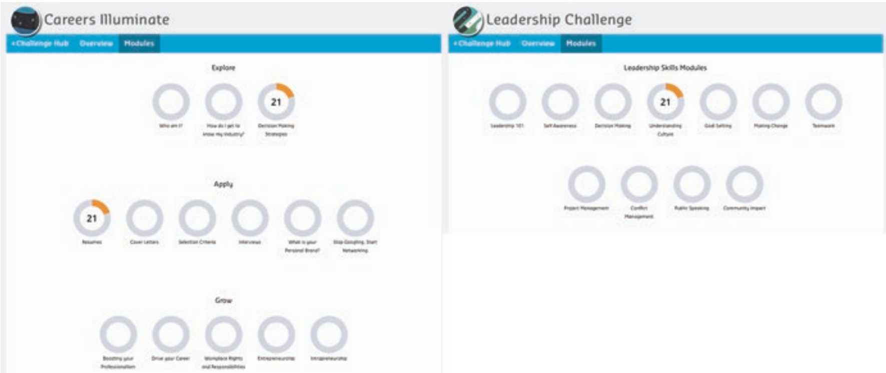


Fig. 5.2 Modules overview for Career and Leadership Challenges

5.4 The Present Study

In light of previous empirical findings on learning engagement (Chen 2017; Flowerday and Shell 2015; Kirschner et al. 2011; Miller 2015; Miller et al. 2014), we expect that learning engagement is positively related to learning performance in a challenge-based digital learning environment. Attributes of learning engagement in the challenge-based digital learning environment are conceptualised through several actions: (a) launching a specific activity (task), (b) spending active time on the task, (c) entering a written response and (d) finishing a task. The learning performance measured in this study is computed by the number of correct answers in a subset of tasks designed with embedded feedback to the student. The hypotheses of this study focus on the attributes of learning engagement and its relation to learning performance in both Career and Leadership Challenges. We assume that launching specific activities (tasks) is related to the learning performance in challenge-based digital learning environments (Hypothesis 1). Further, we assume that spending active time on tasks is related to the learning performance (Hypotheses 2). Also, we expect that the length of written responses is related to the learning performance (Hypothesis 3). The final assumption focusses on the relationship between finishing tasks and learning performance (Hypothesis 4).

5.5 Method

5.5.1 Data Source

The data set of the Career Challenge consists of 52,675,225 rows of raw data containing information of $N_C = 8951$ students (3571 male; 5380 female) with an average age of $M = 25.72$ years ($SD = 6.64$). The Leadership Challenge includes data from N_L = 4704 students (1825 male; 2879 female) with an average age of $M = 23.96$ years ($SD = 5.47$) with information stored in 19,517,647 rows of raw data. In a period of 24 months (January 2016–January 2018), students spent a total of 10,239 h interacting with the Career Challenge and 14,546 h interacting with the Leadership Challenge.

5.5.2 *Data Analytics Strategy*

Raw data from the Career and Leadership Challenge were cleaned and transformed into a transaction data set in which each row represents an event of one user. The dependent variable *learning_performance* (LP) was computed as the number of correct answers in an activity. The variables reflecting attributes of learning engagement were computed as follows: *launching_task* (LT) as the number of activities started by a student; *time_on_task* (TT) as the duration in seconds spent in an activity; *written_response* (WR) as the number of words submitted by a student; *finishing_task* (FT) as the number of activities finished by a student.

5.6 Results

In order to test the above presented four hypotheses, regression analyses were computed to determine whether attributes of learning engagement (i.e. launching task, time on task, written response, finishing task) were significant predictors of learning performance in challenge-based digital learning environments. The analyses were computed separately for the Career and Leadership Challenge.

5.6.1 *Career Challenge*

Table 5.1 shows zero-order correlations of attributes of learning engagement and learning performance for the Career Challenge. All correlations were significant at $p < 0.001$. High positive correlations were found between launching task (LT; $M = 6.73$; $SD = 8.95$) and learning outcome (LP; $M = 8.38$; $SD = 13.19$), time on task (TT; $M = 4118.09$; $SD = 6623.88$) and written response (WR; $M = 166.92$; $SD = 284.62$). Moderate positive correlations were found for written response and learning outcome as well as time on task. Low positive correlations were found for the remaining variable combinations.

The linear regression analysis for the Career Challenge is presented in Table 5.2, yielding a ΔR^2 of 0.713 ($F(4, 8950) = 5568.79$, $p < 0.001$). Clearly, the number of activities started by a student (LT; $\beta = 0.80$, $p < 0.001$) positively predicted the learning performance. In addition, the number of activities finished by a student

Table 5.1 Zero-order correlations, means and standard deviations of attributes of learning engagement and learning performance for the Career Challenge

	Zero-order *r*				
	LT	TT	WR	FT	LP
LT	–				
TT	0.771***	–			
WR	0.724***	0.685***	–		
FT	0.355***	0.290***	0.331***	–	
LP	0.839***	0.628***	0.660***	0.340***	–
M	6.73	4118.09	166.92	1.24	8.38
SD	8.95	6623.88	284.62	4.40	13.19

Note: ***$p < 0.001$; *LP* learning outcome, *LT* launching task, *TT* time on task, *WR* written response, *FT* finishing task; $N_C = 8951$

Table 5.2 Regression analyses predicting learning performance by attributes of learning engagement for the Career Challenge

	R^2	ΔR^2	*B*	*SE B*	β
LP	0.713	0.713			
LT			1.177	0.015	0.80***
TT			0.001	0.001	−0.09***
FT			0.115	0.018	0.04***
WR			0.006	0.001	0.13***

Note: ***$p < 0.001$; *LP* learning performance, *LT* launching task, *TT* time on task, *FT* finishing task, *WR* written response; $N_C = 8951$

(FT; $\beta = 0.04$, $p < 0.001$) and the number of words submitted by a student (WR; $\beta = 0.13$, $p < 0.001$) positively predicted the learning performance. In contrast, the duration students spent on a task (TT; $\beta = -0.09$, $p < 0.001$) was negatively correlated with the learning performance.

In sum, the four hypotheses are accepted for the Career Challenge, confirming significant relationships between attributes of learning engagement and learning performance.

5.6.2 Leadership Challenge

Table 5.3 shows zero-order correlations of attributes of learning engagement and learning performance for the Leadership Challenge.

The linear regression analysis for the Leadership Challenge is presented in Table 5.4, yielding a ΔR^2 of 0.850 ($F(4, 4703) = 6652.32$, $p < 0.001$). The number of activities started by a student (LT; $\beta = 1.50$, $p < 0.001$) positively predicted the learning performance. In addition, the duration students spent on a task (TT; $\beta = 0.05$, $p < 0.001$) positively predicted the learning performance. In contrast, the

Table 5.3 Zero-order correlations, means and standard deviations of attributes of learning engagement and learning performance for the Leadership Challenge

	Zero-order r				
	LT	TT	WR	FT	LP
LT	–				
TT	0.698***	–			
WR	0.759***	0.789***	–		
FT	1.00***	0.697***	0.759***	–	
LP	0.901***	0.667***	0.711***	0.921***	–
M	26.74	11132.30	661.78	26.52	10.76
SD	22.97	14535.29	782.97	23.05	11.96

Note: ***p < 0.001; *LP* learning outcome, *LT* launching task, *TT* time on task, *WR* written response, *FT* finishing task; $N_L = 4704$

Table 5.4 Regression analyses predicting learning performance by attributes of learning engagement for the Leadership Challenge

	R^2	ΔR^2	*B*	*SE B*	β
LP	0.850	0.850			
LT			0.782	0.127	1.50***
TT			0.038	0.000	0.05***
FT			−0.318	0.129	−0.61*
WR			0.001	0.000	0.00

Note: *p < 0.05; ***p < 0.001; *LP* learning performance, *LT* launching task, *TT* time on task, *FT* finishing task, *WR* written response; $N_L = 4704$

number of activities finished by a student (FT; $\beta = -0.61$, $p < 0.05$) was negatively correlated with the learning performance.

In sum, the hypotheses 1, 2 and 4 are accepted for the Leadership Challenge, confirming significant relationships between attributes of learning engagement and learning performance.

5.7 Discussion

The times of direct comparisons of technology-mediated and face-to-face learning environments are over (Alavi and Leidner 2001); hence, research needs to identify key factors influencing learning processes and learning outcomes. This study aimed to investigate the dynamics of engagement in challenge-based digital learning environments and its relationship to learning performance. Hypotheses were developed based on previous research from face-to-face learning environments. Our analyses focussed on data from the challenge platform including transaction data from 13,655 students.

The analytic results showed that learning engagement in challenge-based digital learning environments is significantly related to learning performance. These findings support previous studies conducted in face-to-face situations (Chen 2017; Lin et al. 2016; Pourbarkhordari et al. 2016). Significant attributes predicting the learning performance of the student appeared to be the number of activities started and the number of activities finished by a student. This is a reflection of active engagement with the learning environment (Kirschner et al. 2011). At the same time, better learners seem to spend less time on a specific task in the Career Challenge. This may be interpreted as a reflection of existing prior knowledge or a progression towards an advanced learner (Ifenthaler and Seel 2005). Another significant indicator predicting learning performance in the Career Challenge was the number of words submitted in open text activities. On a surface level, these findings are also related to studies conducted in writing research and clearly reflect the impact of the variation in learning engagement (Graesser et al. 1997; Miller et al. 2014).

This study and its findings are limited in several aspects that must be addressed. First, due to limited access of student data, for example, course load, past academic performance, or personal characteristics, linking additional data to the reported engagement and performance measures has not yet occurred. Combining such additional data, we expect to provide a more detailed insight into the multidimensional concepts to be investigated in a future study. Second, both challenges did not include an overall performance measure which has been validated against an outside criterion. Accordingly, a revision of the learning and assessment design should include additional or revised measures which follow accepted criteria or competence indicators. However, without the externally validated benchmarks, there is sufficient available data which can be used to improve the existing learning design through algorithms focussing on design features and navigation sequences of learners (Agrawal et al. 2016; Ifenthaler et al. 2018; Lockyer et al. 2013). Third, as we included the analysis of open text answers in our analysis model, this approach is limited by the overall potential of the simple approach natural language processing (NLP). Further development of our analysis in future studies will include a focus on deeper levels of syntactic complexity, lexical sophistication and quality of writing as well as a deep semantic analysis compared to expert solutions (Crossley 2013; Ifenthaler 2014).

5.8 Implications and Future Research

Analyses of the learning performance transcript, even when automated and multi-leveled, are a mixture of *conditional and inferential interpretation* that can utilise several frames of reference while adding layers of interpreted evidence, insights concerning the complexity and additional dimensionality to our understanding of the performance and our ability to represent the performance in the light of our understandings (Gibson and Ifenthaler 2018).

The data traces captured by the Curtin Challenge platform are highly detailed, with many events per learning activity, which brings the potential for measuring indicators of physical, emotional and cognitive states of the learner. The data innovation of the Curtin Challenge platform is the ability to capture event-based records of higher frequency with the potential to analyse higher-dimensional aspects of learning engagement, which we believe may be in turn useful for analysis of the embedded learning design's effectiveness and impact on the physical, emotional and cognitive layers of learning caused or influenced by digital engagements. The data from the challenge-based learning platform forms a high-resolution analytics base on which researchers can conduct studies into learning design and into how to achieve better outcomes in scalable digital learning experiences (Gibson 2018; Gibson and Jackl 2015).

Future research will focus on the analysis of several large extent data sets from the Curtin Challenge platform. Currently, the possibility of adaptive algorithms based on learning engagement and learning performance is being investigated. Such algorithms will enable meaningful micro-analysis of individual performance as well as personalised and adaptive feedback to the learner whenever it is needed.

Acknowledgement This work is part of the UNESCO Chair of Data Science in Higher Education Learning and Teaching (http://www.curtin.edu.au/UNESCO) which focusses on advancing global knowledge, practice and policy in applying data science to transform higher education learning and teaching that improves personalisation, access and effectiveness of education for all.

References

Agrawal, R., Golshan, B., & Papalexakis, E. (2016). Toward data-driven design of educational courses: A feasibility study. *Journal of Educational Data Mining, 8*(1), 1–21.

Alavi, A., & Leidner, D. E. (2001). Research commentary: Technology-mediated learning—A call for greater depth and breadth of research. *Information Systems Research, 12*(1), 1–10.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*(2), 117–148. https://doi.org/10.1207/s15326985ep2802_3.

Carini, R. M. (2012). Engagement in learning. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning* (pp. 1153–1156). Boston: Springer.

Carini, R. M., Kuh, G. D., & Klein, S. P. (2006). Student engagement and student learning: Testing the linkages. *Research in Higher Education, 47*(1), 1–32. https://doi.org/10.1007/s11162-005-8150-9.

Chen, I.-S. (2017). Computer self-efficacy, learning performance, and the mediating role of learning engagement. *Computers in Human Behavior, 72*, 362–370. https://doi.org/10.1016/j.chb.2017.02.059.

Corbalan, G., Kester, L., & van Merriënboer, J. J. G. (2011). Learner-controlled selection of tasks with different surface and structural features: Effects on transfer and efficiency. *Computers in Human Behavior, 27*, 76–81. https://doi.org/10.1016/j.chb.2010.05.026.

Crossley, S. A. (2013). Advancing research in second language writing through computational tools and machine learning techniques. *Language Teaching, 46*(2), 256–271.

Eseryel, D., Law, V., Ifenthaler, D., Ge, X., & Miller, R. B. (2014). An investigation of the interrelationships between motivation, engagement, and complex problem solving in game-based learning. *Journal of Educational Technology & Society, 17*(1), 42–53.

Flowerday, T., & Shell, D. F. (2015). Disentangling the effects of interest and choice on learning, engagement, and attitude. *Learning and Individual Differences, 40*, 134–140. https://doi.org/10.1016/j.lindif.2015.05.003.

Fredricks, J. A., & McColskey, W. (2012). The measurement of student engagement: A comparative analysis of various methods and student self-report instruments. In S. I. Christenson, A. L. Reschly, & W. C. (Eds.), *Handbook of research on student engagement* (pp. 763–781). New York: Springer.

Gibson, D. C. (2018). Unobtrusive observation of team learning attributes in digital learning. *Frontiers in Psychology, 9*(834), 1–5. https://doi.org/10.3389/fpsyg.2018.00834.

Gibson, D. C., & Ifenthaler, D. (2018). Analysing performance in authentic digital scenarios. In T.-W. Chang, R. Huang, & Kinshuk (Eds.), Authentic learning through advances in technologies (pp. 17–27). New York: Springer.

Gibson, D. C., & Jackl, P. (2015). Theoretical considerations for game-based e-learning analytics. In T. Reiners & L. Wood (Eds.), *Gamification in education and business* (pp. 403–416). New York: Springer.

Graesser, A. C., Millis, K. K., & Zwaan, R. A. (1997). Discourse comprehension. *Annual Review of Psychology, 48*, 163–189. https://doi.org/10.1146/annurev.psych.48.1.163.

Ifenthaler, D. (2014). AKOVIA: Automated knowledge visualization and assessment. *Technology, Knowledge and Learning, 19*(1–2), 241–248. https://doi.org/10.1007/s10758-014-9224-6.

Ifenthaler, D., & Seel, N. M. (2005). The measurement of change: Learning-dependent progression of mental models. *Technology, Instruction, Cognition and Learning, 2*(4), 317–336.

Ifenthaler, D., Gibson, D. C., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology, 34*(2), 117–132. https://doi.org/10.14742/ajet.3767.

Kirschner, F., Kester, L., & Corbalan, G. (2011). Cognitive load theory and multimedia learning, task characteristics and learning engagement: The current state of the art. *Computers in Human Behavior, 27*(1), 1–4. https://doi.org/10.1016/j.chb.2010.05.003.

Klein, S. P., Kuh, G. D., Chun, M., Hamilton, L., & Shavelson, R. (2005). An approach to measuring cognitive outcomes across higher education institutions. *Research in Higher Education, 46*(3), 251–276. https://doi.org/10.1007/s11162-004-1640-3.

Kuh, G. D. (2009). What student affairs professionals need to know about student engagement. *Journal of College Student Development, 50*(6), 683–706. https://doi.org/10.1353/csd.0.0099.

Lin, W., Wang, L., Bamberger, P. A., Zhang, Q., Wang, H., Guo, W., et al. (2016). Leading future orientations for current effectiveness: The role of engagement and supervisor coaching in linking future work self salience to job performance. *Journal of Vocational Behavior, 92*, 145–156. https://doi.org/10.1016/j.jvb.2015.12.002.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439–1459. https://doi.org/10.1177/0002764213479367.

Miller, B. W. (2015). Using reading times and eye-movements to measure cognitive engagement. *Educational Psychologist, 50*(1), 31–42. https://doi.org/10.1080/00461520.2015.1004068.

Miller, B. W., Anderson, R. C., Morris, J., Lin, T. J., Jadallah, M., & Sun, J. (2014). The effects of reading to prepare for argumentative discussion on cognitive engagement and conceptual growth. *Learning and Instruction, 33*, 67–80. https://doi.org/10.1016/j.learninstruc.2014.04.003.

Peng, C., Cao, L., & Timalsena, S. (2017). Gamification of Apollo lunar exploration missions for learning engagement. *Entertainment Computing, 19*, 53–64. https://doi.org/10.1016/j.entcom.2016.12.001.

Pourbarkhordari, A., Zhou, E. H. I., & Pourkarimi, J. (2016). How individual-focused transformational leadership enhances its influence on job performance through employee work engagement. *International Journal of Business and Management, 11*(2), 249–261. https://doi.org/10.5539/ijbm.v11n2p249.

Schunk, D. H., & Zimmerman, B. J. (1994). *Self-regulation of learning and performance: Issues and educational applications*. Hillsdale: Erlbaum.

Schwamborn, A., Thillmann, H., Opfermann, M., & Leutner, D. (2011). Cognitive load and instructionally supported learning with provided and learner-generated visualizations. *Computers in Human Behavior, 27*, 89–93. https://doi.org/10.1016/j.chb.2010.05.028.

van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review, 17*(2), 147–177.

Wolters, C. A., & Taylor, D. J. (2012). A self-regulated learning perspective on student engagement. In S. Christenson, A. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 635–651). Boston: Springer.

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

Chapter 6
Implementation of Adaptive Learning Systems: Current State and Potential

Christof Imhof, Per Bergamin, and Stéphanie McGarrity

6.1 Introduction

Countless aspects of our lives have become increasingly digitalized in the past few decades, learning being no exception. In the wake of digitalization, new forms of learning have emerged such as distance learning or technology-based learning, which are increasingly gaining importance today (Bergamin et al. 2012). Due to their flexible nature, these new forms of learning allow learners more independence and autonomy than ever before. Moreover, they overcome space-time barriers, thus granting many people the opportunity to pursue academic studies in circumstances that usually prevent or at least hinder such ambitions, e.g. full- or part-time employment or parenthood. Such flexibility allows for the inclusion of personal needs and contexts, which can differ considerably between individual learners. In higher education, such characteristics might be prior knowledge, learning skills, experience in regard to certain topics, use of strategies or affective states. Even with these differences, learners are usually expected to develop the same competences throughout their studies.

One way to achieve these comparable learning outcomes despite heterogeneous preconditions is to continuously adapt the learning process to the needs of the learners. This and related concepts can be covered under the umbrella term *adaptive learning*. In contrast to other technology-based learning approaches, adaptive learning enables the presentation of learning resources (e.g. content, support or navigation) in a dynamic form. This mostly occurs as a reaction to collected and evaluated data which can change during the learning processes, e.g. due to learning progress. In essence, adaptive learning systems continuously identify what a learner does or does not understand and provide help accordingly until a certain learning goal is

C. Imhof (✉) · P. Bergamin · S. McGarrity
Swiss Distance University of Applied Sciences, Brig, Switzerland
e-mail: christof.imhof@ffhs.ch; per.bergamin@ffhs.ch; stephanie.mcgarrity@ffhs.ch

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*,
Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_6

met. This help can take different forms. One described by Oxman and Wong (2014) is the presentation of content situated just above the learner's current level in order to balance challenge and frustration. On this basis, adaptive learning has the potential to reduce dropout rates, lead to better learning outcomes and help students to achieve their learning goals faster. The notion of providing learners with assistance tailored towards their specific needs has a long history in pedagogy (e.g. in the form of one-to-one teacher support). However, technology-based adaptive learning systems provide forms of adaptivity beyond what can realistically be accomplished in traditional classroom settings in terms of resources or scale (cf. Koedinger et al. 2013).

The overall research problem addressed in this chapter is how the theoretical and conceptual foundation of an adaptive system needs to be specified in order for such a system to be implemented successfully in a university setting. This chapter aims to contribute the following to the discussion: We will first determine what it entails for a learning system to operate adaptively. In order to characterise the research in this area, we will then explore six basic questions in the design process of adaptive learning systems: why, what, what to, when, where and how a system can or should adapt (Brusilovsky 1996, 2001; Knutov 2012). We will also address the features and functions that are central to adaptive systems, followed by an overview over the current state of research in the area of adaptive learning. Practical implications and future potential of the research will also be discussed.

6.2 Definition of Adaptive Learning

Adaptive learning may be viewed from different theoretical and disciplinary perspectives, which is reflected in the definitions found in the literature. Depending on the perspective, the definitions may thus emphasise different elements. Jameson (2003), for example, approaches adaptivity from a computer science perspective and highlights the system's interactivity and its adaptation to different users based on user models (see below) as its core functionalities. He therefore defines a user-adaptive system as "an interactive system that adapts its behaviour to individual users on the basis of processes of user model acquisition and application that involve some form of learning, inference, or decision making" (p. 2). Interactivity and a focus on individual learners are elements also present in a more recent conceptualization by Aleven et al. (2017). In contrast to Jameson (2003), the authors argue from an educational point of view and further specify which kind of measure a system should base its adaptation upon. The authors identify three conditions a learning environment must meet in order to be considered adaptive. First off, its design needs to reflect topic-related challenges that learners often encounter. Secondly, the environment's pedagogical decision-making has to be based on psychological measures of individual learners (such as current knowledge, skills or affective states). Lastly, it is required to respond interactively to learner actions. All three of these aspects require data about learners, which are either pre-existing (condition 1) or collected and processed by the system (conditions 2 and 3).

In our view, these two definitions, although emphasising important learning-related components of adaptivity, do not explicitly address instructional aspects of adaptive learning. One element we deem crucial in this context is the monitoring of changes regarding the learners' progress. In our understanding, adaptive learning thus refers to technologies that monitor learning progress and repeatedly or continuously adapt the teaching process to the behaviours and needs of individual learners (see Adams Becker et al. 2018).

6.3 Core Components of Adaptive Learning Systems and Their Implementation

As indicated by the definitions of adaptive learning systems, there are certain elements that need to be accounted for when implementing such systems. Three core elements commonly found in adaptive learning systems, regardless of their degree of sophistication, are the domain model, the learner model and the adaptive model (cf. Vagale and Niedrite 2012). The *domain model* (also known as *content model* or *expert model*) refers to the content and structure of the topic to be taught, i.e. the relationships between the domain elements, and can address the intended learning outcomes as well as their sequence. The *learner model* (also known as *user model* or *student model*) is – as the name implies – a representation of the learner. The model consists of sensors and the learner modeller. The sensors capture and measure specific learner characteristics and pass the information to the learner modeller which then either uses the information as is (e.g. age, gender, prior knowledge) or further processes it (e.g. current knowledge, abilities, learning styles, motivational or emotional state). Depending on what characteristics the sensors measure, learner models can be either static or dynamic. While static models assess learner characteristics once, dynamic variants repeatedly measure and update them. In order for the learner model to be sound, the assessment of the learner characteristics (and the ensuing inferences) needs to be reliable and valid (see Shute and Towle 2003). The information from the sensors is in turn processed by the learner model and then further relayed to the *adaptive model* (also known as *adaptation model*, *instructional model*, *pedagogical model* or *tutoring model*). This model combines the processed information from the learner model with information from the domain model. The adaptive model can proceed to adapt content, instruction, or recommendations accordingly to support the learner in their progress. The model encompasses an instructional strategy that determines not only what can be adapted but also the context in which the adaptive process will occur.

Another way to look at adaptive learning systems is to focus on the design process. One way to characterise this process and its facets is by considering the six dimensions of the classic adaptive hypermedia approach (cf. Brusilovsky 1996): the

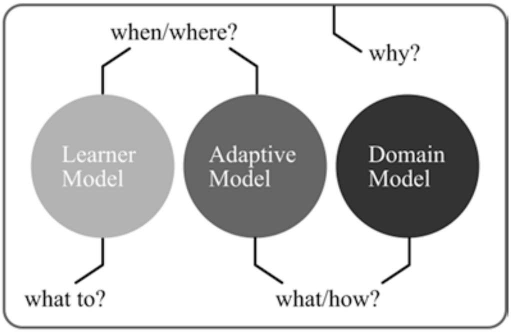


Fig. 6.1 Core components of adaptive learning systems and facets of the design process

goals, targets, sources, temporal contexts, situational contexts and methods/techniques of adaptation. These dimensions can be rephrased as the following six questions: *Why* is adaptation wanted? *What* can or should a system adapt? *What* can or should it adapt *to*? *Where* and *when* can it be applied? And *how* does the system adapt? These questions will be elaborated on in the following sections, starting with the *why* question. Due to similarities between them, some of the subsequent questions will be bundled, specifically the *when* and *where* questions that both concern the context of adaptation and the *what* and *how* questions which both address the adaptive model. The relation between the three core components and the six questions is illustrated in Fig. 6.1.

6.3.1 Why *Is Adaptation Wanted? The Reasons for and Goals of Adaptation*

The first didactic question for the development of adaptive learning objects or entire systems is why adaptation of learning to particular needs is even desired (Knutov 2012). On the one hand, it relates to the identification and fulfilment of user-related needs that require such methods and techniques in the first place (i.e. the goals of adaptation). Through adaptive learning, personal learning paths, assistance and advice, a variety of learning requirements can be met, which is difficult to achieve in traditional learning settings. For instance, uneven levels of prior knowledge between learners, which could lead to adverse effects (e.g. overwhelming inexperienced learners while simultaneously boring advanced learners), can be mitigated through adaptive instructional design. Another example is adaptive learning systems can support novices that require navigational help, e.g. by limiting the amount of alternatives or recommending relevant links (Brusilovsky 1996). On the other hand, this question concerns the course designers' motivation behind applying different adaptive methods and techniques (i.e. the reasons for adaptation). In principle, the *why* question thus concerns the pedagogical rationale underlying the implementation of adaptive systems (cf. Mavroudi et al. 2018). The pedagogical rationale itself can be derived from a variety of different basic theories, such as aptitude-treatment interactions, the zone of proximal development, fading scaffolds, the expertise reversal paradigm and self-regulated learning.

The concept of *aptitude-treatment interactions* (see Cronbach and Snow 1977) refers to the circumstance that instructional strategies (Cronbach and Snow refer to these as "treatments") are not equally successful for each individual learner and may instead depend on specific abilities of the learners that forecast their potential success – in other words, their *aptitude*. From this point of view, adaptive learning provides options to find optimal treatments to match individual learners' aptitudes. Another concept which adaptive learning can build on is the *zone of proximal development* (see Vygotsky 1978). The core idea of this concept is to give the learners tasks they are able to complete with guidance, as opposed to tasks they are able to do unaided or task they cannot complete even with guidance. As the learner progresses, this guidance can gradually be reduced (cf. the concept of *fading scaffolds*; Collins et al. 1988; van Merriënboer and Sluijsmans 2009). The importance of adapting the learning process to characteristics of the learner is further supported by the finding that instructional techniques (e.g. guidance by a tutor or detailed instructions) that benefit novices can lose their effectiveness or even be counterproductive to experts, a phenomenon known as the *expertise reversal effect* (Kalyuga et al. 2003).

In this context, "reversal" refers to the idea that the effectiveness of instructional techniques may be reversed for different levels of expertise, e.g. that instructions may help novices yet hinder experts (Lee and Kalyuga 2014). The expertise reversal effect is usually explained by the *Cognitive Load Theory* (Sweller 1988). The basis of the theory is the notion that the cognitive load, i.e. information that is currently stored and processed in the working memory, cannot exceed its limitations. While the long-term memory holds cognitive schemata with varying degrees of complexity within an unlimited storing capacity, the working memory is thought to be quite limited in its capacity to store information, both in terms of amount and duration (van Merriënboer and Sweller 2005). Classic accounts of the Cognitive Load Theory differentiate between two kinds of cognitive load, the intrinsic load and the extraneous load. *Intrinsic load* refers to cognitive processes involved in processing novel learning materials, which may be affected by the (perceived) complexity of the material. *Extraneous load* concerns factors that affect cognitive processes despite not being directly related to the task at hand, such as convoluted instructional design or unfavourable presentation of the learning material (Kalyuga 2009).

The two forms of cognitive load interact with one another so that an abundance of extraneous load (e.g. by giving learners too much unnecessary information or by having a cluttered visual design) reduces the capacity left for proper processing of the learning material due to the working memory's limitations. Importantly, the current cognitive load of a learner also depends on learner characteristics such as expertise. In parts, expertise is represented by cognitive schemata with varying degrees of complexity and automation housed by the long-term memory (van Merriënboer and Sweller 2005). When schemata become automated through training, space in the working memory is freed, which then reduces the intrinsic load, leaving more cognitive capacity for the processing of new content (Kalyuga 2009). This implies that instructional interventions should be adjusted (adapted) to the learners' cognitive load when teaching complex content (Rey and Buchwald 2011; Somyürek 2015). This may be achieved through instructional guidance: low levels of guidance or instructional scarcity can affect novices negatively as they might lack the expertise to compensate for the missing or incomplete information, which can lead to poor problem-solving strategies or mere guess work. Experts on the other hand are not affected as much since they can rely on their prior knowledge. When the amount of guidance is overabundant, the inverse effect may occur: novices benefit from the detailed instructions while experts' cognitive load is increased since they need to compare and contrast the flux of incoming information with their prior knowledge, inflating their intrinsic load (cf. Kalyuga 2007). Consequently, at the start of the learning process, novices should be provided with instructional guidance (e.g. step-by-step instruction) in order to guide them through their tasks and reach an optimal level of cognitive load. The concept of fading scaffolds applies here again (Collins et al. 1988; van Merriënboer and Sluijsmans 2009).

The educational implications of the Cognitive Load Theory and its role in explaining the expertise reversal effect have been explored and confirmed in numerous studies (e.g. Rey and Buchwald 2011). However, the cognitive load approach is limited to a specific learning goal in its application, namely, the acquisition of subject-specific knowledge (Kalyuga and Singh 2016). Other learning goals such as enhancing self-regulated learning are beyond the scope of the approach and may best be addressed by other theoretical perspectives within adaptive learning. *Self-regulated learning* refers to self-directive processes and motivational self-beliefs that learners use to proactively acquire academic skills (Zimmerman 2008). These skills include the setting of challenging goals, the employment of appropriate strategies to achieve these goals and the self-monitoring of one's activities and effectiveness until said goals are met. Adaptive learning environments can support self-regulated learning, e.g. by facilitating monitoring via continuous self-assessments and improving regulation of learning processes via instructional guidance (Scheiter et al. 2017).

These theories all provide guidelines for pedagogical decision-making. Despite representing vastly different perspectives, they are not mutually exclusive. The pedagogical strategies of adaptive learning systems can draw from multiple theoretical sources at once, e.g. by combining self-regulated learning with fading scaffolds.

6.3.2 What Can or Should Be Adapted and How? The Objects, Methods and Techniques of Adaptation

The next questions concern what can be adapted within a system to meet the guidelines illustrated above and how this may be accomplished. On one hand, the *what* question depends on the domain model since that model provides a structure of the topic also entailing which aspects can be adapted (see Knutov 2012). Brusilovsky (2001) suggests two aspects that can be adapted, namely, presentation and navigation support. *Adaptive presentation* focusses – as the name implies – on the presentation of the content in accordance with various learner characteristics (which will be discussed later). For example, a more experienced learner may be provided with less detailed instructions for a task, while novices may receive additional explanations to support their understanding of the topic. *Adaptive navigation support* is based on personalised learning paths that are supposed to guide the learner to appropriate learning content. Knutov (2012) adds a third approach in the form of *content adaptation support*, which addresses the presence or absence of specific bits of information, thus regulating their accessibility. This kind of support may also vary the emphasis that is put on the information. Other parts of the instructional design that can be adapted include hints, prompts and recommendations.

On the other hand, the *what* question also revolves around the adaptive model, as does the *how* question. How the adaptive process works can be described on two levels, either on a conceptual/design level or on an implementation level. The adaptive process involves *techniques*, which are usually applied at the implementation level of a system and adhere to specific approaches or algorithms, as well as *methods*, which are generalisations of techniques (Knutov 2012). Examples for techniques in content adaptation support include inserting, removing or modifying information, which change the accessibility of information, thus altering the content itself. Other techniques, which are also shared by adaptive presentation support, do not change the content but rather lead the learner to focus only on parts of the content. These include dimming, sorting, zooming or stretchtext (Knutov 2012). The latter two are also useful techniques when presenting information that only needs to be seen by a subset of learners. Techniques applied in the context of adaptive navigation support can either be enforced or recommended. These techniques include guidance (e.g. by recommending links, which can also be classified as an adaptive presentation support technique), link generation or link hiding (Knutov 2012).

The decision between enforced or recommended paths taps into the self-regulation dilemma, which concerns the amount of control that is given to the system versus the control given to its user (see Bergamin and Hirt 2018; Kobsa et al. 2001). On one end of the spectrum, learners are given complete control over their learning process (i.e. choice of topics, resources and support). Such systems are also called *adaptable* systems. The learner-control approach might entail positive consequences since freedom can be a motivating factor and learners may enjoy being in control. However, this level of freedom may also overwhelm and thus demotivate learners, especially at the beginning of the learning process, when learners lack self-regulation skills, or when a complex topic is concerned. On the other end of the spectrum, *adaptive* systems choose and present learning content, which may lead to decisions that are more sound than decisions that novices would make, but the lack of control on the learner's part may frustrate them, especially when the decisions by the system are faulty or not what the learner anticipates. This may be the case when the learner model is not accurate enough or when the learner's view is skewed. One way to bypass the dilemma is by allowing the control to be shared between the system and the learner, which is often achieved by implementing *recommender systems*. These systems offer learners recommendations or advice on how to adapt their learning process (e.g. by recommending tasks, supplementary material and so on) instead of forcing a system-made decision upon them. The learner is thus free to follow the recommendation or ignore it.

Since instructional interventions in this type of system are dependent on the learner's initiative, they are referred to as *non-embedded* (Clarebout and Elen 2006). A more *embedded* alternative exists in the form of the *two-step approach* (cf. Bergamin and Hirt 2018). In the first step, the system selects a set of appropriate learning objects (e.g. tasks), which the learner is then able to choose from. The main advantage of this approach is that learners can be prevented from being overwhelmed by countless options or from selecting counterproductive tasks while still being allowed to be in control, at least to a degree. Chou et al. (2015) present another option that allows simultaneous shared control between the system and the learner, the *negotiation-based adaptation mechanism*. This mechanism compares the system's learner model with the student's self-assessment, and if they do not match, modifications to the learner model will be "negotiated" between the learner and the system. It supports learners with low meta-cognitive skills while allowing learners to correct inaccurate learner models.

Moreover, methods and techniques applied in adaptive learning systems can vary substantially in terms of complexity and level of detail. A common distinction is made between *rule-based* and *algorithm-based systems* (Murray and Pérez 2015; cf. Oxman and Wong 2014). The former usually relies on a series of if-then functions with varying degrees of complexity (e.g. through different branching paths). If learners get answers right, the system directs them to the next task, and if they do not, it provides assistance in the form of a hint, repeated content or different explanations of the same content. Rule-based adaptive systems are transparent in their functionalities, which makes them easier to use; however, they do not tap into the computational potential that more sophisticated systems do. Algorithm-based approaches are far more complex and often involve methods related to machine learning, such as item-response theory (e.g. Wauters et al. 2010; Pliakos et al. 2019), Bayesian Knowledge Tracing (Corbett and Anderson 1995), fuzzy-logic (Ennouamani and Mahani 2019) or deep learning (Goodfellow et al. 2016). Additionally, they may involve elaborated techniques such as (big) data mining (e.g. Yuan 2019) or learning analytics in order to continuously predict the success of an individual learner based on specific bits of information. As Ge et al. (2019) note in their literature review, there is a tendency for adaptive systems to rely on established algorithms, rather than implementing game engines or developing their own algorithms.

A noteworthy example for algorithm-based approaches are *micro-adaptive systems* (Vandewaetere et al. 2011). Micro-adaptive systems are learning systems that employ micro-adaptive instructions that dynamically decide which instructional treatments are the most appropriate at any given time (e.g. intelligent tutoring systems). They accordingly provide tailored on-time instructions based on within-task measures. The fine-grained and precise measures this approach requires are thought to warrant the implementation of artificial intelligence techniques. However, this alleged necessity has attracted controversy since some authors, e.g. Essa (2016), argue that domain-specific micro-adaptivity should be regarded as "the primary realm of the instructor" (p. 11). The authors speculate that for the foreseeable future, machine learning will not surpass the instructor's knowledge and experience, at least as far as providing feedback and correcting errors is concerned. We would like to emphasise that machine learning and the instructor's experience are not mutually exclusive and may complement one another. Examples for this are supervised machine learning and co-creation strategies (see Dollinger and Lodge 2018).

6.3.3 What Can or Should Be Adapted to? The Basis of Adaptation

The fourth question concerns which characteristics of the learner should be captured by the sensor part of the learner model. As these characteristics form the basis for adaptive processes, they need to be selected carefully. What characteristics are most valuable in the context of a learning task, a course or even degree programmes to be adapted in regard to a particular goal is not a trivial question and has led to some disagreement in the literature (see Granić and Nakić 2010). In order to provide a potential answer, Nakić et al. (2015) conducted one of the most encompassing literature reviews regarding adaptation to learner characteristics. The authors explored 22 different learner characteristics over 98 studies released between 2001 and 2013, which include age, gender, working memory capacity, (meta-)cognitive abilities, anxiety and so on.

Given how wide the variety of characteristics to choose from is, several attempts have been made to categorise them. Vandewaetere et al. (2011) differentiate between three categories, which they derive from the combination of empirical research with theoretical propositions. These three categories are (1) cognition (working memory capacity, intelligence, prior knowledge, cognitive and learning styles), (2) affect (frustration, confusion, delight, mood and self-efficacy) and (3) behaviour (need for learner control, help and/or feedback, self-regulated learning, number of tries per task and grades). Although these categories seem to differ clearly, the boundaries between them are often blurred. The category *affect* includes states that are blends between affect and cognition (e.g. confusion and self-efficacy), while the characteristics in the *behaviour* category can be viewed as consequences of cognitive and affective states. Another classification stems from Aleven et al. (2017) who identify five groups of learner characteristics: prior knowledge and knowledge growth; strategies and errors; affect and motivation; self-regulated learning strategies, metacognition and effort; and learning styles. As they note, determining which characteristics are worth adapting to the most is ultimately an empirical question. Based on the results of the studies that Nakić et al. (2015) examined, the authors conclude that adapting to one or more of the following characteristics proves to be the most successful: learning styles, prior knowledge, cognitive styles, preferences for particular types of learning materials and motivation. The latter is noted to have been subject to increasing attention in research, along with characteristics such as emotions and metacognitive abilities (Nakić et al. 2015). Adapting to cognitive abilities and personality is also deemed promising, although those characteristics have been explored to a lesser degree (see, e.g. Afini Normadhi et al. 2019). Further details will be provided in the section discussing the current state of the research.

6.3.4 When and Where Can Adaptation Be Applied? The Context of Adaptation

Knowing on which pedagogical basis we want to adapt what aspects to which characteristics with which techniques, the final questions are when and where adaptation takes place. One way to answer both of these questions at once is by addressing loop levels, which determine when and where instructions can be varied within the adaptive model. According to Bergamin and Hirt (2018), there are three levels on which adaptation can occur: the curriculum loop, the task loop and the step loop. In the *curriculum loop*, the adaptive system recommends (or enforces) learning domains (curricula) based on the learners' needs and preconditions. This can be illustrated with an example: A learner succeeds in a particular course and may thus be recommended an advanced course on the same topic. Since it concerns in-between-course adaptation, the curriculum loop only occasionally adapts to the learner model.

In the *task loop* (also known as *outer loop*), the system makes decision regarding the instructional support, complexity of the content or sequencing (i.e. task selection) depending on the individual learner's current conditions. An adaptive system may thus recommend (or enforce) more challenging tasks to successful learners while presenting tasks that involve more assistance to less proficient learners. Since it concerns tasks, the task loop adapts to the learner model more frequently than the curriculum, but less frequently than the step loop. In the *step loop* (also known as *inner loop*), the system provides hints, feedback and prompts regarding the current learning activity within a learning object (e.g. a task). This adaptation depends on the individual learner's most recent learning behaviour. Aleven et al. (2017) also differentiate between three loop levels; but instead of the curriculum loop, they include a *design loop* in their conceptualisation. Design-loop adaptivity refers to data-driven changes between different iterations of the same course on the basis of similarities between learners. For example, a course designer may receive the feedback that a high percentage of students displayed the same misconception in a physics task, which leads to them accounting for that misconception in the next version of the course. In contrast to the other loops, this loop does not concern the individual learner and takes on a different perspective (namely, that of a course designer charged with redesigning an existing course).

The *when* and *where* questions can further be addressed by considering another aspect of adaptive systems, namely, their application area. While e-learning remains the main application area of adaptive learning, its range has expanded significantly over the years. Adaptive learning systems are applied in various educational institutions (primary school, secondary school, senior school, university, etc.) as well as organisations, e.g. for training purposes. Moreover, there has been an increase in context-aware adaptive systems that try to incorporate context characteristics in addition to learner characteristics, e.g. the time and place of a learning activity or the device used by the learner. This can be achieved by either expanding the learner model or adding a fourth model to the three core components (for instance, a *context model*; see Knutov 2012).

6.4 Current State of the Research

In this next part, we will concentrate on three aspects of current application-oriented research: the evaluation of the effectiveness and efficiency of adaptive learning systems, the satisfaction of learners with such systems and their actual implementation. We highlight application-oriented research over theoretical literature to emphasise the practical implementation of adaptive learning systems.

6.4.1 Learner Performance: Effectiveness and Efficiency of Adaptive Learning Systems

Instructional effectiveness and efficiency are key aspects of adaptive learning since optimising learning is one of the central objectives of this approach (Sottilare and Goodwin 2017). *Instructional effectiveness* refers to enhancing learning capacity to acquire knowledge or skill. Importantly, the time in which this learning gain is supposed to transpire is fixed and the learning content is varied, so that at the end of the course, learners may be below, at or above their expected level (Sottilare and Goodwin 2017). In contrast, *instructional efficiency* refers to the acceleration of learning, which means a reduction of the time learners need to reach a desired level of knowledge or skill. By providing learners with instruction tailored to their needs (e.g. based on their current level of knowledge), the amount of information they are presented with can be reduced. However, allowing learners to skip information is not always recommended since learning materials may need to be revisited from time to time to retain proficiency (Sottilare and Goodwin 2017). Adaptive learning reveals its potential addressing both of these points, as it permits a large variety of learning materials and instructional strategies to be tailored to the needs of individual learners. Effectiveness and efficiency depend, among other things, on the context of the deployment of adaptive learning, higher education being by far the most common context (see Xie et al. 2019, for an overview).

One part of the literature concerns the effectiveness and efficiency of adaptive learning systems. This line of research is concerned with the research question how effective and efficient adaptive learning systems are, usually in comparison to either non-adaptive alternatives or other adaptive systems with diverging features. Accordingly, most researchers hypothesise that adaptive learning systems are more effective and efficient than their non-adaptive counterparts. While some studies have assessed both effectiveness and efficiency of adaptive learning systems, others have focussed on one of these two performance measures. Verdú et al. (2008), for example, examined the evidence for the effectiveness of adaptive learning by comparing studies that analysed adaptive systems in various institutional contexts. They found that with varying levels of statistical significance and effect sizes, all 18 of the studies in their pool reported positive results, i.e. students improved in their academic achievement when using adaptive systems in comparison to control groups. The variation between effect sizes indicates a vast range of effects. One study yielded an effect size of 0.1, which indicates a small, statistically not significant learning gain. Large effects (i.e. effect sizes of at least 0.66) were found in ten of the studies, with the remainder yielding medium to small effects. Further studies show that the results concerning the effectiveness and efficiency of adaptive learning are rather mixed: while there is evidence to suggest that the implementation of adaptive learning can lead to improved achievements, higher self-perceived learning gains and reduced cognitive load (e.g. Yang et al. 2013), other studies were only able to detect positive effects on learning outcomes under specific conditions. In their evaluation of an adaptive online learning system, Griff and Matter (2013) only found positive effects in two out of the six participating institutions. Similarly, Murray and Pérez (2015), who implemented a micro-level adaptive approach, only found a negligible impact of adaptive learning on learning outcomes when compared to a traditional non-adaptive approach. In a recent experimental classroom study, Eau et al. (2019) did not find any significant impact of adaptive learning on exam scores, course grades or progress. In contrast, Ghergulescu et al. (2016), who conducted a field study with a total sample size of 10,000 students across 1700 mathematics sessions, report significant improvements across ability levels (i.e. ranging from low to high achievers). Low achievers improved more than high achievers, thus reducing the achievement gap.

Another part of the literature addresses effectiveness and efficiency in relation to the temporal context the systems operate in as well as the learner characteristics their learner model is based on. Here we will illustrate this based on the findings by Aleven et al. (2017), who evaluated the effectiveness of adapting to various learner characteristics by systematically reviewing studies that either addressed design-loop, task-loop or step-loop adaptations to learner characteristics stemming from their previously presented five categories (prior knowledge, strategies and errors, affect and motivation, self-regulation of learning and learning styles). Since we do not consider design-loop adaptivity to be on the same dimension as the task and step loops as explained above, we will only include the latter two in our overview.

First off, Aleven et al. (2017) present evidence to support the effectiveness of adapting to prior knowledge. Evidence on the task-loop adaptivity suggests that adapting the task selection to the learners' prior knowledge improves both effectiveness and efficiency of learning. Corbett et al. (2000), for instance, observed that students scored twice as high in the assessment of an algebra problem and 10% higher in a standard test when using the Cognitive Tutor Algebra I in comparison to traditional courses. Cognitive Tutors are intelligent tutoring systems that present tasks which train aspects students are unlikely to have mastered yet. Comparable results have been achieved by promoting learning by analogue problem-solving, where students solve problems by transferring knowledge from an analogue, adaptively selected example (cf. Muldner and Conati 2007). Increased learning gains were also observed when examining step-loop adaptivity, even though the evidence is not quite as abundant in this context. Conati (2013), for example, reported larger learning gains after implementing a self-explanation coach for physics problem-solving (i.e. a system that adaptively selected steps of worked examples and provided a structure template as well as feedback). This effect was larger for students with low levels of prior knowledge, which is also what Albacete and VanLehn (2000) observed. The opposite was found by Own (2006): in his study, the difference in learning progress was only significant for students that had more prior knowledge. E. Verdú et al. (2008) identified differences in contexts, systems and analyses between the studies as the most likely cause for this discrepancy.

Overall, Aleven et al. (2017) note that the evidence supporting the value of adapting to prior knowledge is consistent with the widespread notion that learners' prior knowledge is a key factor in learning. In fact, the authors assert that adapting to prior knowledge within the task-loop yielded the largest effects out of all the possible combinations between the learner characteristics and loops they examined.

Adapting to learners' affect was also found to improve effectiveness and efficiency. An example concerning task-loop adaptivity is a study by Walkington (2013), who implemented interest in her tutoring system by adapting the cover stories of algebra problems to students' interests. This resulted in higher accuracy and increased learning efficiency in the course and led to accelerated learning later on. Regarding the step loop, affect-aware tutoring systems were found to enhance learning. Examples include studies by D'Mello et al. (2010), who used *AutoTutor*, a system capable of detecting boredom, confusion, frustration and neutral affective states, or D'Mello et al. (2012), who implemented eye-trackers in their tutoring system in order to detect and adaptively counteract disengagement. Some systems even feature hybrid adaptivity, i.e. algorithms that combine affective with cognitive factors (e.g. Mazziotti et al. 2015). In contrast, Aleven et al. (2017) note that research focussed on adapting to learners' motivation has been comparatively scarce with only the groundwork being laid, e.g. in the form of self-efficacy-detecting algorithms using machine-learning models (McQuiggan et al. 2008).

Task-loop adaptivity to self-regulation can be effective as well, even though the evidence seems to be mixed. The most promising approach appears to be a combination between open learner models (i.e. a representation of the learner characteristics used by the system, often presented to the learner in a visual form) and self-assessment support (cf. Arroyo et al. 2014; Long and Aleven 2013). There is also evidence to suggest that adapting to self-regulated learning yields positive results in the step loop by improving learners' self-regulated learning processes (e.g. help-seeking, Tai et al. 2013).

In contrast, the evidence for the effectiveness and efficiency of adapting to learners' learning strategies and error patterns is mixed (Aleven et al. 2017). While step-loop adaptivity to strategies and errors is also deemed effective, particularly when applied in the form of step-level feedback (see Koedinger and Aleven 2007), the evidence presented by Aleven et al. (2017) does not support any clear advantage of task-loop adaptivity over non-adaptive tutoring. Adapting to learning styles also yielded little conclusive evidence, despite the popularity of the concept in past and present research (e.g. Kolekar et al. 2019). Many researchers argue that learning styles lack a firm theoretical basis (e.g. Aleven et al. 2017; Kirschner and van Merriënboer 2013; Lu et al. 2003), an issue that is further compounded by other controversies surrounding the topic, with some researchers even dismissing them as a "myth" (see Kirschner 2017).

A learner characteristic not present in the overview presented by Aleven et al. (2017) that was recently investigated was aptitude (Eldenfria and Al-Samarraie 2019). In their study, Eldenfria and Al-Samarraie (2019) found their aptitude-based adaptive mechanism to be effective, which was supported by EEG data.

Current research thus shows that adaptive learning can be both effective and efficient, be it in general or addressing specific temporal contexts (i.e. loops) or learner characteristics. The effects found in the literature may vary in their size from no effect to large effects, but all reported effects are positive, supporting the potential for future research.

6.4.2 *Satisfaction Among Learners*

Effectiveness and efficiency are not the only measures to indicate the success of a learning system. No matter how effective a system is, the prospects of success are jeopardised if students and/or teachers reject it. Assessing student satisfaction is therefore key when judging the quality of a system. Moreover, studies have shown positive links between student satisfaction and motivation, student retention and recruitment (see Schertzer and Schertzer 2004). Levy (2007) additionally shows that dropouts occur at substantially higher rates in e-learning as compared to offline courses, stressing the importance of student satisfaction for student retention. The research question that guides this strand of research is thus how satisfied students are with adaptive learning systems. Usually, students are hypothesised to feel satisfied with adaptive learning systems. Verdú et al. (2008) compared the results of 11 studies that assessed the level of students' satisfaction with adaptive learning systems via questionnaires. Since the results were based on questionnaires with different scales, the values were normalised before the comparison. One study reported medium (0.5) and the others high learner satisfaction (0.66–0.81) with adaptive learning systems. They conclude that most learners thought that the adaptive systems supported their learning progress and met their requirements.

In a more recent study, Dziuban et al. (2017) investigated how students from two contextually different universities reflected on the adaptive learning platform *Realizeit*. Despite differing in demographic and educational backgrounds, most students reacted positively to the adaptive system by giving it high marks regarding its perceived educational effectiveness and were able to make a near-seamless transition from non-adaptive systems. However, there are certain conditions that have to be met in order for learners not to reject adaptive systems. If systems are unstable, unreliable, too cumbersome in their use or plagued by usability problems, the risk of students (and teachers) abandoning it rises. Lack of transparency is an additional risk factor that can lead to trust issues (e.g. when the system is perceived as a "black box" without any comprehensible rationale behind its decisions; see Khosravi et al. 2020).

Assessing the usability of adaptive systems is therefore worthwhile (cf. Khosravi et al. 2020). Alshammari et al. (2015), for example, compared an adaptive learning system with a non-adaptive version in an experimental setting and found that the adaptive learning system yielded higher ratings regarding its perceived usability than its non-adaptive counterpart. Similarly, Vesin et al. (2018) examined the usability of the adaptive learning system *ProTuS* using the *System Usability Scale* (*SUS*). The resulting score was 67.2 out of 100, indicating a marginally acceptable usability, i.e. on the verge of being acceptable (with a score of 70 being the threshold). More recently, a German translation of the SUS was used to assess the usability of adaptive courses in the learning management system *Moodle* (Pancar et al. 2019). In contrast to previous results, the adaptive courses yielded lower usability scores (55.08 and 57.8) than their non-adaptive counterparts (62.87 and 67.51), meaning their usability was "ok".

As the research above illustrates, adaptive learning systems tend to be satisfying to learners, which is an important condition for the success of such systems. However, research on their usability opened up a clear gap which needs to be further addressed. Given how crucial usability is to the acceptance of adaptive learning systems, improving it is a key challenge.

6.4.3 Implementation of Adaptive Learning Systems

Another avenue of research within adaptive learning concerns the actual implementation of adaptive systems in practice, providing potential answers to the *how* and *when*/*where* dimensions. The research questions in this area are thus if adaptive learning systems can be successfully implemented in educational practice and under what conditions. Despite the wealth of studies on adaptive learning systems, there has been a notable lack of successfully implemented adaptive technology-based learning systems in practice (Cavanagh et al. 2020; Somyürek 2015), with a few exceptions, e.g. the previously mentioned study by Ghergulescu et al. (2016). Scanlon et al. (2013) found what they called a "surprising failure" (p. 4) to translate research results in the field of technology-enhanced learning, including prototypes, into commercial products. This gap between research and successful application is the so-called valley of death, which can be caused by a lack of funding, weaknesses in the didactic concept, scalability-related issues, inaccuracies in the core components or lack of sustainability.

Moreover, as Lerís et al. (2017) point out, technological issues are a contributing factor as well since one of the main reasons why some adaptive systems have failed is a lack of easy-to-use technology for the teachers meant to design adaptive tasks and instructions. Instructors that produce and follow sound instructional designs are essential to adaptive learning, which is why it is key to involve them from the very beginning (cf. Shelle et al. 2018). One potential solution is to implement adaptive learning within environments that teachers are already familiar with, such as learning management systems (e.g. *Moodle*). In one of our own studies, we demonstrate how a simple rule-based adaptive design based on a recommender system can be implemented in a physics course on Moodle (see Imhof et al. 2018). Our system recommended tasks with either detailed or non-detailed instructions to our students, depending on their current level of knowledge (i.e. a prior knowledge test score for the first task and task performance for the remainder of the task set). We deemed the implementation successful enough to serve as a good basis for future, more complex adaptive instructional designs in the same or similar contexts.

6.5 Practical Implications and Future Potential of Adaptive Learning Systems

The results presented above have practical implications for designing and implementing adaptive learning systems. In this discussion, we will refer to the six questions introduced in the beginning of this chapter again. *Why* is adaptation wanted? Research reveals arguments for the implementation of adaptive learning systems by demonstrating effectiveness and efficiency. *Where* and *when* can adaptation be applied? Adaptive learning systems have yielded positive effects in a variety of different contexts, be it in terms of institutions, the topics to be learned (despite the noticeable focus on STEM topics, especially in the realm of micro-adaptivity; cf. Essa 2016), the target audience or the loop levels within the adaptive model. *What* can or should it adapt *to*? Not all options are equally recommendable in regard to learner characteristics. For instance, the evidence for adapting to learning styles is mixed at best (cf. Aleven et al. 2017), despite their popularity. Importantly, no matter which learner characteristics are chosen, they need to be assessed reliably and validly in order for the system to adapt to the learners' needs accurately. *What* can or should it adapt and *how*? In contrast to the other questions, these two are difficult to answer on the basis of the literature we considered. To our knowledge, systems usually follow one specific approach in terms of methods and techniques and stick to them. This renders direct, unbiased comparisons with other approaches nigh impossible, since the list of potential confounding variables is vast (e.g. learning support, learning topics, educational contexts, outcome variables, learning devices, differences between learners and so on; cf. Xie et al. 2019).

Moreover, adaptivity on its own is no guarantee for success. In our view, the success of an adaptive system is instead linked to three crucial elements of its adaptive design, each addressing multiple of the six basic questions:

1. The concept behind an adaptive learning system needs to be specific and sound. Adaptive learning has unique requirements and is, as Freda (2016) states, not a "magic bullet". The quality of the adaptive design (and thus the recommendations a system makes) depends on the monitoring and diagnosis of changing learning requirements, which could result in insufficient adaptation rules if neglected (cf. Dounas et al. 2019).
2. The loop level the system operates on has to be specified. As Essa (2016) notes, a considerable amount of research has been dedicated to the inner loop (i.e. step loop or micro-adaptivity), whereas research on the outer loop (i.e. task loop or macro-adaptivity) has been described as "modest" (Rus et al. 2013).
3. Special care ought to be given to the algorithms behind the adaptive learning system. Most systems rely on existing algorithms (cf. Ge et al. 2019) which are not necessarily the ideal solution in every individual case.

In summary, adaptive systems need a concise concept behind them as well as a suitable adaptive mechanism supported by the proper algorithms. Differences in these three design elements could explain why some studies found adaptive learning systems to be effective (Eldenfria and Al-Samarraie 2019; Ghergulescu et al. 2016) while others did not (Eau et al. 2019) or had mixed results (Griff and Matter 2013). This is especially important when estimating the effectiveness of adaptive learning systems in practice.

Furthermore, the results illustrated above highlight that usability should be a major focal point when designing and implementing such systems (Khosravi et al. 2020). Systems burdened with usability problems satisfy neither learners nor teachers, increasing the risk of systems being swiftly abandoned.

As our overview depicts, the processes of designing and implementing adaptive learning systems are very complex since there are countless options one could choose when designing adaptive systems. Not only are these processes non-linear since the questions inform and influence each other; there is also a notable lack of guidance for them, at least currently (Hou and Fidopiastis 2017).

All in all, the practical implications of adaptive learning are somewhat limited at the moment since there are still various challenges that adaptive learning systems have to overcome in order to truly bridge the gap between research prototypes and application tools. In their Delphi study, Mirata and Bergamin (2019) identified three dimensions of the challenges for adaptive learning: technology; teaching and learning; and organisation. In the dimension *technology*, the challenges are *infrastructure and hard- and software*, which include the usability of adaptive learning systems, and *perceptions and beliefs about adaptive technology*, e.g. acceptance and attitude towards technology, both from the lecturers' and students' points of view. In the context of the dimension *teaching and learning*, the identified challenges are *instructional and curriculum elements* (e.g. the need to redesign courses) as well as *lecturer and learner characteristics* (e.g. their motivation and commitment). The final dimension, *organisation*, contains *institutional strategies* (including commitment on the part of the management), *management* (e.g. support for lecturers and learners) and *resources* (e.g. the hiring of instructional designers). Further challenges are identified by Zliobaite et al. (2012), who present additional technological challenges, and Freda (2016), who highlights the organisational challenges. Zliobaite et al. (2012) add scalability and having to deal with "realistic data" as additional challenges for technology. In order to improve usability, trust and acceptance, they state that the practical application of adaptive learning systems might have to be broken down into adaptive tools that non-experts are also able to use. This latter point is also stressed by Cavanagh et al. (2020), who include understanding of the mechanism behind adaptive learning systems as one of the items on their list of pedagogical best practices.

Similar to Mirata and Bergamin (2019), Freda (2016) stresses securing monetary resources and convincing parties other than students and teachers of the value of adaptive learning (e.g. project managers and instructional technologists) as two important obstacles when transitioning from traditional to adaptive learning systems.

Future research has the potential to address most if not all of these issues, thereby getting closer to bridging the gap between research and application, potentially leading to widespread successful implementations of adaptive learning systems. As the research presented in this chapter shows, adaptive learning systems hold considerable potential to improve scalability (i.e. reaching more learners with less effort) and learners' performance. This complex development is still ongoing, but the current state of the research indicates great promise for the future.

References

Adams Becker, S., Brown, M., Dahlstrom, E., Davis, A., DePaul, K., Diaz, V., & Pomerantz, J. (2018). *NMC horizon report 2018: higher education edition* (p. 60). Retrieved from https://library.educause.edu/{~}/media/files/library/2018/8/2018horizonreport.pdf

Afini Normadhi, N. B., Shuib, L., Md Nasir, H. N., Bimba, A., Idris, N., & Balakrishnan, V. (2019). Identification of personal traits in adaptive learning environment: Systematic literature review. *Computers and Education, 130*, 168–190. https://doi.org/10.1016/j.compedu.2018.11.005.

Albacete, P., & VanLehn, K. (2000). Evaluating the effectiveness of a cognitive tutor for fundamental physics concept. *Proceedings of the 22nd Annual Meeting of the Cognitive Science Society* (pp. 25–30). Mahwah, NJ: Erlbaum.

Aleven, V., McLaughlin, E. A., Glenn, R. A., & Koedinger, K. R. (2017). Instruction based on adaptive learning technologies. In R. E. Mayer & P. Alexander (Eds.), *Handbook of research on learning and instruction* (pp. 522–560). New York: Routledge.

Alshammari, M., Anane, R., & Hendley, R. J. (2015). Design and usability evaluation of adaptive e-learning systems based on learner knowledge and learning style. In *Human-computer interaction – Interact 2015* (Vol. 9297, pp. 584–591). https://doi.org/10.1007/978-3-319-22668-2.

Arroyo, I., Woolf, B.P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2014). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. *International Journal of Artificial Intelligence in Education, 24*(4), 387–426.

Bergamin, P. B., & Hirt, F. S. (2018). Who's in charge? – Dealing with the self-regulation dilemma in digital learning environments. In K. North, R. Maier, & O. Haas (Eds.), *Knowledge management in digital change – New findings and practical cases*. Cham: Springer.

Bergamin, P. B., Werlen, E., Siegenthaler, E., & Ziska, S. (2012). The relationship between flexible and self-regulated learning in open and distance universities. *International Review of Research in Open and Distance Learning, 13*(2), 101–123. https://doi.org/10.19173/irrodl.v13i2.1124.

Brusilovsky, P. (1996). Methods and techniques of adaptive hypermedia. *User Modeling and User-Adapted Interaction, 6*(2–3), 87–129. https://doi.org/10.1007/BF00143964.

Brusilovsky, P. (2001). Adaptive hypermedia. *User Modeling and User-Adapted Interaction, 11*(1/2), 87–110. https://doi.org/10.1023/A:1011143116306.

Cavanagh, T., Chen, B., Lahcen, R. A. M., & Paradiso, J. (2020). Constructing a design framework and pedagogical approach for adaptive learning in higher education: A practitioner's perspective. *The International Review of Research in Open and Distributed Learning, 21*(1), 172–196. https://doi.org/10.19173/irrodl.v21i1.4557.

Chou, C.-Y., Lai, K. R., Chao, P.-Y., Lan, C. H., & Chen, T.-H. (2015). Negotiation based adaptive learning sequences: Combining adaptivity and adaptability. *Computers & Education, 88*, 215–226. https://doi.org/10.1016/J.COMPEDU.2015.05.007.

Clarebout, G., & Elen, J. (2006). Tool use in computer-based learning environments: Towards a research framework. *Computers in Human Behavior, 22*(3), 389–411. https://doi.org/10.1016/J.CHB.2004.09.007.

Collins, A., Brown, J. S., & Newman, S. E. (1988). Cognitive apprenticeship. *Thinking: The Journal of Philosophy for Children, 8*(1), 2–10. https://doi.org/10.5840/thinking19888129.

Conati, C. (2013). Modeling and scaffolding self-explanation across domains and activities. In R. Azevedo & V. Aleven (Eds.), *International handbook of metacognition and learning technologies* (pp. 367–383). New York: Springer. https://doi.org/10.1007/978-1-4419-5546-3_24.

Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing. *User Modeling and User-Adapted Interaction, 4*(4), 253–278.

Corbett, A. T., McLaughlin, M., & Scarpinatto, K. C. (2000). Modeling student knowledge: Cognitive tutors in high school and college. *User Modeling and User-Adapted Interaction, 10*(2/3), 81–108. https://doi.org/10.1023/A:1026505626690.

Cronbach, L. J., & Snow, R. E. (1977). *Aptitudes and instructional methods: A handbook for research on interactions*. New York: Irvington.

D'Mello, S. K., Lehman, B., Sullins, J., Daigle, R., Combs, R., Vogt, K., et al. (2010). A time for emoting: When affect-sensitivity is and isn't effective at promoting deep learning. https://doi.org/10.1007/978-3-540-69132-7.

D'Mello, S. K., Olney, A., Williams, C., & Hays, P. (2012). Gaze tutor: A gaze-reactive intelligent tutoring system. *International Journal of Human Computer Studies, 70*(5), 377–398. https://doi.org/10.1016/j.ijhcs.2012.01.004.

Dollinger, M., & Lodge, J. M. (2018). Co-creation strategies for learning analytics. In *Proceedings of the 8th international conference on learning analytics and knowledge – LAK'18* (pp. 97–101). New York: ACM Press. https://doi.org/10.1145/3170358.3170372.

Dounas, L., Salinesi, C., & El Beqqali, O. (2019). Requirements monitoring and diagnosis for improving adaptive e-learning systems design. *Journal of Information Technology Education: Research, 18*, 161–184. https://doi.org/10.28945/4270.

Dziuban, C., Moskal, P., Johnson, C., & Evans, D. (2017). Adaptive learning: A tale of two contexts. *Current Issues in Emerging eLearning, 4*(1). Retrieved from https://scholarworks.umb.edu/ciee/vol4/iss1/3/

Eau, G., Judah, K., & Shahid, H. (2019). How can adaptive platforms improve student learning outcomes? A case study of open educational resources and adaptive learning platforms. http://dx.doi.org/10.2139/ssrn.3478134

Eldenfria, A., & Al-Samarraie, H. (2019). The effectiveness of an online learning system based on aptitude scores: An effort to improve students' brain activation. *Education and Information Technologies, 24*(5), 2763–2777. https://doi.org/10.1007/s10639-019-09895-2.

Ennouamani, S., & Mahani, Z. (2019). Towards adaptive learning systems based on fuzzy-logic. In *Advances in intelligent systems and computing* (Vol. 997, pp. 625–640). Cham: Springer. https://doi.org/10.1007/978-3-030-22871-2_42.

Essa, A. (2016). A possible future for next generation adaptive learning systems. *Smart Learning Environments, 3*. https://doi.org/10.1186/s40561-016-0038-y.

Freda, B. (2016). *Clearing the hurdles to adaptive learning*. Retrieved from https://universitybusiness.com/clearing-the-hurdles-to-adaptive-learning/

Ge, Z., Xi, M., & Li, Y. (2019). A literature review of the adaptive algorithms adopted in adaptive learning systems. In *2019 IEEE 4th international conference on signal and image processing, ICSIP 2019* (pp. 254–258). Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/SIPROCESS.2019.8868893.

Ghergulescu, I., Flynn, C., & O'Sullivan, C. (2016). Learning effectiveness of adaptive learning in real world context. In *EdMedia+ innovate learning* (pp. 1391–1396). Waynesville: Association for the Advancement of Computing in Education (AACE).

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. Cambridge, MA: MIT Press.

Granić, A., & Nakić, J. (2010). Enhancing the learning experience: Preliminary framework for user individual differences. In (pp. 384–399). Berlin/Heidelberg: Springer. https://doi.org/10.1007/978-3-642-16607-5_26.

Griff, E. R., & Matter, S. F. (2013). Evaluation of an adaptive online learning system. *British Journal of Educational Technology, 44*(1), 170–176. https://doi.org/10.1111/j.1467-8535.2012.01300.x.

Hou, M., & Fidopiastis, C. (2017). A generic framework of intelligent adaptive learning systems: From learning effectiveness to training transfer. *Theoretical Issues in Ergonomics Science, 18*(2), 1–30.

Imhof, C., Bergamin, P. B., Moser, I., & Holthaus, M. (2018). Implementation of an adaptive instructional design for a physics module in a learning management system. In *Proceedings of the 15th international conference on cognition and exploratory learning in the digital age, CELDA 2018*.

Jameson, A. (2003). Adaptive interfaces and agents. In J. A. Jacko & A. Sears (Eds.), *The human-computer interaction* handbook (pp. 305–330). Hillsdale: Lawrence Erlbaum. Retrieved from https://chusable.com/archives/homepage-2017/pdf/hci-handbook.jameson.pdf

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review, 19*(4), 509–539. https://doi.org/10.1007/s10648-007-9054-3.

Kalyuga, S. (2009). Instructional designs for the development of transferable knowledge and skills: A cognitive load perspective. *Computers in Human Behavior, 25*(2), 332–338. https://doi.org/10.1016/j.chb.2008.12.019.

Kalyuga, S., & Singh, A.-M. (2016). Rethinking the boundaries of cognitive load theory in complex learning. *Educational Psychology Review, 28*(4), 831–852. https://doi.org/10.1007/s10648-015-9352-0.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist, 38*(1), 23–31. https://doi.org/10.1207/S15326985EP3801_4.

Khosravi, H., Gasevic, D., & Sadiq, S. (2020). Development and adoption of an adaptive learning system. https://doi.org/10.1145/3328778.3366900.

Kirschner, P. A. (2017). Stop propagating the learning styles myth. *Computers & Education, 106*, 166–171. https://doi.org/10.1016/J.COMPEDU.2016.12.006.

Kirschner, P. A., & van Merriënboer, J. J. G. (2013). Do learners really know best? Urban legends in education. *Educational Psychologist, 48*(3), 169–183. https://doi.org/10.1080/00461520.2013.804395.

Knutov, E. (2012). *Generic adaptation framework for unifying adaptive web-based systems*. Eindhoven: Technische Universiteit Eindhoven. https://doi.org/10.6100/IR732111

Kobsa, A., Koenemann, J., & Pohl, W. (2001). Personalised hypermedia presentation techniques for improving online customer relationships. *The Knowledge Engineering Review, 16*(2), 111–155. https://doi.org/10.1017/s0269888901000108.

Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. *Educational Psychology Review, 19*(3), 239–264. https://doi.org/10.1007/s10648-007-9049-0.

Koedinger, K. R., Brunskill, E., Baker, R. S. J., McLaughlin, E. A., & Stamper, J. C. (2013). New potentials for data-driven intelligent tutoring system development and optimization. *AI Magazine, 34*(3), 27. https://doi.org/10.1609/aimag.v34i3.2484.

Kolekar, S. V., Pai, R. M., & Manohara Pai, M. M. (2019). Rule based adaptive user interface for adaptive e-learning system. *Education and Information Technologies, 24*(1), 613–641. https://doi.org/10.1007/s10639-018-9788-1.

Lee, C. H., & Kalyuga, S. (2014). Expertise reversal effect and its instructional implications. In *Applying science of learning in education: Infusing psychological science into the curriculum* (pp. 32–44). Washington, DC: Society for the Teaching of Psychology. Retrieved from http://psycnet.apa.org/record/2013-44868-003

Lerís, D., Sein-Echaluce, M. L., Hernández, M., & Bueno, C. (2017). Validation of indicators for implementing an adaptive platform for MOOCs. *Computers in Human Behavior, 72*, 783–795. https://doi.org/10.1016/j.chb.2016.07.054.

Levy, Y. (2007). Comparing dropouts and persistence in e-learning courses. *Computers & Education, 48*(2), 185–204. https://doi.org/10.1016/J.COMPEDU.2004.12.004.

Long, Y., & Aleven, V. (2013). Skill diaries: Improve student learning in an intelligent tutoring system with periodic self-assessment. In *International Conference on Artificial Intelligence in Education* (pp. 249–258). Springer, Berlin, Heidelberg.

Lu, J., Yu, C.-S., & Liu, C. (2003). Learning style, learning patterns, and learning performance in a WebCT-based MIS course. *Information & Management, 40*(6), 497–507. https://doi.org/10.1016/S0378-7206(02)00064-2.

Mavroudi, A., Giannakos, M., & Krogstie, J. (2018). Supporting adaptive learning pathways through the use of learning analytics: Developments, challenges and future opportunities. *Interactive Learning Environments, 26*(2), 206–220. https://doi.org/10.1080/10494820.2017.1292531.

Mazziotti, C., Holmes, W., Wiedmann, M., Loibp, K., Rummel, N., Mavrikis, M., et al. (2015). Robust student knowledge: Adapting to individual student needs as they explore the concepts and practice the procedures of fractions. *CEUR Workshop Proceedings, 1432*, 32–40.

McQuiggan, S. W., Mott, B. W., & Lester, J. C. (2008). Modeling self-efficacy in intelligent tutoring systems: An inductive approach. *User Modeling and User-Adapted Interaction, 18*(1–2), 81–123. https://doi.org/10.1007/s11257-007-9040-y.

Mirata, V., & Bergamin, P. B. (2019). Developing an implementation framework for adaptive learning: A case study approach. In *Proceedings of the 18th European conference on e-learning*. Copenhagen, Denmark, 7–8 November 2019.

Muldner, K., & Conati, C. (2007). Evaluating a decision-theoretic approach to tailored example selection. In *IJCAI 2007, proceedings of the 20th international joint conference on artificial intelligence*. Hyderabad, India. Retrieved from https://www.ijcai.org/Proceedings/07/Papers/076.pdf

Murray, M. C., & Pérez, J. (2015). Informing and performing: A study comparing adaptive learning to traditional learning. *Informing Science, 18*(1), 111–125. https://doi.org/10.28945/2165.

Nakić, J., Granić, A., & Glavinić, V. (2015). Anatomy of student models in adaptive learning systems: A systematic literature review of individual differences from 2001 to 2013. *Journal of Educational Computing Research, 51*(4), 459–489. https://doi.org/10.2190/EC.51.4.e.

Own, Z. (2006). The application of an adaptive web-based learning environment on oxidation–reduction reactions. *International Journal of Science and Mathematics Education, 4*(1), 73–96. https://doi.org/10.1007/s10763-004-8129-6.

Oxman, S., & Wong, W. (2014). White Paper: Adaptive learning systems. Retrieved from http://kenanaonline.com/files/0100/100321/DVx{_}Adaptive{_}Learning{_}White{_}Paper.pdf

Pancar, T., Holthaus, M., & Bergamin, P. B. (2019). Enhanced system usability scale for adaptive courses. In *The twelfth international conference on advances in human-oriented and* *personalized mechanisms, technologies, and services, centric 2019,* Valencia, Spain, 24–28 November 2019.

Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., & Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers and Education, 137*, 91–103. https://doi.org/10.1016/j.compedu.2019.04.009.

Rey, G. D., & Buchwald, F. (2011). The expertise reversal effect: Cognitive load and motivational explanations. *Journal of Experimental Psychology: Applied, 17*(1), 33–48. https://doi.org/10.1037/a0022243.

Rus, V., Baggett, W., Gire, E., Franceschetti, D., Conley, M., & Graesser, A. (2013). *Towards learner models based on learning progressions in DeepTutor*. Retrieved from www.semantic-similarity.org

Scanlon, E., Sharples, M., Fenton-O'Creevy, M., Fleck, J., Cooban, C., Ferguson, R., et al. (2013). *Beyond prototypes: Enabling innovation in technology-enhanced learning*. Milton Keynes: Open University. Retrieved from http://beyondprototypes.com/

Scheiter, K., Fillisch, B., Krebs, M.-C., Leber, J., Ploetzner, R., Renkl, A., et al. (2017). How to design adaptive information environments to support self-regulated learning with multimedia. In *Informational environments* (pp. 203–223). Cham: Springer. https://doi.org/10.1007/978-3-319-64274-1_9.

Schertzer, C. B., & Schertzer, S. M. B. (2004). Student satisfaction and retention: A conceptual model. *Journal of Marketing for Higher Education, 14*(1), 79–91. https://doi.org/10.1300/J050v14n01.

Shelle, G., Earnesty, D., Pilkenton, A., & Powell, E. (2018). Adaptive learning: An innovative method for online teaching and learning. *Journal of Extension, 56*(5). Retrieved from https://joe.org/joe/2018september/pdf/JOE{_}v56{_}5a5.pdf

Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist, 38*(2), 105–114. https://doi.org/10.1207/S15326985EP3802_5.

Somyürek, S. (2015). The new trends in adaptive educational hypermedia systems. *The International Review of Research in Open and Distance Learning, 16*(1), 221–241. https://doi.org/10.19173/irrodl.v16i1.1946.

Sottilare, R. A., & Goodwin, G. A. (2017). *Adaptive instructional methods to accelerate learning and enhance learning capacity*. Retrieved from https://gifttutoring.org/attachments/download/2427/Sottilare and Goodwin DHSS2017.pdf

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*, 257–285.

Tai, M., Arroyo, I., & Woolf, B. P. (2013). Teammate relationships improve help-seeking behavior in an intelligent tutoring system. *International Conference on Artificial Intelligence in Education* (pp. 239–248). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-39112-5_25 .

van Merriënboer, J. J. G., & Sluijsmans, D. M. A. (2009). Toward a synthesis of cognitive load theory, four-component instructional design, and self-directed learning. *Educational Psychology Review, 21*(1), 55–66. https://doi.org/10.1007/s10648-008-9092-5.

van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review, 17*(2), 147–177. https://doi.org/10.1007/s10648-005-3951-0.

Vagale, V., & Niedrite, L. (2012). Learner model' s utilization in the e-learning environments. In *Tenth international Baltic conference on databases and information systems*. Vilnius, Lithuania, pp. 162–174.

Vandewaetere, M., Desmet, P., & Clarebout, G. (2011). The contribution of learner characteristics in the development of computer-based adaptive learning environments. *Computers in Human Behavior, 27*, 118–130. https://doi.org/10.1016/j.chb.2010.07.038.

Verdú, E., Regueras, L. M., Verdú, M. J., De Castro, J. P., & Pérez, M. Á. (2008). An analysis of the research on adaptive learning: The next generation of e-learning. *WSEAS Transactions on Information Science and Applications, 5*(6), 859–868.

Vesin, B., Mangaroska, K., & Giannakos, M. (2018). Learning in smart environments: User-centered design and analytics of an adaptive learning system. *Smart Learning Environments, 5*(1). https://doi.org/10.1186/s40561-018-0071-0.

Vygotsky, L. S. (1978). *Mind in society: the development of higher psychological processes* (p. 159). Cambridge, MA: Harvard University Press.

Walkington, C. A. (2013). Using adaptive learning technologies to personalize instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology, 105*(4), 932–945. https://doi.org/10.1037/a0031882.

Wauters, K., Desmet, P., & Van Den Noortgate, W. (2010). Adaptive item-based learning environments based on the item response theory: Possibilities and challenges. *Journal of Computer Assisted Learning, 26*(6), 549–562. https://doi.org/10.1111/j.1365-2729.2010.00368.x.

Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education, 140*, 103599. https://doi.org/10.1016/J.COMPEDU.2019.103599.

Yang, T. C., Hwang, G.-J., & Yang, S. J. H. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Educational Technology and Society, 16*(4), 185–200.

Yuan, X. (2019). Model and implementation of personalized adaptive learning and analysis technology based on large data. *International Conference on Artificial Intelligence and Advanced Manufacturing* (pp. 202–205), Dublin, Ireland. https://doi.org/10.1109/AIAM48774.2019.00048.

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

Zliobaite, I., Bifet, A., Gaber, M., Gabrys, B., Gama, J., Minku, L., & Musial, K. (2012). Next challenges for adaptive learning systems. *ACM SIGKDD Explorations Newsletter, 14*(1), 48. https://doi.org/10.1145/2408736.2408746.

Chapter 7
Sequential Analysis of Online Learning Behaviors According to E-Learning Readiness

Muhittin Şahin, Sinan Keskin, and Halil Yurdugül

7.1 Introduction

Nowadays, e-learning and distance learning are offered to learners by many educational institutions. E-learning is rapidly being adopted by learners as it has many advantages, such as ease of access to the learning environment and convenience to individual pace and flexibility. However, the level of readiness of learners as an important psycho-educational structure for e-learning directly affects the learning process. Online learners' readiness (OLR) is a complex structure that encompasses learners' competence in using learning technologies, autonomous learning skills and some affective structures. The most important of the sub-constructs of OLR are self-directed learning, learner control, motivation, etc. According to the level of having these skills, learners' online learning behaviors may also differ (which is the hypothesis of this research). If these learning behaviors can be determined in advance, changes can be made in the learning, instructional design, learning design, learning experience design and even in the design of the learning environment. In the scope of this research, the navigation patterns of the learners are examined using

M. Şahin (✉)
Department of Computer Education and Instructional Technology, Ege University, Bornova, Izmir, Turkey
e-mail: muhittin.sahin@ege.edu.tr

S. Keskin
Department of Computer Education and Instructional Technology, Van Yüzüncü Yıl University, Tuşba/Van, Turkey
e-mail: sinan.keskin@hacettepe.edu.tr

H. Yurdugül
Department of Computer Education and Instructional Technology, Hacettepe University, Beytepe, Cankaya, Ankara, Turkey
e-mail: yurdugul@hacettepe.edu.tr

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_7

sequential analysis. For this purpose, firstly, the literature is summarized and then the findings obtained in the research are presented.

7.1.1 Literature Review

The way in which learners learn in relatively new e-learning environments, the learning behavior patterns that are implemented here, is one of the areas of research that is currently unexplained and curious. Data mining, descriptive statistics, inferential statistics, etc. methods are used for determining the behavioral patterns in the e-learning environment. There are a significant number of researches which aim to explain the navigational behavior patterns of learners according to their personal characteristics (Graf et al. 2010; Abdullah et al. 2015; Keskin et al. 2019).

In the scope of this research, the navigation patterns of the learners are studied using sequential analysis. Sequential analyses were performed according to two different levels of OLR, both low and high. In this study, OLR is addressed in the context of self-directed learning, learner control and motivation towards e-learning. Learning approaches are also examined and discussed (deep approach and surface approach). The interaction of the learners with the e-learning system is covered under three sub-themes: learner-content, learner-assessment and learner-learner, as proposed by Moore (1989). The learner–content theme was derived from interactions with textual materials, SCORM packages and videos. The learner–learner theme is based on the interaction data in the forum pages. The interactions with the assessment tasks in the e-learning environment are considered as the learner–assessment theme. Interactions with content can be considered as a stage of information acquisition. After this phase, the interaction between the other learners in the forum pages can be named as the constructing knowledge. At this stage, the learners have the opportunity to structure the information obtained in the previous schema in the context of socio-cultural theories. Finally, the interaction with assessment can be said to be the reflection phase of e-learning. In the context of self-assessment, learners who constructed the knowledge interact with the assessment. This process is summarized in Fig. 7.1.

The expected interaction patterns of online learners in online learning environments are presented in Fig. 7.1. In this study, it is assumed that learners have a linear learning experience/strategy in online learning environment by interacting with content, discussion and e-evaluation themes in a linear order. In other words, it's expected that learners interact with the content first. Then, construct their knowledge in discussion environments in the light of the information obtained from the content interaction. And finally, it's expected they evaluate themselves through assessment interactions. In this research, this situation is discussed in the context of learner characteristics (online readiness and learning approach) by using sequential (consecutive) analysis. The three main pedagogical sub-dimensions of e-learning readiness, namely self-directed learning, learner control and motivation, are considered as learner characteristics. Then, learning approaches which are significantly

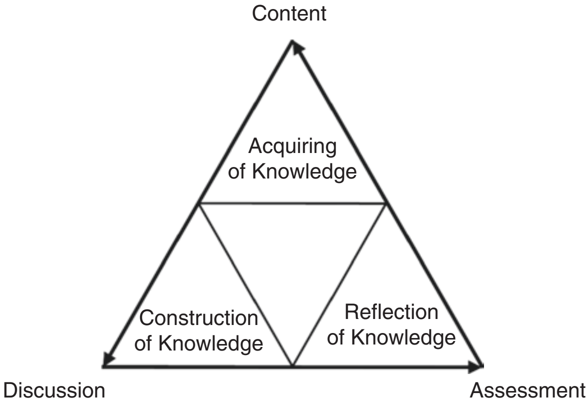


Fig. 7.1 Online learning interaction themes and knowledge structuring process

related to learner success and readiness in the e-learning process were considered and examined consecutively.

7.1.2 E-Learning Readiness

E-learning readiness is a pivotal construct that affects both institutional and learner success on e-learning. Kaur and Abas (2004) define e-learning readiness as the ability to make use of e-learning resources and multimedia technologies to improve the quality of learning. A review of the studies on e- learning readiness in the literature shows that readiness has been discussed from two main perspectives. These main perspectives are use of technologies and psychosocial competences (Hung et al. 2010; Moftakhari 2013; Yurdugül and Demir 2016). The studies that analyze readiness based on the use of technologies examine the extent to which individuals can use computer and internet technologies for learning. The studies that employ psychosocial constructs to explore e-learning readiness focus on constructs such as self-directed learning, learner control, and e- learning motivation. From this standpoint, e-learning readiness can be defined as the degree to which learners have the basic technological and pedagogical competencies required to make the best of e-learning resources.

One of the main components of e-learning readiness is self-directed learning. Self-directed learning is a process by which individuals take the initiative, with or without the assistance of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies and evaluating learning outcomes (Knowles 1975). Self-directed learning emphasizes autonomy, personal motivation, personalization, self- discipline and critical reflection and may also help learners become more focused, directed and successful. Knowles (1990) reports that learning takes place not in an isolated environment but with teachers, instructors and peers.

Despite various advantages offered by online learning environments, these environments have certain limitations compared to traditional learning environments, such as the need for learners to take more initiatives. For that reason, online learning and self-directed learning are considered as related concepts in the literature. There is considerable research demonstrating that learners with self-directed learning skills are more successful in the online learning process (Lee 2012). Since online learning environments are in favor of self-directed learners. Unlike a self-directed learner, a dependent learner needs more introductory material and appreciates lecture, drill and immediate correction, whereas a self-directed learner can engage in independent projects, learner-directed discussions and discovery learning (Merriam 2001). An individual is required to have the following competencies to become a self-directed learner: (a) self-assessment of learning gaps, (b) readiness for learning, (c) information gathering, (d) information management, (e) critical thinking and (f) critical appraisal (Patterson et al. 2002). Besides, self-directed learning consists of certain stages: (a) reacting to a triggering event, (b) searching for and selecting the specific information and resources to be obtained, (c) organizing and structuring the information and strategies to be used, (d) gathering and integrating the newly acquired information, (e) assessing the quality of learning outcomes and learning strategies (f) utilizing the new information (Danis 1992).

Learner control is one of the important elements of readiness for e-learning environments. Learner control is a sub-dimension to measure the ability of an individual to manage the online learning process, to determine his/her needs and to make plans. E-learning environments differ significantly from traditional learning environments in terms of access to information, process management and flexible learning opportunities. Particularly with the introduction of customizable learning environments, learners have more control over the learning process. Thus, learner control is considered as a significant construct in the process of e-learning readiness (Reigeluth 1999). Learner motivation towards e-learning is regarded as a component of e-learning readiness, and it seeks to determine the eagerness and interest of the learners in the e-learning process (Hung et al. 2010). Learners with high levels of self-directed learning, learner control and motivation are assumed to have autonomous learning skills in regard to e-learning (Yurdugül and Demir 2016). The present study discusses e-learning readiness in relation to autonomous learning skills rather than technological skills among learners.

One of the considerations regarding e-learning success is how learning takes place online (Omoda-Onyait and Lubega 2011). How learning takes place can be discussed in the framework of learning approaches. Learning approaches can be considered as the sources of motivation and strategies used by learners to achieve their objectives (Batı et al. 2010). Learning approaches are one of the decisive learner characteristics that are used to explain the differences observed in learner behaviors and success (Biggs et al. 2001). Two learning approaches as deep and surface approaches have been identified. The learners who perform surface learning memorize and learn the information just to pass the course. In deep learning, learners focus on the meaning and importance of the message presented by establishing relationships with the message. Analytical skills are essential to achieve a deep learning strategy. One makes less effort in surface learning. When a lot of information is presented in a short time, a surface learning strategy is often used. That said, this study discusses learning approaches and explores interaction patterns in the context of learning approaches to validate the models developed for the constructs of readiness that are mentioned in this study.

7.2 Research Methodology

The aim of this study is to investigate learners' navigations in the e-learning environment according to the level of readiness for e-learning. Lag sequential analysis was used when learners' system interactions were analyzed sequentially. Log and self-report data were used in the research. The data sources are explained in detail in the next subtitle.

7.2.1 Data Collection

The data of this research was obtained from the e-learning environment designed for a course based on blended learning strategy and self-report data collection tools. The log records used in this study were collected from learners who had a sixteen-week learning experience at Moodle learning management system. The course content is designed to have seven units in an electronic environment. Within the scope of this research, the interactions of the learners with LMS were examined under three different interaction themes: learner-content, learner-assessment and learner-learner. For seven different units in the e-learning environment, different types of content, assessment tasks and discussion topics were prepared by the researchers. Textual content, SCORM packages and videos were presented to the learners as content. Assessment tasks were presented to the learners as learner- assessment interaction. And, for the learner-learner interaction, some discussion topics were structured. In the scope of this research, these interactions were discussed and examined. E-learning tasks were constructed and learners were able to interact with these themes within the LMS. Log records were kept in Moodle database regarding the interaction of learners with these learning tasks. Log records based on user interactions in the Moodle database were used, when logging interactions were modeled. An example of these data recordings is given in Table 7.1.

The "id", "user_id" and "url" columns shown in Table 7.1 have an important role in conducting the research. "User_id" points to each learner's id. "Id" column is the id given to each learner for each different session. The "Url" column was used to determine which theme the learners interacted with.

In addition to log records, self-report data were also collected, through two self-report data collection tools. One of them is "e-learning readiness scale," and the other one is "learning approach scale". Undergraduate learners' "e-learning

Table 7.1 User log records

Id	Timestamp	User_id	Ip	Module	Action	Url
84729	1496620204	94	xxx	book	view	view.php?id=206
84730	1496620204	94	xxx	book	view chapter	view.php?id=206&chapterid=253
84731	1496620213	94	xxx	course	view	view.php?id=12
84732	1496620217	94	xxx	forum	view forum	view.php?f=23
84733	1496620226	94	xxx	forum	view discussion	discuss.php?d=88
84728	1496620188	94	xxx	course	view	view.php?id=12

readiness scale" was developed by Yurdugül and Demir (2016). The scale form was rated on a 7-point type. Self-directed learning, learner control and motivation sub-dimensions were used in this study. The research also deals with learning approaches that are closely related to autonomous learning. The reliability coefficients (Cronbach alpha) obtained during the development of the scale are as follows: 0.88 for learner control, 0.91 for self-directed and 0.95 for motivation towards e-learning sub-structures. In this study, Cronbach alpha reliability coefficients were calculated, which are as follows: 0.90 for self-directed, 0.86 for learner control and 0.92 for motivation towards e-learning sub-structures. "Biggs' Revised Two Factor Learning Approaches Scale" was used for gathering data about learning approaches. The scale was developed by Biggs, Kember and Leung (2001) and adapted to Turkish by Batı, Tetik and Gürpınar (2010). The scale is structured on a 5-point Likert type. The Cronbach alpha reliability was calculated 0.77 for deep approach and 0.80 for surface approach sub-structure by Batı, Tetik and Gürpınar. In this study, the Cronbach alpha reliability coefficient obtained was 0.64 for deep approach and 0.70 for surface approach sub-structure. When the psychometric properties of these scales are examined, it is seen that they are valid and reliable measurement tools.

7.2.2 *E-Learning Environment Design*

Moodle LMS was used as an e-learning environment in the research. Fifty-nine learners participated in the research, and learners had a sixteen-week learning experience in the e-learning environment. Learners interact with the content, discussion, and assessment tasks in the system. The learner-content theme was derived from interactions with textual materials, SCORM packages, and videos. Video content includes lectures made by the instructor of the course. The learner-learner theme is based on the interaction data in the forum pages. Learners interact with their friends and teachers on the forum pages. The interactions with the assessment materials in the e-learning environment are considered as the learner-assessment theme. The system has assessment tasks that are configured separately for each course chapter.

7.2.3 Lag Sequential Analysis

Lag sequential analysis (LSA) (Bakeman and Gottman 1997) is one of the widely used methods to reveal the consecutive model of human behavior and communication patterns. Consecutive analyses have emerged, considering that sequential and conditional examination of behavioral probabilities will provide more information rather than simple probabilities. Because in sequential measurements, results of measurements are not independent of each other. Subsequent measurements are influenced by the results of previous measurements (Gottman and Roy 1990).

$$Z = \frac{f_{rc} - f_r p_c}{\sqrt{f_r p \left(1 - p_c\right)\left(1 - p_r\right)}} \left(\text{Bakeman}\,1991\right)$$

In lag sequential analysis, firstly, a transitional frequency matrix, which shows the transitions between the behaviors, is created. Transition probabilities are calculated using matrix values. The Z-statistics are used to test the significance of transitions between behaviors. The following formula is used in the calculation of the Z score (Bakeman 1991). The Z score is calculated by using the conditional probabilities, which we express as the transition probabilities of the behaviors. If the Z score is greater than 1.96, we can say that the transition is significant at the 0.05 significance level.

7.3 Results

Online readiness levels and learning approaches of the learners are discussed within the scope of this research. Online readiness of learners consists of self-directed learning, learner control and motivation towards e-learning structures. Deep learning and surface learning are handled as learning approaches.

In order to reveal the structures related to the learners, firstly, the scores given by the self-report scales were collected and the total scores were obtained. Then, in order to reveal the structures more clearly, the learners in the upper and lower 27% groups were identified and lag sequential analysis was performed based on these data. In this context, learners are categorized into low and high level learners according to their self-directed, learner control and motivation towards e-learning structures. In the context of learning approaches, the learners were handled who are in the lower group were surface learners and those in the higher group were deep learners.

Each of the psycho-educational structures was handled separately, and sequential analyses related to them were carried out. In this section, the transitional frequency matrix and sequential patterns related to the sequential navigations of the learners are given. In Table 7.2, transitional probability matrices for self-directed learners are given.

Table 7.2 Transitional probability matrices for self-directed learners

Frequency	C	D	A	Total
High self-directed				
Content (C)	0.64	0.19	0.17	0.49
Discussion (D)	0.47	0.41	0.13	0.18
Assessment (A)	0.27	0.07	0.67	0.33
Total	0.49	0.18	0.33	1.00
Low self-directed				
Content (C)	0.59	0.13	0.28	0.48
Discussion (D)	0.56	0.28	0.17	0.11
Assessment (A)	0.31	0.04	0.65	0.41
Total	0.47	0.11	0.42	1.00

Table 7.3 Transitional probability matrices for learner control

Frequency	C	D	A	Total
High learner control				
Content (C)	0.62	0.19	0.19	0.47
Discussion (D)	0.51	0.35	0.14	0.17
Assessment (A)	0.27	0.06	0.67	0.35
Total	0.48	0.17	0.35	1.00
Low learner control				
Content (C)	0.61	0.14	0.26	0.50
Discussion (D)	0.52	0.31	0.18	0.12
Assessment (A)	0.31	0.05	0.64	0.39
Total	0.48	0.12	0.40	1.00

As can be seen in Table 7.2, it was determined that both high- and low-level learners interacted with content the most and then interacted in assessment and discussion environments, respectively. In the case of high-level self-directed learners, the interaction consists of 49% interactions of content, 33% assessment and 18% discussion. In the case of low-level self-directed learners, the interaction consists of 47% interactions of content, 42% assessment and 11% discussion. The transition probability matrices for learner control, which is another readiness structure, are presented in Table 7.3.

As can be seen in Table 7.3, it was determined that both high- and low-level learners interacted with content the most and then interacted in assessment and discussion environments, respectively. In the case of learners who have high-level learner control, the interaction consists of 48% interactions of content, 35% assessment and 17% discussion. In the case of learners who have low-level learner control, the interaction consists of 48% interactions of content, 40% assessment and 12% discussion. The transition probability matrices for motivation towards e-learning, which is another readiness structure, are presented in Table 7.4.

As can be seen in Table 7.4, it was determined that both high- and low-level learners interacted with content the most and then interacted in assessment and discussion environments, respectively. In the case of learners who have high-level

Table 7.4 Transitional probability matrices for motivation towards e-learning

Frequency	C	D	A	Total
High motivation towards e-learning				
Content (C)	0.58	0.16	0.25	0.47
Discussion (D)	0.47	0.37	0.16	0.15
Assessment (A)	0.33	0.06	0.61	0.38
Total	0.47	0.16	0.37	1.00
Low motivation towards e-learning				
Content (C)	0.63	0.18	0.18	0.46
Discussion (D)	0.51	0.34	0.15	0.16
Assessment (A)	0.22	0.05	0.74	0.38
Total	0.46	0.16	0.38	1.00

Table 7.5 Transitional probability matrices for deep and surface learning approaches

Frequency	C	D	A	Total
Deep approach				
Content (C)	0.66	0.18	0.16	0.51
Discussion (D)	0.49	0.40	0.11	0.18
Assessment (A)	0.26	0.07	0.67	0.31
Total	0.50	0.19	0.31	1.00
Surface approach				
Content (C)	0.63	0.18	0.18	0.46
Discussion (D)	0.51	0.34	0.15	0.16
Assessment (A)	0.22	0.05	0.74	0.38
Total	0.46	0.16	0.38	1.00

motivation towards e-learning, the interaction consists of 47% interactions of content, 37% assessment and 16% discussion. In the case of learners who have low-level motivation towards e-learning, the interaction consists of 46% interactions of content, 38% assessment and 16% discussion.

This research also examined the learning approaches of the learners, which are highly related to the sub-structures of online readiness. Learners' learning approaches are categorized as deep and surface approach. The transitional probability matrices for learning approaches are presented in Table 7.5.

As can be seen in Table 7.5, it was determined that both high- and low-level learners who have deep and surface learning approach interacted with content the most and then interacted in assessment and discussion environments, respectively. In case of learners who have deep approach, the interaction consists of 50% interactions of content, 31% assessment and 19% discussion. In the case of learners who have surface approach, the interaction consists 46% interactions of content, 38% assessment and 16% discussion.

After the transition probability matrix for the online readiness sub-factors and learning approaches of the learners was given, the statistical significance of these transition possibilities was tested. The statistical significance of the transitions in the sequential navigations of the learners was examined by calculating the z-score.

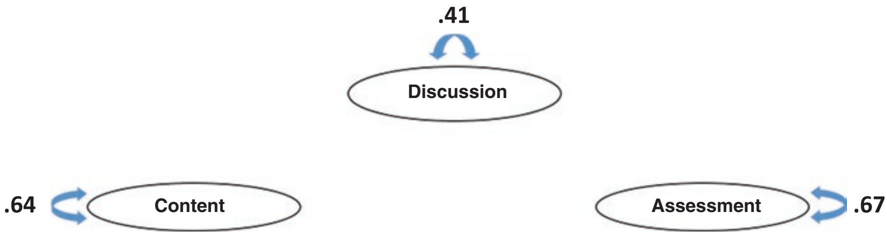


Fig. 7.2 High-level self-directed learner group results

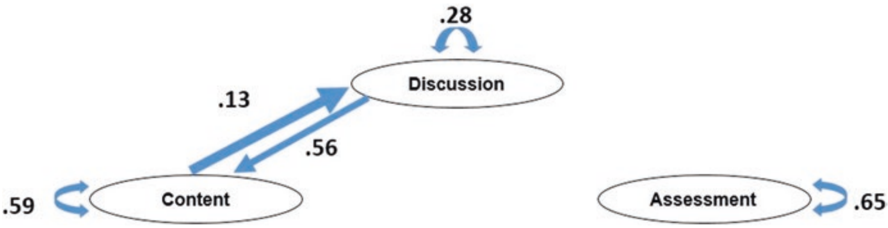


Fig. 7.3 Low-level self-directed learner group results

As a result of these calculations, statistically significant patterns based on psycho-educational characteristics are presented in this section. Firstly, sub-dimensions of OLR are discussed. The results of the lag sequential analysis are then studied according to the learning approach of the learners. The results of the high-level self-directed learner group are presented in Fig. 7.2.

As can be seen in Fig. 7.2, it is possible to say that the learners in the high-level self-directed learner group have a persistent navigation pattern. While there was no significant transition between all three themes, the themes seemed to provide statistically significant loops within themselves. The cyclical transition was found to be significant $P^{tr} = 0.64$ in content ($z = 13.00$; $p < 0.05$), $P^{tr} = 0.41$ in discussion ($z = 11.32$; $p < 0.05$) and $P^{tr} = 0.67$ in assessment ($z = 21.65$; $p < 0.05$). The results of low-level self-directed learners are presented in Fig. 7.3.

As can be seen in Fig. 7.3, it is possible to say that the learners in the low-level self-directed learner group have a transitional pattern between the themes. The cyclical transition was found to be significant $P^{tr} = 0.59$ in content ($z = 9.78$; $p < 0.05$), $P^{tr} = 0.28$ in discussion ($z = 11.73$; $p < 0.05$) and $P^{tr} = 0.65$ in assessment ($z = 17.75$; $p < 0.05$). Besides, for the low-level self-directed learner group, the transitions from content to discussion ($P^{tr} = 0.13$, $z = 3.21$) and discussion to content ($P^{tr} = 0.56$, $z = 2.51$) were found to be statistically significant. The results of learners who have high-level learner control are presented in Fig. 7.4.

As can be seen in Fig. 7.4, it is possible to say that the learners in the high-level learner control group have a transitional pattern between the themes. The cyclical transition was found to be significant $P^{tr} = 0.62$ in content ($z = 15.29$; $p < 0.05$), $P^{tr} = 0.35$ in discussion ($z = 12.21$; $p < 0.05$) and $P^{tr} = 0.67$ in assessment ($z = 28.07$;

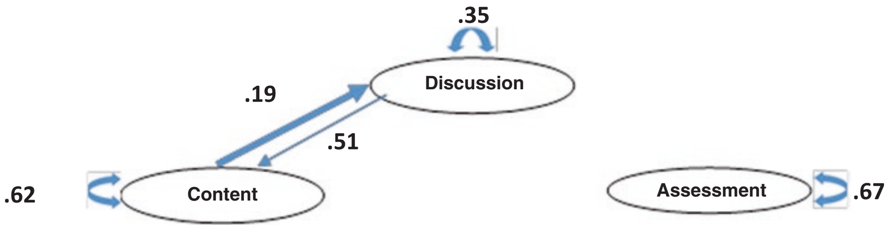


Fig. 7.4 High-level learner control group result

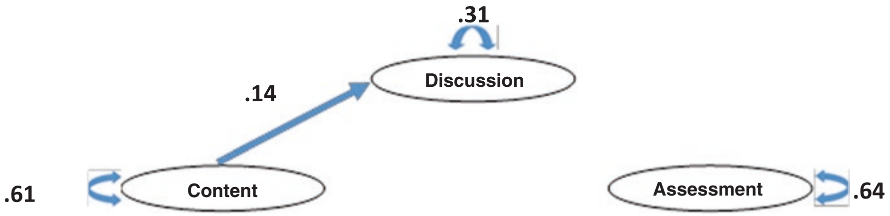


Fig. 7.5 Low-level learner control group results

Fig. 7.6 Navigational patterns of learners with high motivation towards e-learning

$p < 0.05$). Besides, for the high-level learner control group, the transitions from content to discussion ($P^{tr} = 0.19$, $z = 2.53$) were found to be statistically significant. It was determined that there was a transition from discussion to content at a significance level of 0.10. The results of learners who have low-level learner control are presented in Fig. 7.5.

As can be seen in Fig. 7.5, it is possible to say that the learners in the low-level learner control group have a transitional pattern between the themes. The cyclical transition was found to be significant $P^{tr} = 0.61$ in content ($z = 12.65$; $p < 0.05$), $P^{tr} = 0.31$ in discussion ($z = 10.52$; $p < 0.05$) and $P^{tr} = 0.64$ in assessment ($z = 20.25$; $p < 0.05$). Besides, for the low-level learner control group, the transitions from content to discussion ($P^{tr} = 0.14$, $z = 2.35$) were found to be statistically significant. The results of learners who have high-level motivation towards e-learning are presented in Fig. 7.6.

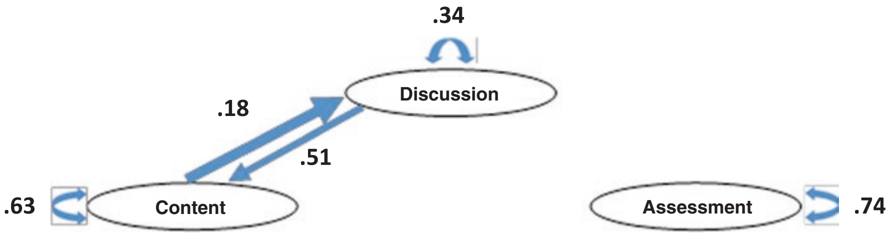


Fig. 7.7 Navigational patterns of learners with low motivation towards e-learning

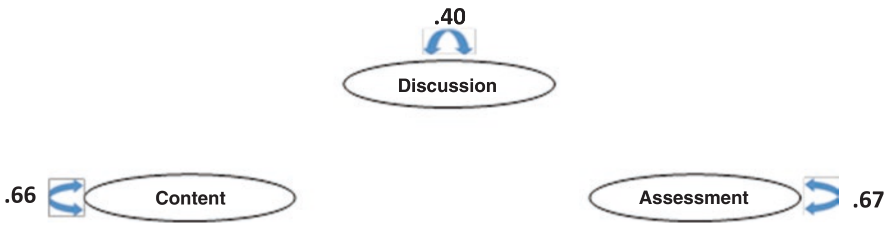


Fig. 7.8 Navigational patterns of learners with deep learning approach towards e-learning

In Fig. 7.6, navigational patterns of learners with high motivation towards e-learning are given. Accordingly, it can be said that there is a persistent navigational pattern. While there was no significant transition between all three themes, the themes seemed to provide statistically significant loops within themselves. The cyclical transition was found to be significant $P^{tr} = 0.58$ in content ($z = 9.78$; $p < 0.05$), $P^{tr} = 0.37$ in discussion ($z = 11.73$; $p < 0.05$) and $P^{tr} = 0.61$ in assessment ($z = 17.75$; $p < 0.05$). The results of learners who have low-level motivation towards e-learning are presented in Fig. 7.7.

In Fig. 7.7, navigational patterns of learners with low motivation towards e-learning are given. Accordingly, it can be said that there is a transitional pattern between the themes. While there were only two significant transitions between the content and discussion themes, the themes seemed to provide statistically significant loops within themselves. The cyclical transition was found to be $P^{tr} = 0.63$ in content ($z = 15.65$; $p < 0.05$), $P^{tr} = 0.34$ in discussion ($z = 10.50$; $p < 0.05$) and $P^{tr} = 0.38$ in assessment ($z = 26.52$; $p < 0.05$).

In addition to OLR, sequential navigations based on the learners' learning approaches have been examined in this research. Findings according to the learners' learning approaches are presented in Figs. 7.8 and 7.9.

When we examine navigational patterns of learners with deep learning approach, it is seen that only cyclic transitions are statistically significant (Fig. 7.7). The cyclical transition was found to be significant $P^{tr} = 0.67$ in content ($z = 13.88$; $p < 0.05$), $P^{tr} = 0.40$ in discussion ($z = 11.55$; $p < 0.05$) and $P^{tr} = 0.41$ in assessment ($z = 23.40$; $p < 0.05$).

Fig. 7.9 Navigational patterns of learners with surface learning approach towards e-learning

In Fig. 7.9, navigational patterns of learners with surface learning approach towards e-learning are given. Accordingly, it can be said that there is a transitional pattern between the themes. The cyclical transition was found to be significant $P^{tr} = 0.57$ in content ($z = 9.54$; $p < 0.05$), $P^{tr} = 0.33$ in discussion ($z = 9.17$; $p < 0.05$) and $P^{tr} = 0.64$ in assessment ($z = 16.88$; $p < 0.05$). Besides, for learners with surface learning approach, the transitions from content to discussion ($P^{tr} = 0.17$, $z = 3.24$) are found to be statistically significant.

7.4 Discussion and Conclusion

In this study, OLR and the learners' navigation (interaction) sequences in e-learning environments are examined. According to findings, learners who have high levels of self-directed learning, learning control and learning motivation tend to have a consistent interaction in interaction types. On the other hand, it has been observed that learners who have low-level psycho-educational structures prefer non-persistent interaction rather than persistent interaction. These learners' interactions with content and other themes were intertwined. In a LMS environment the expected behaviors of learners respectively as follows; (a) knowledge acquisition via interaction with content, (b) knowledge construct via interaction with learner and finally (c) reflection and examining themselves via interaction with assessment. Another pattern observed in the findings is the learners that have low-level psycho-educational structures have intertwining interactions. This situation reveals that learners need mentoring and scaffolding in e-learning environments.

This study concludes that the learners with low levels of OLR and engaged in surface learning browsed through content and discussion without completing the learning task. On the other hand, the learners with high levels of OLR and engaged in deep learning made consistent visits between learning themes. These learners also browsed through the content, discussion and evaluation, although these transitions between the themes are not shown on diagrams. As these transitions are proportionally lower than the transitions within the themes, they are not marked as significant transitions based on the sequential analyses performed in the study. The constructivist learning approach assumes that learners do not learn in a linear way and that the process of learning is a cyclical process by which learners occasionally move back and forth. In this regard, this study reveals that the learners with high levels of OLR and engaged in deep learning performed e-learning behaviors that were more relevant to the constructivist learning approach.

Readiness is perhaps the first step in learning. Readiness consists of two basic skills. One is the using instructional technology (computer using, internet using) and the other is autonomous learning skills. Learners with high self-directed learning and motivation levels, which are considered to be autonomous learning skills, are consistent in online interactions, while those who are at low levels are more likely to cross between themes. According to this, it can be said that these learners are weak in online learning skills. Because these learners have continuously transitioned to discussion and to content without completing a learning task. The behavior of these learners was observed to be deep-learner behaviors because the high level of readiness is typical of deep learning behavior. The instruction designer and environment designer should consider this study similar finding. If we know the learners' interaction patterns, we can give them some individual recommendations and also design adaptive systems based on them. In addition to this, sequential pattern also provides tips for developing a new generation of LMS (LMS 3.0).

The study by Dawson, McWilliam and Tan (2008) finds out that most of the interactions of the learners with LMS took place at the discussion forum, which was followed by content pages, and that there was a low level of interaction with online quizzes, wikis and blogs. However, the findings of this study point out that the learners had a low level of interaction in the discussion forums, relative to other interactions, as they were expected to structure the information in the discussion forums. Further, as learners communicate with each other in discussions, they can emotionally support each other (Totaro et al. 2016). In conclusion, this study suggests that discussion forums in LMSs may be restructured to enhance learner interaction in these forums and that it is essential to develop system designs to achieve this.

References

Abdullah, M., Daffa, W. H., Bashmail, R. M., Alzahrani, M., & Sadik, M. (2015). The impact of learning styles on learner's performance in e-learning environment. *International Journal of Advanced Computer Science and Applications, 6*(9), 24–31.

Bakeman, R. (1991). From lags to logs: Advances in sequential analysis. *Revista Mexicana de Análisis de la Conducta/Mexican Journal of Behavior Analysis, 17*(3), 65–83.

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis* (2nd ed.). Cambridge: Cambridge University Press.

Batı, A. H., Tetik, C., & Gürpınar, E. (2010). Assessment of the validity and reliability of the Turkish adaptation of the study process questionnaire (R-SPQ-2F). *Turkiye Klinikleri Journal of Medical Sciences, 30*(5), 1639–1646.

Biggs, J., Kember, D., & Leung, D. Y. (2001). The revised two-factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology, 71*(1), 133–149.

Danis, C. (1992). A unifying framework for data-based research into adult self-directed learning. In H. B. Long & Associates (Ed.), *Self-directed learning: Application and research* (pp. 47–72).

Norman: Oklahoma Research Center for Continuing Professional and Higher education at the University of Oklahoma.

Dawson, S. P., McWilliam, E., & Tan, J. P. L. (2008). *Teaching smarter: How mining ICT data can inform and improve learning and teaching practice*.

Gottman, J. M., & Roy, A. K. (1990). *Sequential analysis: A guide for behavorial researchers*. Cambridge: Cambridge University Press.

Graf, S., Liu, T. C., & Kinshuk. (2010). Analysis of learners' navigational behaviour and their learning styles in an online course. *Journal of Computer Assisted Learning, 26*(2), 116–131.

Hung, M. L., Chou, C., Chen, C. H., & Own, Z. Y. (2010). Learner readiness for online learning: Scale development and learner perceptions. *Computers & Education, 55*(3), 1080–1090.

Kaur, K., & Abas, Z. W. (2004). *An assessment of e-learning readiness at the Open University Turkey*. In International conference on computers in education 2004.

Keskin, S., Şahin, M., & Yurdugül, H. (2019). Online learners' navigational patterns based on data mining in terms of learning achievement. In D. Sampson, M. Spector, D. Ifenthaler, P. Isaías, & S. Sergis (Eds.), *Learning technologies for transforming large-scale teaching, learning, and assessment* (pp. 105–121). London/Berlin/Cham: Springer.

Knowles, M. S. (1975). *Self-directed learning: A guide for learners and teachers* (Vol. 2, No. 2, p. 135). New York: Association Press.

Knowles, M. S. (1990). *The adult learner: A neglected species* (4th ed.). Houston: Gulf Publishing.

Lee, G. (2012). *Development study on supporting strategies for leaners' task selection in self-directed e-learning environment (doctoral dissertation)*. Seoul: Seoul National University.

Merriam, S. B. (2001). Andragogy and self-directed learning: Pillars of adult learning theory. *New Directions for Adult and Continuing Education, 2001*(89), 3–14.

Moftakhari, M. M. (2013). *Evaluating E-learning readiness of faculty of letters of Hacettepe (unpublished master thesis)*. Ankara: Hacettepe Üniversitesi.

Moore, M. G. (1989). Three types of interaction. *American Journal of Distance Education, 3*(2), 1–6.

Omoda-Onyait, G., & Lubega, J. T. (2011, August). E-learning readiness assessment model: A case study of higher institutions of learning in Uganda. In *International conference on hybrid learning* (pp. 200–211). Berlin/Heidelberg: Springer.

Patterson, C., Crooks, D., & Lunyk-Child, O. (2002). A new perspective on competencies for self-directed learning. *Journal of Nursing Education, 41*(1), 25–31.

Reigeluth, C. M. (1999). The elaboration theory: Guidance for scope and sequence decisions. *Instructional Design Theories and Models: A New Paradigm of Instructional Theory, 2*, 425–453.

Totaro, S., Toffol, E., & Scocco, P. (2016). Suicide prevention and the internet, risks and opportunities: A narrative review. *Sucidology Online, 7*, 63–73.

Yurdugül, H., & Demir, Ö. (2016). An investigation of pre-service teachers' readiness for e-learning at undergraduate level teacher training programs: The case of Hacettepe University. *H. U. Journal of Education, 32*(4), 896–915.

Part III
Case Studies of Online Higher Education

Chapter 8
Problem-Based Learning and Computer-Based Scaffolds in Online Learning

Mahnaz Moallem and Elizabeth Igoe

8.1 Introduction

Problem-based learning (PBL) is an instructional approach rooted in constructivist and experiential learning theories. Research and theory on learning suggest that by having students learn through the experience of solving problems, they can learn both content and thinking strategies (Hmelo-Silver 2004; Savery 2006). In PBL, student learning centers around a complex problem that does not have a single correct answer or solution. Students learn content, strategies, and self-directed learning skills through collaboratively engaging in problem-solving, reflecting on their own experiences, and engaging in self-directed inquiry (Hmelo-Silver et al. 2007). It has been maintained in the literature that PBL positively influences learning outcomes along with learners' higher-order thinking skills such as creative thinking, problem-solving, logical thinking, and decision-making (Şendağ and Odabaşı 2009). With the advent of reform movements in education, such as twenty-first century learning skills, PBL is increasingly being advocated for and adopted by institutions of higher education.

However, while the literature has established convincing evidence in support of the effectiveness of problem-based instructional models (Belland 2017; Belland et al. 2014, 2015; Swanson and Deshler 2003; Swanson and Lussier 2001) and the utilization of PBL has expanded, disputes exist regarding the amount of scaffolding and guidance provided to students during implementation. Scaffolding is temporary guidance provided by a teacher/parent, peer, or a computer or other print materials

M. Moallem (✉)
Department of Educational Technology and Literacy, College of Education,
Towson University, Towson, MD, USA
e-mail: mmoallem@towson.edu

E. Igoe
Manager of Learning Experience Design, Association of International Certified
Professional Accountants, Raleigh, NC, USA

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*,
Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_8

to assist learners with the learning process (Belland 2017). Kirschner, Sweller, and Clark (2006) argue that PBL represents a minimally guided instructional practice. They maintain that as minimally guided instruction, PBL is less effective and less efficient than instructional approaches, such as direct instruction that place a strong emphasis on the guidance of the student learning process (Kirschner et al. 2006). In contrast, Hmelo-Silver, Duncan, and Chinn (2007) contend that PBL is not a minimally guided instructional approach but "rather provides extensive scaffolding and guidance to facilitate student learning" (p. 99). As PBL situates learning in complex tasks, the tasks require scaffolding to help students engage in sensemaking, managing their investigations and problem-solving processes, and encouraging students to articulate their thinking and reflect on learning (Hmelo-Silver et al. 2007).

The disagreement on the amount of scaffolding to facilitate student learning in PBL is relevant in the context of higher education as online education is now a popular alternative to face-to-face classroom instruction. Today, almost one-third of college students take courses online, half of which are enrolled in exclusively online programs (Protopsaltis and Baum 2019). Most online courses are delivered asynchronously to offer more flexibility, allowing instruction and communication between students and instructors to occur independently of time and location. Problem-based learning approaches represent a major, complex, and widespread change in educational practice (Dolmans et al. 2005) in higher education. However, PBL has traditionally been conducted in face-to-face settings using collaborative learning groups. Thus, less is known regarding the successful implementation and facilitation of PBL in online learning environments. The traditional implementation process of PBL poses significant challenges to asynchronous online instructors in terms of scaffolding both individuals and collaborative groups. Review of the literature on scaffolding suggests that software applications used in interactive, computer-supported learning environments can provide scaffolding and support to online learners rather than solely depending on teachers/facilitators and peers (Davis and Linn 2000; Quintana et al. 1999; Reiser 2004).

The purposes of this study were to (1) design, develop, implement, and test three self-directed, computer-based modules that supported scaffolding in an online graduate-level course applying problem-/project-based learning (PBL); (2) collect data to assess the effectiveness of computer-supported scaffolding provided in the modules to assist students in problem identification, application of conceptual and domain-specific knowledge, and skills of argumentation; and (3) use the results of the data to identify recommendations for future researchers and designers.

8.2 Conceptual Framework

8.2.1 Problem-Based Approach

PBL is one of a family of constructivist, experiential learning approaches, which situate learning in a meaningful task (Hmelo-Silver 2004), such as project-based learning (PjBL) and inquiry learning (IL) (Savery 2006). PjBL tends to focus on a longer-term project, which concentrates on the application of knowledge toward a complex problem. Learners create a project or product that is close to professional reality (Mills and Treagust 2003). Within a project-based approach, the learner is usually provided with specifications for the desired end product (Savery 2006). This is a key difference from PBL as it tends to reduce the learner's role in setting the goals and outcomes for the "problem" (Savery 2006). Despite some differences among these and other similar PBL approaches, they share the following essential characteristics proposed by Barrows (1980, 1988, 1996a, b) and distinguish the PBL approaches from other methods:

- **Learning is student-centered.** Students take an active role in their learning by shifting the responsibilities of organizing, analyzing, synthesizing, and evaluating content from the teacher to the student (Brush and Saye 2002; Means 1994).
- **Learning occurs in small student groups.** Learning most naturally occurs not in isolation but by teams of people working together to solve problems (Jonassen 1999). In PBL, students work together in small collaborative groups to co-construct knowledge and explanations. Every group member is expected to participate, and by distributing the learning responsibilities, it is assumed that the complex task becomes more manageable for the group (Hmelo-Silver 2004).
- **Teachers act as facilitators or tutors in the learning process.** PBL requires a shift in the traditional role of the teacher as a knowledge provider to tutor as manager and facilitator of learning (Savery 2006). "Coach," "guide," and "facilitator" are metaphors used to convey the fundamental nature of the instructor's role in PBL and to differentiate it from the more traditional didactic role (Simons and Ertmer 2005).
- **Authentic problems are the focus and stimulus for learning.** Learning is set within the context of an authentic, real-world problem. In PBL, a problem is presented to the students at the beginning of the learning process. "The problem represents the challenge students face in practice and provides relevance and motivation for learning" (Barrows 1996, p.5). As students work through the problem-solving process, they learn domain content to solve the problem, rather than solving the problem as an application of learning (Jonassen 1999).
- **Problems are ill-structured.** The problem presented must be appropriately complex, ill-structured, and open-ended (Hmelo-Silver 2004; Simons and Ertmer 2005). Such problems do not have a single correct answer, and there are multiple pathways to the solution(s) (Hmelo-Silver and Barrows 2006; Jonassen 2011; Simons and Ertmer 2005).
- **Students engage in self-directed learning.** Students are responsible for their own learning, which necessitates reflective, critical thinking about what is being learned (Hmelo-Silver 2004). Students are expected to engage in their own study and research to accumulate knowledge. During self-directed learning, students work together, discussing, comparing, reviewing, and debating what they have learned (Barrows 1996a, b).

8.2.2 Process of Implementing PBL

PBL, as its name implies, situates learning in the context of a problem. The PBL learning cycle, also known as the PBL tutorial process, typically starts with the presentation of an authentic, ill-structured problem rather than a lecture or reading assignment intended to impart discipline-specific knowledge to the student (Savery 2009). To solve the problems, students work in small collaborative groups to identify relevant facts from the provided problem scenario. As a group, students analyze the problem, generate possible explanations, as well as identify key issues and concepts they need to learn more about to solve the problem (Hmelo-Silver 2004; Savery 2009; Yew and Schmidt 2012). After this period of teamwork, students disperse for a phase of self-directed study. Students independently research and investigate selected learning issues identified by the group. "They then regroup to share what they have learned, reconsider their hypotheses, and/or generate new ideas in light of their new learning" (Hmelo-Silver 2004, p. 242). A tutor/facilitator is present during the group discussions to help facilitate the learning processes and the development of metacognitive skills (Savery 2009; Yew and Schmidt 2012).

In summary, the cycle of PBL is essentially comprised of three phases: initial problem analysis, followed by self-directed learning, and a subsequent reporting phase (Barrows 1988; Hmelo-Silver 2004; Yew and Schmidt 2012).

8.2.2.1 Role of the Tutor or Facilitator in PBL

In PBL, the traditional role of the "teacher" is transformed into that of a "facilitator" or "tutor." PBL tutors/facilitators do not directly transmit/teach the content knowledge to students. Instead, they support the students' learning process by observing the students, pushing them to think deeply by asking probing questions and encouraging students to articulate their thinking, modeling problem-solving strategies, and promoting collaboration among group members (Hmelo-Silver et al., 2007; Sockalingam, Rotgans and Schmidt 2011).

It is noted in the literature that the role of the tutor or facilitator is critical to the successful implementation of PBL (Hmelo-Silver 2004; Savery 2009). The tutor provides the initial guidance and supports with process skills, such as metacognitive modeling for individuals and groups, during collaborative group work (Savery 2009). The tutor is responsible for both moving the students through the various stages of PBL and for monitoring the group process to assure that all students are actively involved (Barrows 1988; Hmelo-Silver 2004). The PBL tutor guides the development of higher-order thinking skills by challenging students to justify their thinking (Barrows 1988) and externalizes self-reflection by directing appropriate questions to individuals (Hmelo-Silver 2004).

8.2.2.2 Role and Types of Scaffolding or Guidance in PBL

Scaffolding can be defined as the support provided by a teacher, facilitator, tutor, peer, or a computer- or paper-based tool that allows students to meaningfully participate in and gain skill at a task that they would be unable to complete unaided (Belland 2017). This concept of scaffolding has been connected to Vygotsky's zone of proximal development (ZPD), defined as the "distance between the child's actual developmental level as determined by independent problem-solving and the level of potential development as determined through problem-solving under adult guidance and in collaboration with more capable peers" (Vygotsky 1978, p. 86). Enabling the learner to bridge this gap between the actual and the potential depends on the resources or the kinds of support provided (Puntambekar and Hübscher 2005).

The original notion of scaffolding assumed that a single more knowledgeable person, such as a parent or a teacher, or a peer would help an individual learner, providing him or her with exactly the help he/she needed to move forward (Puntambekar and Hübscher 2005). However, the reality of modern classrooms and the emergence of computer technologies have broadened the definition of scaffolding, expanding the potential sources of scaffolding and how scaffolds are delivered to students. Thus, scaffolds can be defined as tools, strategies, or guides that support students in gaining higher levels of understanding that would otherwise be beyond their reach (Brush and Saye 2002; Hannafin et al. 1999; Simons and Ertmer 2005). Scaffolds may assume multiple forms depending on the learning environment, the content, the instructor, and the learners (Simons and Ertmer 2005). Belland (2017) categorizes scaffolding in terms of its functions. He explains that scaffolding functions include *conceptual scaffolding* (things to consider when solving problems), *strategic scaffolding* (bootstrap a strategy to use to solve a problem), *metacognitive scaffolding* (evaluate one's own thinking), and *motivational scaffolding* (enhance willingness to deploy effort to carry out learning tasks) (Belland 2017). Brush and Saye (2002) conceptualize two categories of scaffolds: *soft* and *hard scaffolds* (Brush and Saye 2002; Saye and Brush 2002). *Soft scaffolds* are dynamic situational aid provided by a teacher or peer. Soft scaffolding requires teachers to continuously diagnose the understandings of learners and provide timely support based on student responses (Brush and Saye 2002; Saye and Brush 2002). This type of support is generally provided "just in time," where the teacher monitors the progress that students are making (while engaged in a learning activity) and intervenes when support or guidance is needed. In contrast, *hard scaffolds* are static supports that can be anticipated and planned based on typical student difficulties with a task (Brush and Saye 2002; Saye and Brush 2002). Such scaffolds can take the form of printed materials, such as worksheets, scripted cooperation and structured journals (Hmelo-Silver 2004; Schmidt et al. 2011), or embedded within multimedia and hypermedia software to support students, while they are using the software (Brush and Saye 2002).

8.3 Computer-Supported Scaffolding: A Design Framework

Incombered by the review of the PBL literature, a conceptual framework was constructed to guide the design and development of problem-based, self-directed, learning modules that incorporate scaffolding for an online graduate-level course. As shown in Fig. 8.1, the framework was designed to propose how the cycle and core characteristics and process of PBL can be used to create computer-supported, hard and soft scaffolds to facilitate PBL in the absence of an instructor or facilitator.

As Fig. 8.1 suggests, learning should be set within the context of an authentic, ill-structured problem. In small collaborative groups, students are presented with a case scenario, which represents a realistic problem they may face in practice. The problem statement should be complex and not have a clear answer. To support the collaborative groups in problem analysis, hard scaffolds are provided in the form of "thinking questions" which intend to serve as a human tutor by posing questions to help learners examine the problem and identify what they need to know or learn more about the problem. Past research has found question prompting to be an effective instructional strategy for directing students to the most important aspects of a problem as well as encouraging self-explanation, elaboration, planning, monitoring and self-reflection, and evaluation (Ge et al. 2010). Thus, offering this line of questioning supports a student-centered learning experience because students must derive the key issues out of the problem they are presented with, identify their knowledge gaps, and, then in their individual self-study, pursue and acquire the missing knowledge. As PBL implementation process suggests, the scaffolding provided at this stage should be followed by a period of self-study, or self-directed

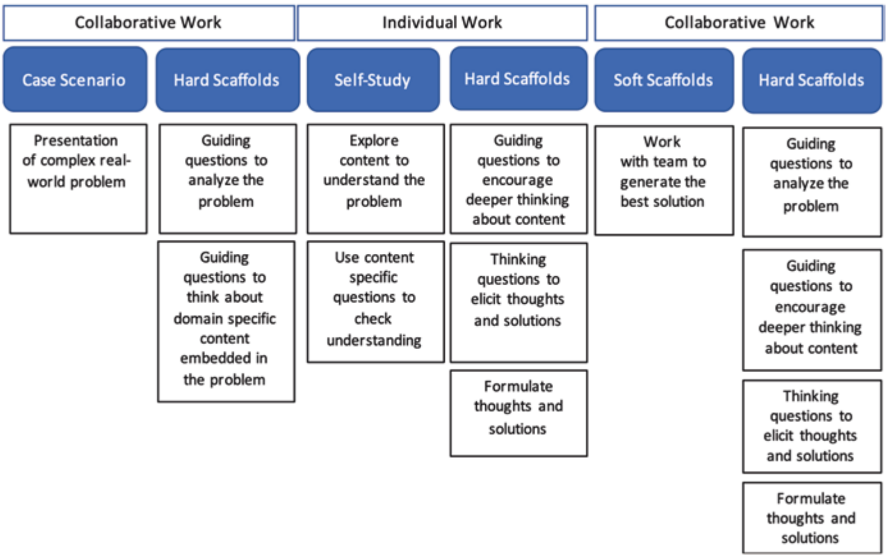


Fig. 8.1 A design framework for including scaffolding in online PBL modules

learning, where the learners explore the instructional content. Hard scaffolds in the form of prompts and guiding questions assist students in exploring content-specific resources and allow them to check their understanding of domain content. Within the content, guiding questions can be used as scaffolds to help students consider the domain content more deeply and apply domain thinking. Open-ended questions can scaffold students to elaborate on their thinking and justify their responses concerning prior experiences or the context of the problem. The guiding questions should promote critical thinking and the authentic application of skills and knowledge.

Once students have analyzed the problem and explored content on their own, they work with a small collaborative group to formulate a solution to the problem. At this stage, peers would provide soft scaffolding to each other as they discuss and debate their thoughts regarding the problem. The collaborative sessions would allow students to learn from each other and formulate a shared knowledge base. Hard scaffolds are presented in the form of thinking questions to encourage communication and sharing of ideas and perspectives among group members to analyze the problem again and discuss possible solutions. Guiding questions prompt can guide students to consider and apply domain-specific knowledge and skills (explored during self-study). Open-ended questions (hard scaffolds) are used to elicit elaboration of thinking and justification of decisions within the context of the case.

8.3.1 **TopHat***: An Interactive Content Development Tool*

A web-based PBL environment was specifically designed and developed for this study. *TopHat* was selected and used to develop instructional materials. *TopHat* (tophat.com) is a commercially available, web-based teaching platform which offers two products marketed toward engaging higher education students in and outside of class: "*Lecture*," a classroom response system which allows for interactive slide presentations, and "*InteractiveText*," interactive learning materials to help students study. The latter product were used to develop the PBL modules for this study.

InteractiveText is a modern conceptualization of traditional textbooks. Unlike a traditional static textbook, *InteractiveText* allows a designer to develop custom written content and integrate a variety of media like videos, hyperlinks, and interactive elements within the text. One of the unique elements of *InteractiveText* is the ability to embed questions within the content. *TopHat* provides multiple question formats, such as multiple-choice, word answer, numeric answer, sorting, and click on the target. There is also the option to include discussions questions, which allow for versatility for students to respond to subjective or interpretive questions that may not have an absolute answer. There is also a feature to allow students to respond with a drawing or graphical representation. Moreover, students can view each other's responses and engage in dialogue within the threaded discussion. These questioning functions allow an instructor to assess students' understanding in real-time or in advance of a class session. An instructor could use the data from assigned *InteractiveText* to identify issues and direct instruction toward areas where students are struggling. Instructors can assign *InteractiveText* in two different modes: practice and homework. In the practice mode, students can answer close-ended questions multiple times and receive "hints" and "explanations" depending on their responses. In the homework mode, students can only submit an answer one time and do not receive any responsive feedback. Questions can be graded based on participation, correctness, or both or not be graded. This feature allows the instructor to remove the scaffolding support if needed.

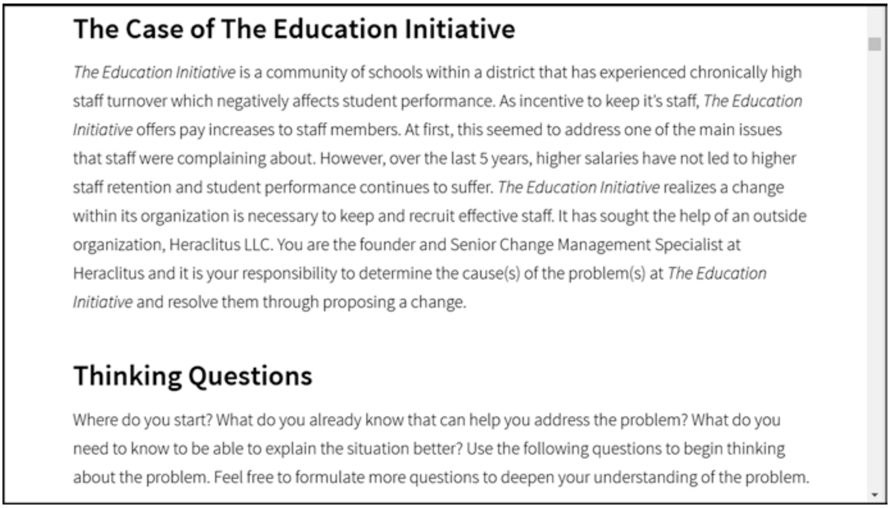
8.3.2 Incorporating Scaffolds in **TopHat** *Modules*

The *TopHat* environment and the proposed framework were used to develop three online modules. Each module focused on a targeted content embedded in an ill-defined problem statement. The students were to carefully read and analyze the problem statement to identify underlying concepts and issues, study them individually, and then meet with their collaborative group to discuss and come up with the best solution. Thus, each module began with a real-world, ill-defined problem, which was used as the context for the instruction. To replace the human tutor, who would normally guide learners' discussion when reviewing and analyzing the problem statement, a series of hard scaffolds in the form of consecutive questioning were provided to assist students in problem identification and analysis while exploring and applying conceptual and domain-specific knowledge. Furthermore, the successive questioning as a hard scaffold was aimed to encourage deeper thinking, elaboration, and argumentation. The following explains two types of hard scaffolds in the form of questioning that was used to assist the learners.

Analytical Questions Following the presentation of the problem, a series of "thinking questions" were provided to assist the learner in analyzing the problem. This line of questioning was designed to act as cognitive and metacognitive scaffolds by modeling the types of questions students should be asking of themselves. The thinking questions were related to both the domain-specific thinking and self-regulation skills. Figure 8.2 provides an example of analytical questions.

Domain-Specific Guiding Prompts and Questions In addition to analytical questions, students were guided to review related readings and other multimedia materials to explore domain-specific knowledge. The resources provide real-world examples and explanations of theoretical concepts, model expert behavior/thinking, or demonstrate a concept in action. An example of a content-related resource prompt is shown in Fig. 8.3.

Additionally, following instructional content and resource prompts, a series of guiding questions were used to provoke deeper thinking about the content. These guiding questions modeled the type of domain thinking questions students should be asking of themselves during their self-study. An example of domain-specific guiding questions is shown in Fig. 8.4. Often guiding questions were utilized before question prompts (discussed below) to assist students in the application of domain knowledge.



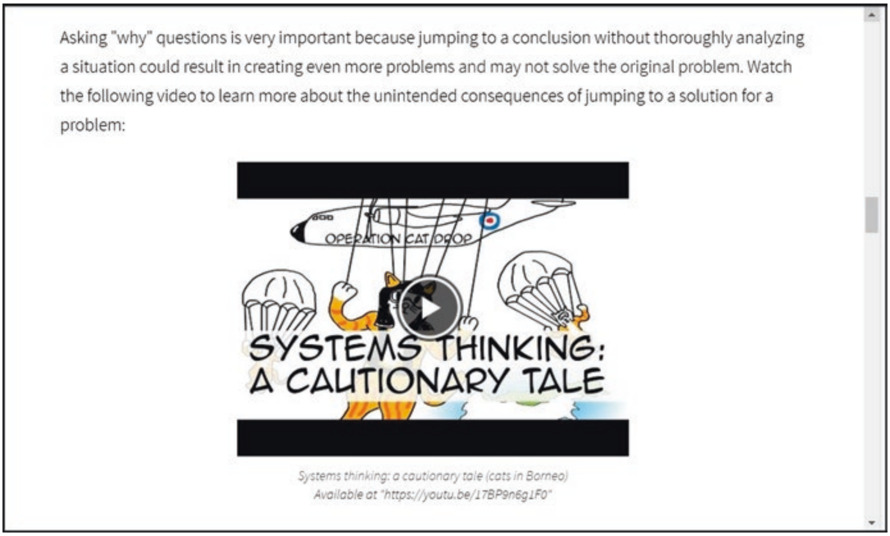
The Case of The Education Initiative

The Education Initiative is a community of schools within a district that has experienced chronically high staff turnover which negatively affects student performance. As incentive to keep it's staff, *The Education Initiative* offers pay increases to staff members. At first, this seemed to address one of the main issues that staff were complaining about. However, over the last 5 years, higher salaries have not led to higher staff retention and student performance continues to suffer. *The Education Initiative* realizes a change within its organization is necessary to keep and recruit effective staff. It has sought the help of an outside organization, Heraclitus LLC. You are the founder and Senior Change Management Specialist at Heraclitus and it is your responsibility to determine the cause(s) of the problem(s) at *The Education Initiative* and resolve them through proposing a change.

Thinking Questions

Where do you start? What do you already know that can help you address the problem? What do you need to know to be able to explain the situation better? Use the following questions to begin thinking about the problem. Feel free to formulate more questions to deepen your understanding of the problem.

Fig. 8.2 Example of analytical questions in online modules



Asking "why" questions is very important because jumping to a conclusion without thoroughly analyzing a situation could result in creating even more problems and may not solve the original problem. Watch the following video to learn more about the unintended consequences of jumping to a solution for a problem:

Systems thinking: a cautionary tale (cats in Borneo)
Available at "https://youtu.be/17BP9n6g1F0"

Fig. 8.3 Example of content resource prompts in online modules

Furthermore, question prompts were posed to elicit knowledge acquisition and allow students to check their understanding. Open-ended questions were used to elicit elaboration and allow students to provide justification or argumentation to support their thinking, as well as demonstrate the application of content knowledge and domain-specific thinking. Figure 8.5 is an example of an open-ended question that followed knowledge acquisition prompts.

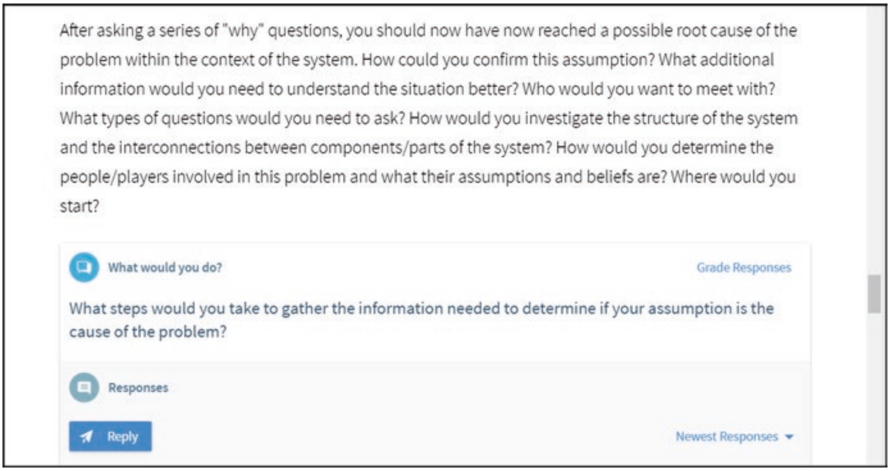


Fig. 8.4 Example of domain thinking guiding questions in online modules

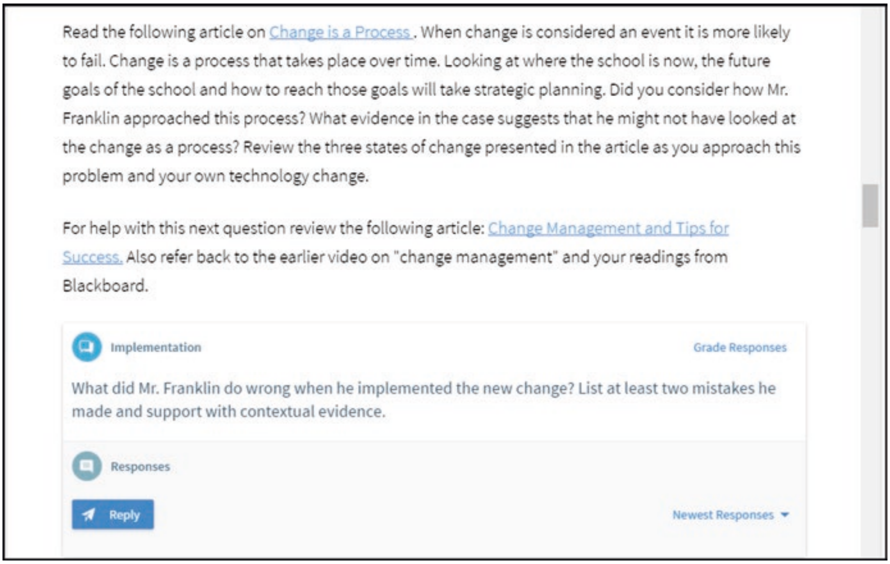


Fig. 8.5 Example of question prompt following knowledge acquisition in online modules

8.4 The Methodology

A design-based approach was used to systematically study the process of implementing and evaluating the learning materials. According to this iterative approach, the intervention could simultaneously be designed, developed, implemented, and studied (Wang and Hannafin 2005). During pilot implementation, formative evaluation data was collected to systematically analyze the effectiveness of the modules and identify changes before implementing it again in spring 2018. Both qualitative and quantitative data were collected and analyzed to inform decisions. Data was collected from multiple sources. The following questions guided the data collection process:

- To what extent do the *TopHat* modules with embedded scaffolding strategies impact students' content knowledge acquisition and thinking skills?
- To what extent do the scaffolds in the *TopHat* modules affect students' thinking and argumentation skills?
- What were students' perceptions of the *TopHat* modules and its embedded scaffolding strategies?

8.4.1 The Context

As indicated earlier, the *TopHat* modules were designed to support and be incorporated into the activities of an existing online course. "*Organization and Management of Instructional Technology*" is an elective course offered to students in an instructional technology graduate program. Participants enrolled in this course are primarily graduate students seeking a master's degree or a certificate in instructional technology. The course examines the planning and management of a technology change in public or private schools as well as other organizations. It aims to enable students to assume the role of a technology leader by identifying a need for technology change; determining the change management team; conducting an assessment of technology infrastructure, resources, and levels of competency of staff; and finally developing a technology plan. It is designed using PjBL as its overarching framework. But within the context of the project-based approach, students work in collaborative teams and engage in a series of authentic problem-solving tasks and activities in which they apply basic principles of change management and technology planning. The course PBL tasks and activities culminate in a project. The culminating project is divided into three main sections that are scheduled to be due at various points throughout the semester and require students to build on previous sections to form the final culminating product.

The course is delivered online using the Blackboard learning management system (LMS) with the option of offering live meetings using WebEx teleconferencing software. Required and optional course texts and resources are provided within the Blackboard course shell, allowing students the ability to access materials anytime, anywhere. WebEx virtual meeting is available for weekly group meetings or class sessions to be conducted synchronously, allowing for real-time communication between the instructor and students, as well as "break out rooms" for collaborative group meetings.

8.4.2 Implementation Procedures

The study was piloted during the fall semester of 2016 before it was conducted again in the spring semester of 2018. The three pilot course modules were carried out over three separate class sessions (once a week for 3 hours via WebEx virtual classroom), one for each interactive module (total of three *TopHat* modules). The researchers (one of the researchers was also the instructor of the course) were present in the classroom during WebEx virtual class sessions to observe live discussions and take observation notes. The *TopHat* modules were modified given the results of the pilot course. The course and its modified *TopHat* models were then offered again in the spring of 2018. The spring 2018 course, however, was delivered asynchronously. Thus, no weekly WebEx, virtual meeting was scheduled, although synchronous group meetings were available for live interaction with the instructor and group members if students chose to use it.

Participants In 2016 pilot course, five students (two males and three females) volunteered to participate in evaluating the *TopHat* intervention. None of the volunteers had previously participated in or completed the course. Additionally, three of five participants were completely new or a novice to the PBL process (one student attended the synchronous class meetings on campus, while four logged in from a distance in the WebEx virtual room). Three female participants had background and experience in teaching in public schools, while the two male participants had experience working in higher education. Participants were between the age of 24 and 55).

Eleven students participated in the spring of 2018 course (seven females and four males). None of the students had previously participated in or completed the course. All participants except for one were a novice to the process of PBL, and the course was one of the first courses they had taken in their master's degree program. Nine of the 11 participants were either educator at a public or private school or worked in the district central office, and 2 had business and industry work experience. Participants' age ranged from 24 to 45.

Procedure During the pilot course, at the beginning of each class session, students completed an online pretest based on the weekly module's performance objectives. After completing the pretest, students were instructed to meet with their team members and then log in to the *TopHat* course environment with their username and password. Students were then directed to complete the assigned interactive module. All PBL activity content was distributed through the *TopHat* modules online, while other course materials were available in the course Blackboard shell. Once all students had completed the individual components of the module, breakout rooms were established in WebEx, and the students were divided into two collaborative teams. In their breakout rooms, students could share a screen and engage in conversation and discourse to complete the team activity. However, one member of the team was responsible for recording and submitting the team's responses in the *TopHat* module, as the platform does not have a collaborative workspace.

Approximately 5 days following the live class session, students were asked to complete a posttest online, identical to the pretest. Following the completion of the third and final *TopHat* module, participants were asked to complete an online survey to self-report their experience and perception of the impact of the intervention.

In the spring of 2018, for the first week of the class, students attended an optional virtual orientation meeting and completed "the introduction to the course" module within the course Blackboard shell. During the second week of the course, students established their *TopHat* account, formed in a team of two and three, and began the first *TopHat* PBL module. No pretest was conducted before starting each *TopHat* module. Students were directed to review the problem statement, as a team, before completing the individual portion of the *TopHat* module. In the revised course, the contents of the *TopHat* modules were divided into two sections: individual self-study and group work. The individual sections were further divided into sections using analytical questions. For each module, students had a week to complete the individual section of the *TopHat* module and then meet with their team member to discuss the problem and post their solutions. Students also used the results of their PBL activity for each module to assist them in their course project.

Data Sources (Fall of 2016) The following data were collected during the implementation of the pilot course.

Pre-posttests A pre-posttest was used to investigate the effects of each *TopHat* module on content knowledge. The pre-posttest questions were developed based on the performance objectives of the weekly learning modules. The tests consisted of closed-ended, such as multiple-choice and true/false, as well as open-ended questions.

Observation During each implementation of the three *TopHat* modules, the students were observed by one of the researchers. The researcher kept notes of observations and discussions, including their impressions of instructor-student interactions, student collaborative team interactions, and student behaviors and perceptions regarding the progress students were making in completing the modules.

Students' Written Responses in TopHat Modules Students were prompted to respond to numerous open-ended questions eliciting elaboration and argumentation throughout the online modules (e.g., Is offering "pay raise increase" considered as a change? Why and why not? Give an example of an organizational change that you have been part of? What was the scope of that change? How did it affect you?). Responses were submitted and archived in the web-based platform.

Student Perception Survey A survey instrument was developed to elicit participants' feedback regarding their experience completing the *TopHat* modules, participating in PBL online and the effect of the online modules on their learning (e.g., It was easier to learn with the guidance of questions incorporated in the *TopHat* materials; the questions in the modules promoted me to think more deeply; the questions in *TopHat* helped me identify critical issues in the case).

Data Sources (Spring of 2018) The spring of 2018 data collection was focused on students' narrative responses to the various scaffolding prompts for each of the three modules. Student's responses to the open-ended prompts and discussion questions were analyzed and scored. Each student's responses to scaffolding prompts were also compared throughout the three modules to examine improvement in student's analytical thinking and argumentation skills.

8.4.3 Data Analysis

A scoring rubric was created to assess open-ended responses. The rubric was used to score students' responses to open-ended questions on pre-posttests as well as the module's scaffolding prompts or questions. Each question had either one or two levels of scoring. Level 1 questions involved students making an identification, providing a list or an example, and the scoring criteria ranged from 0 to 1; the student either made an identification or did not. Level 2 questions involved students supporting their thinking with explanation, reasoning, or argumentation, scoring criteria ranged from 0 to 3. Many questions included both Level 1 and Level 2 components. A sample of the scoring rubric is shown in Table 8.1.

The summative points earned for each of the criteria formed the total score for each question. To increase scoring objectivity, both researchers (one of the researchers was the instructor of the course) scored the students' responses separately. For any criterion where the interrater scores varied, the average of the two scores was used.

Pre-posttest responses were analyzed to determine the effects of the PBL *TopHat* modules on learners' content knowledge. Growth was calculated based on the difference between pre- and posttest scores for each individual. Additionally, to determine the quality of the assessment items, the average difference in score among all participants per item was calculated.

Table 8.1 Scoring rubric for open-ended responses

Level 1		Level 2			
Identification/provide an example or list		Level of justification/argumentation/explanation/reasoning			
0	**1**	**0**	**1**	**2**	**3**
No – does not make any identification or provide an example or list	Yes – provides an identification, example or list	None – does not provide any justification	Weak – demonstrates gaps in conceptual knowledge	Developing – demonstrates developing understanding of main concepts, able to apply knowledge to case and prior experiences	Strong – demonstrates understanding or mastery, makes connections to course readings and prior experiences

Observation data collected by one of the researchers was used to assess the implementation of each of the three *TopHat* modules. The researcher observed participants' responses to open-ended questions in real-time and noted the individual's progression through the modules. Group work was observed effectively due to the use of WebEx breakout rooms and teams sharing a screen. The researcher was able to see and hear collaboration during group meetings.

The open-ended responses submitted within the online modules were analyzed to examine the impact of the online PBL modules and scaffolds. Participants' responses were scored using the rubric described above. Total scores were calculated for each participant, and an average score was calculated for each item. The participants' score reflects the learners' performance, while the item's score reflects the quality of the assessment and product.

Additionally, survey data were analyzed using descriptive statistics to determine participants' perceptions of the *TopHat* intervention. Participants responded to a series of statements and rated each item by the degree to which they agreed or disagreed with each statement.

8.5 Results

8.5.1 Results of Pilot Course

8.5.1.1 To What Extent Do the *TopHat* Modules Impact Students' Content Knowledge Acquisition and Thinking Skills?

Pre-posttest results for three modules were analyzed. Tests contained both close-ended questions (i.e., multiple-choice and true/false) and open-ended questions which required short written responses. Close-ended questions were scored for correctness, while open-ended responses were scored using the rubric described above. In general, participants achieved an increase in their overall score from the pretest to the posttest. The average score among participants demonstrated growth in content knowledge and achievement for all three modules (Table 8.2).

While the results demonstrate that participants' scores improved from pre- to posttest, each module pre-posttest included items which resulted in an average decline or minimal gain in scores among participants (Table 8.3).

Item 6 in Module 2 experienced a 6% decline in average scores. The majority of participants' scores did not change between pre and post, while one participant's score declined. Additionally, Item 3 showed little gain (6%) compared to the other items. Each of these items asks participants to explain a concept and provide an example to support their answer. The lower scores reflect a difficulty providing reasoning and argumentation for more complex concepts within written responses. It is worth noting that Item 4 required participants to use the context of their course project in their response. While the item did achieve a small gain (5%), it is telling that the module did not appear to improve their performance when applying the content to their project.

Table 8.2 Summary of average pre-posttest growth

Test	Points possible		Average pretest score		Average posttest score		Average growth	
Module 2	22	100%	13	59%	16.5	75%	3.5	16.5%
Module 3	23	100%	14.6	63%	18.3	80%	3.7	16%
Module 4	19	100%	11.5	62%	13.75	72%	2	11%

Table 8.3 Summary of items with negative or minimal gain

Test	Item	Points possible	Average pretest score		Average posttest score		Average growth	
			#	%	#	%	#	%
Module 2	3	4	2.5	63%	2.75	69%	0.25	6%
	6	4	2.5	63%	2.25	56%	−0.25	−6%
Module 3	1	5	4.6	92%	4.2	84%	−0.40	−8%
Module 4	2	3	1.25	42%	2	67%	0.75	25%
	4	5	3	60%	3.25	65%	0.25	5%

8.5.1.2 To What Extent Did the Hard Scaffolds in the *TopHat* Modules Affect Students' Thinking and Argumentation Skills?

To assess the effects of hard scaffold on students' thinking and argumentation skills, written responses to open-ended assessment items within the *TopHat* modules were scored and analyzed (see Table 8.3). The online activities for Modules 3 and 4 consisted of two parts; an individual activity followed by a team activity. The two parts were scored separately.

The average scores for open-ended responses were low (Table 8.4). However, it should be noted that among the five participants' scores often varied widely per item. Scores appear to have been impacted by the weight placed on the level of argumentation and justification. Many open-ended questions consisted of both Level 1 and Level 2 components described in the scoring rubric (worth 4 points or more). The mediocre average scores reflect a general difficulty with the skills of argumentation and justification, which made up the bulk of the possible points.

Participants generally lacked detailed reasoning or justification to support and explain their thinking. This could be because students were not used to defending their thoughts in writing (e.g., Kumar and Refaei 2017), lacked skills and knowledge regarding argumentation and reasoning (Cho and Jonassen 2002; Krajcik et al. 1998), or that they felt rushed when completing the individual self-study activity, so they did not take time to expand fully on their thoughts for each question. The low scores could also point to a lack of conceptual content knowledge or prior experiences, which could have affected their ability to provide thoughtful and well-constructed arguments. Furthermore, the low scores could indicate that the metacognitive and cognitive scaffolds did not support or provide enough guidance for students to achieve the learning task.

Table 8.4 Summary of responses to *TopHat* prompts

TopHat module	Points possible	Average score	
		#	%
Module 2	47	28.1	65%
Module 3: Individual activity	5	3.25	65%
Module 3: Team activity	21	12.25	58%
Module 4: Individual activity	8	4.67	58%
Module 4: Team activity	15	7	47%

The results for team activities mirror the findings for individual activities. Scores were affected by the team's level of argumentation within responses. Both teams tended to provide superficial answers with very limited reasoning or justification within their responses. However, it should be noted that the question prompts in team activities focused on the application of domain-specific knowledge and the presentation of team generated solutions. The question prompts did not necessarily specifically request reasoning in writing, but practice in the domain would expect justification for solutions. Teams were observed discussing their answers and reasoning, but this collaboration was not reflected in the written responses. This could be due to the fact that one team member was acting as the scriber for the team and did not include all the conversation or thinking that led up to the compilation of the response. Or, it could be due to the format of the question prompts and embedded scaffolds. The scaffolds did not provide enough guidance to teams to elicit the expected components of the written response.

Team Activity for Module 4 consisted of the three participants who enrolled in the course for a grade. As such, the team activity was designed to allow the team to use the context for the course project during the team activity. The opportunity to work within the context of their project did not appear to improve open-ended responses. However, the team was observed skipping past questioning scaffolds and moving straight from question prompt to question prompt. It can be assumed that the embedded questioning scaffolds did not attract attention within the modules or were perceived to be extraneous. The format of the question prompts directed much more attention as they required action from participants.

8.5.1.3 What Were Students' Perceptions About the *TopHat* Modules?

A survey was conducted to evaluate student perception of the *TopHat* modules. The survey consisted of 23 items, and each item was accompanied by a 5-point Likert scale, with 1 denoting the most disagreeable and 5 denoting the most agreeable. The survey questions were categorized under the dimensions of the *PBL approach*, *scaffolds*, *learning evaluation*, and the *web-based platform* (TopHat). The results of students' perceptions of TopHat materials are shown in Tables 8.5, 8.6, 8.7, and 8.8.

Results indicate that participants generally agreed that the PBL approach was helpful and effective for interacting with and learning the content, as shown in

Table 8.5 Student perceptions of the PBL approach

No.	Statement	N	Mean	Std.
1	The *TopHat* modules helped me identify what I needed to learn more about	5	3.8	0.84
2	The cases presented in the *TopHat* modules were relevant	5	4.4	0.89
3	I used prior knowledge and experiences to help me analyze the cases	5	4.6	0.55
4	I had a chance to collaborate with other students	5	4	1.73
5	Interacting with other students improved my learning	5	4.2	1.10
6	I experienced quality interactions with the other students in terms of learning	5	3.8	1.79
7	Learning by interacting with other students enhanced my confidence	5	3.8	1.79
8	The interactions with the other students enhanced my communication skills	5	3.8	1.79
9	The interactions with the other students enhanced my collaboration skills	5	3.8	1.79
10	Working with group members helped me make connections between ideas	5	3.4	1.67

Table 8.6 Students' perception of *TopHat* scaffolds

No.	Statement	N	Mean	Std.
1	The questions in *TopHat* helped me identify critical issues in the cases	5	3.4	1.67
2	The questions in the modules prompted me to think more deeply	5	3.2	1.48
3	It was easier to learn with the guidance of questions incorporated in the *TopHat* materials	5	3.2	1.48
4	The videos, articles, and other resources included in the *TopHat* modules helped me make sense of the content	5	4.4	0.89
5	The *TopHat* materials provided guidance to the construction of new knowledge	5	3.8	0.84

Table 8.7 Students' evaluation of learning

No.	Statement	N	Mean	Std.
1	*TopHat* materials helped in my learning of the content	5	3.4	1.14
2	The *TopHat* modules improved my understanding of the content	5	3.8	1.10
3	I have gained new knowledge as a result of completing the *TopHat* modules	5	3.8	1.10
4	I feel better prepared to apply the content to my project after completing the TopHat modules	5	3.8	1.10
5	This type of activity is suitable for how I learn	5	3.6	1.14

Table 8.8 Students' perceptions of *TopHat*

No.	Statement	N	Mean	Std.
1	The *TopHat* platform was easy to use	5	4.4	0.89
2	I enjoyed the *TopHat* modules	5	3.8	1.10
3	I would use *TopHat* again if given the opportunity	5	4.4	0.89

Table 8.5. However, questions regarding skills associated with PBL, items 4–10, such as collaboration and communication, demonstrate a slightly wider range of responses, as illustrated by the standard deviation calculations. This is important to note because these skills are typically scaffolded by a facilitator in PBL during collaborative group sessions. During the *TopHat* intervention, early group discussion on problem analysis was not facilitated by the instructor/tutor. The results demonstrate that perhaps the hard scaffolds were not sufficient to take the place of the presence of a facilitator, as scaffolds offered by an instructor or a trained tutor are provided on the spot and in response to learners' thoughts (soft scaffold). Thus, it is likely that a human facilitator could better model thinking processes and promote skills of communication, collaboration, and critical thinking, especially with new or novice students to the PBL approach. However, with such a small sample size, it is difficult to generalize.

Students' perception of the *TopHat* scaffolding questions indicates that participants perceived the recommended resources embedded in the *TopHat* modules to be helpful and effective for interacting with and learning the content.

Table 8.6 shows how the participants evaluated the learning processes that they experienced. The results reveal that participants perceived the TopHat product to be a helpful learning tool and the intervention to be effective.

8.5.2 Revision and Modification

The results of the pilot course prompted several changes in the design and implementation of the *TopHat* modules. First, the pre-posttest questions were embedded in the scaffolding prompts or questions and students' final responses to the problem. Thus, the decision was to have students spend quality time responding to scaffolding questions rather than completing a test. This decision allowed students to analyze their content knowledge by engaging in the problem-solving task for each module. Secondly, compared with the pilot course where students only had an hour to complete the individual section of each *TopHat* module, students were given 1 week to complete the individual section of each *TopHat* module as well as working with their team member to discuss and propose a solution for the problem. Third, the analytical prompts or questions related to each problem statement listed and indexed for clarity, and the individual or self-study part of each module was separated from the group decision-making to help studzzent attention and deliberation. Fourth, the asynchronous delivery of the course made it possible for groups to decide how much time they wanted to spend discussing their solutions. Finally, group size was kept to two members per team (except for one team of three) to avoid scheduling conflicts.

8.5.3 Results of the Modified Modules

The modified *TopHat* modules were used to determine (1) to what extent the changes impacted students' content knowledge acquisition and thinking skill, and (2) whether or not the hard scaffolds in the *TopHat* modules affected students' thinking and argumentation skills.

Individual student responses to the open-ended scaffolding and discussion questions/prompts were scored using the same rubric developed during the pilot test for consistency (see Table 8.1). Individual students' narrative responses to every scaffolding question for the self-study section of each module entered in a spreadsheet. The responses were then coded and scored for each student separately – Module 2 (the first *TopHat* module had more scaffolding questions compared with the other two modules). The majority of the scaffolding questions included both Level 1 and Level 2 of the scoring rubric. Students' responses to each scaffolding prompt or question were often elaborate with explanation and example. For the discussion type of prompts, students could view each other's responses, but were expected to respond to the prompt from their own perspective.

As Table 8.9 shows, the majority of students scored high on all three modules when identifying issues or providing examples and explaining the concepts (Level 1). However, for Module 2, although the majority of students demonstrated an understanding of the content and were able to apply their knowledge to the problem scenario, only four students were able to make connections with the readings and use evidence to support their arguments. Nevertheless, all students seemed to improve in supporting their viewpoints in Modules 3 and 4. Analysis of individual students' responses further showed that those students who scored higher justified their answers using the readings or other evidence. This result suggests that the scaffolding questions guided students to review the reading materials or read/review text/video examples and elaboration resources, before answering the questions or prompts. Students who scored lower, however, tended to reference to or reflect on their peers' justifications or did not support their arguments. Thus, it appears that they did not benefit from the scaffolding questions.

Table 8.10 shows teams' scores on narrative responses to the problem scenarios using the scaffolding prompts. One of two prompts for the team activities guided students to identify specific issues within the case before offering their solutions with justification or evidence. The majority of the teams seemed to have benefited from the scaffolding questions and were able to justify their solutions. Module 4 scenario was designed to allow the teams to use their knowledge to propose a technology change while offering evidence and reasons for such a proposal. This activity was designed to allow students to apply what they learned from the previous activities to their course project. The comparison of students' responses to the scaffolding prompts or questions during the pilot course with the revised implementation of the modules showed notable improvement. Since the scaffolding questions remained constant during the pilot and the second iteration of the course implementation, the improvement in student reasoning could be due to several factors. First,

Table 8.9 Individual students' responses to scaffolding questions and prompts for the individual activity sections of three *TopHat* modules

Student	Module 2 Points (Level 1 & Level 2)	Module 3 Points (Level 1 & Level 2)	Module 4 Points (Level 1 & Level 2)	Total points Points (%)
Student 1	29/31 **(93.5%)** (10/10 & 19/21)	6/6 **(100%)** (3/3 & 3/3)	8/8 **(100%)** (2/2 & 6/6)	43/45 **(95.6)**
Student 2	28/31 **(90.3%)** (10/10 & 18/21)	6/6 **(100%)** (3/3 & 3/3)	8/8 **(100%)** (2/2 & 6/6)	42/45 **(93.3)**
Student 3	27/31 **(87.1)** (10/10 & 17/21)	6/6 **(100%)** (3/3 & 2/3)	8/8 **(100%)** (2/2 & 6/6)	41/45 **(91.1)**
Student 4	27/31 **(87.1)** (10/10 & 17/21)	6/6 **(100%)** (3/3 & 2/3)	7/8 **(87.5%)** (2/2 & 5/6)	40/45 **(88.9)**
Student 5	30/31 **(96.8%)** (10/10 & 20/21)	6/6 **(100%)** (3/3 & 3/3)	8/8 **(100%)** (2/2 & 6/6)	44/45 **(97.8)**
Student 6	30/31 **(96.8%)** (10/10 & 20/21)	6/6 **(100%)** (3/3 & 3/3)	8/8 **(100%)** (2/2 & 6/6)	44/45 **(97.8)**
Student 7	24/31 **(77.1%)** (8/10 & 16/21)	6/6 **(100%)** (3/3 & 3/3)	8/8 **(100%)** (2/2 & 6/6)	38/45 **(84.4)**
Student 8	21/31 **(67.7%)** (8/10 & 11/21)	6/6 **(100%)** (3/3 & 3/3)	6/8 **(75%)** (2/2 & 6/6)	33/45 **(73.3)**
Student 9	16/31 **(51,6%)** (8/10 & 8/21)	5/6 **(83.3%)** (3/3 & 2/3)	7/8 **(87.5%)** (2/2 & 6/6)	28/45 **(62.2)**
Student 10	16.5/31 **(53.2%)** (8.5/10 & 8/21)	4.5/6 **(75%)** (2.5/3 & 2/3)	7/8 **(87.5%)** (2/2 & 6/6)	28/45 **(62.2)**
Student 11	18/31 **(58.1%)** (7/10 & 11/21)	5/6 **(83.3%)** (3/3 & 2/3)	5/8 **(62.5%)** (2/2 & 3/6)	28/45 **(62.2)**
Average	**25.9/31 (83.5%)**	**5.6/6 (93.3%)**	**7.27/8 (90.9%)**	**37.1/45 (82.4%)**

Table 8.10 Students' responses to scaffolding questions and prompts for the team activity sections of three *TopHat* modules

Teams	Module 2 (2 prompts) Points-% (Level 1 & Level 2)	Module 3 (2 prompts) Points-% (Level 1 & Level 2)	Module 4 (2 prompts) Points-% (Level 1 & Level 2)	Total Pts Points (%)
Team 1	5/6 **(83.3)** (2/3 & 3/3)	4/5 **(80)** (2/2 & 2/3)	12/12 **(100)** (3/3 & 9/9)	**21**/23 **(91.3)**
Team 2	5/6 **(83.3)** (2/3 & 3/3)	4/5 **(80)** (2/2 & 2/3)	12/12 **(100)** (3/3 & 9/9)	**21**/23 **(91.3)**
Team 3	6/6 **(100)** (3/3 & 3/3)	4/5 **(80)** (2/2 & 2/3)	12/12 **(100)** (3/3 & 9/9)	**22**/23 **(95.7)**
Team 4	4/6 **(66.7)** (2/3 & 2/3)	4/5 **(80)** (2/2 & 2/3)	11/12 **(100)** (3/3 & 8/9)	**19**/23 **(82.6)**
Team 5	5/6 **(83.3)** (3/3 & 2/3)	4/5 **(80)** (2/2 & 2/3)	11/12 **(100)** (3/3 & 8/9)	**20**/23 **(87.0)**
Average	**5/6 (83.3%)**	**4/5 (80%)**	**11.6/12 (96.6%)**	**20.6 (89.6)**

while the pilot course was synchronous and only allowed an hour and a half for completing the self-study section of the module, the revised course was asynchronous and allowed students 1 week to complete the self-study section before working with the team. Secondly, the individual and team sections of the modules were separated to make the expectations for completing each section more explicit. This change allowed students to attend to the self-study section of the module before starting their team activity. Lastly, during pilot course, the team discussion was synchronous, and teams spent an hour to discuss and write up their responses to the problem scenario. The time limit may have restricted the teams to fully understand their peers' ideas and thoughts before summarizing and posting teams' solutions. Moreover, the option of viewing peers' responses to some of the scaffolding prompts during self-study encouraged students to reflect on their own thoughts and possibly stimulated further review of the readings and other materials. Besides, this feature may have facilitated team discussion and solutions.

8.6 Discussion

The purposes of this study were to (1) design, develop, and test three self-directed, computer-based modules that supported scaffolding in an online graduate-level course applying PBL/PjBL, and (2) collect data to assess the effectiveness of computer-supported scaffolding. A pilot study was conducted with a small group of students to collect data and to identify areas of improvement for the modules. A pre- and posttest was used during the pilot study to compare students' growth in the acquisition of content knowledge as well as their abilities to reason and provide argumentation. The results demonstrated that participants' scores on items assessing their content knowledge increased from pre- to posttest. This result suggested that conceptual hard scaffolds incorporated in the modules appeared to provide an opportunity for students to question their knowledge when solving the problem and encouraged them to dig deeper into the content. However, items designed to assess students' reasoning skills did not seem to show as much improvement. A survey was also administered during the pilot study to evaluate student perception of the *TopHat* modules. Results indicated that participants generally agreed that the PBL approach was useful and effective for interacting with and learning the content. They also agreed that the recommended resources embedded in the *TopHat* modules were helpful and effective for interacting with and learning the content. However, not all students seemed to think that the hard scaffolds were sufficient to take the place of the presence of a facilitator (soft scaffold). Overall, the results of the pilot study pointed to both design and implementation issues. The design issues were related to the format as well as the content of the question prompts. Question prompts did not specifically ask for providing reasoning in writing. Additionally, the time provided for completing each module did not seem to be adequate, and not all issues that were discussed in the live group discussion were put into writing by the scribers of the teams.

The results of the pilot study directed researchers to improve the design and implementation of the modules in its second iteration. The implementation results of the improved modules confirmed that the computer-supported hard scaffolds are more beneficial for asynchronous online PBL course. While participants' reasoning skills did not seem to improve as a result of embedded hard scaffolds in the pilot implementation, both the context-specific knowledge and reasoning skills showed improvement in the second iteration of implementation. This result indicates that computer-supported scaffolding assists participants in gaining deeper understanding of the context-specific knowledge as well as learning how to reason and justify their thoughts and solutions.

Furthermore, as also observed by Reiser (2004), the explicit expectations for the self-study section of the modules show that scaffolded tools can create opportunities, but whether learners capitalize on these opportunities depends on the expectations, conditions, and practices established in the course. Additionally, both the pilot and second iteration of the modules confirm that scaffolding should occur during the stage of problem analysis as well as the stage of applying domain-specific and domain-general knowledge to find solutions. The study also supports the findings of other researchers that given the importance of relating problem-solving task to disciplinary content, skills, and strategies, it is important to guide students in confronting key disciplinary ideas in their work (e.g., Belland 2017; Jonassen 2011; Reiser 2004). Thus, along with most current accounts of scaffolding, this study supports the view that scaffolding helps students proceed through tasks by providing structure (Reiser 2004). However, there remains the issue of how and when computer-supported scaffolding should be faded (gradually removing support as students gain skill) or added again in an online asynchronous learning environment. Instructional designers should develop and test strategies such as self-selection and fixed intervals (Belland 2017) that can use fading based on a dynamic assessment of students' capabilities. In this study, all of the prompts included specific content related to the problem that students were addressing. Future studies should also incorporate generic prompts for reflection and assess student general problem-solving skills that support student learning and performance. Designers should also consider analyzing the nature of the subskills that one wishes to achieve to decide whether to use context-specific or generic scaffolding (Belland et al. 2013).

8.7 Conclusion

The traditional, face-to-face implementation process of PBL poses significant challenges to asynchronous online courses where providing adequate one-to-one scaffolding to all students is challenging. In this study, it is argued that a software application used in interactive, computer-supported learning environments shows promise to provide scaffolding and support needed to online learners rather than solely depending on teachers/facilitators and peers (Davis and Linn 2000; Quintana et al. 1999; Reiser 2004). The study used *TopHat*, an interactive content development tool, to provide scaffolding support for a graduate online course. Given the results, it is cautiously concluded that incorporating well-designed hard scaffolding using the interactive content development tool improves student acquisition of content knowledge and problem-solving skills as well as reasoning and argumentation ability. However, the materials and incorporated scaffolds used in this study were designed and implemented in a small graduate-level course. Therefore, the content, the context, and the conditions under which the course was implemented may have impacted the results. Additionally, the content of the question prompts in this study was determined by the need to provide students with domain-specific knowledge. Hence, the background, experience, and prior knowledge of learners may have influenced the success of the question prompts in this study. The approach that was used in this study, however, could help online designers and instructors to improve students' achievement and stimulate further discussion of scaffolding in online learning environments.

References

Barrows, H. S. (1980). *Problem-based learning: An approach to medical education*. New York: Springer.

Barrows, H. S. (1988). *The tutorial process*. Springfield: Southern Illinois University School of Medicine.

Barrows, H. S. (1996). Problem-based learning in medicine and beyond: A brief overview. In L. Wilkerson & W. Gijselaers (Eds.), *Bringing problem-based learning to higher education: Theory and practice. New Directions For Teaching and Learning, 68*, 3–9. San Francisco: Jossey-Bass.

Barrows, H. S. (1996a). Problem-based learning in medicine and beyond: A brief overview. *New Directions in Teaching and Learning, 68*, 3–9.

Barrows, H. S. (1996b). Problem-based learning in medicine and beyond: A brief overview. *New Directions in Teaching and Learning, 68*, 3–9.

Belland, B. R. (2017). *Instructional scaffolding in STEM education*. https://doi.org/10.1007/978-3-319-02565-0.

Belland, B. R., Gu, J., Armbrust, S., & Cook, B. (2013). Using generic and context-specific scaffolding to support authentic science inquiry. In *Proceedings of the IADIS international conference on Cognition and Exploratory Learning in Digital Age (CELDA 2013)* (pp. 185–192). Fort Worth: IADIS.

Belland, B. R., Walker, A., Kim, N., & Lefler, M. (2014). *A preliminary meta-analysis on the influence of scaffolding characteristics and study and assessment quality on cognitive outcomes in STEM education*. Presented at the 2014 Annual Meeting of the Cognitive Science Society, Québec City, Canada.

Belland, B. R., Walker, A., Olsen, M. W., & Leary, H. (2015). A pilot meta-analysis of computer-based scaffolding in STEM education. *Educational Technology & Society, 18*(1), 183–197.

Brush, T. A., & Saye, J. W. (2002). A summary of research exploring hard and soft scaffolding for teachers and students using a multimedia supported learning environment. *The Journal of Interactive Online Learning, 1*(2), 1–12.

Cho, K., & Jonassen, D. H. (2002). The effects of argumentation scaffolds on argumentation and problem solving. *Educational Technology Research and Development, 50*(3), 5–22.

Davis, E. A., & Linn, M. C. (2000). Scaffolding students' knowledge integration: Prompts for reflection in KIE. *International Journal of Science Education, 22*(8), 819–837.

Dolmans, D. H. J. M., De Grave, W., Wolfhagen, I. H. A. P., & van der Vleuten, C. P. M. (2005). Problem-based learning: Future challenges for educational practice and research. *Medical Education, 39*, 732–741. https://doi.org/10.1111/j.1365-2929.2005.02205.x.

Ge, X., Planas, L. G., & Er, N. (2010). A cognitive support system to scaffold students' problem-based learning in a web-based learning environment. *Interdisciplinary Journal of Problem-Based Learning, 4*(1). https://doi.org/10.7771/1541-5015.1093.

Hannafin, M., Land, S., & Oliver, K. (1999). Open learning environments: Foundations, methods, and models. In C. Reigeluth (Ed.), *Instructional design theories and models* (Vol. II, pp. 115–140). Mahway: Erlbaum Publishers.

Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*(3), 235–266.

Hmelo-Silver, C. E., & Barrows, H. S. (2006). Goals and strategies of a problem-based learning facilitator. *The Interdisciplinary Journal of Problem-based Learning, 1*(1), 21–39.

Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist, 42*(2), 99–107.

Jonassen, D. H. (1999). Designing constructivist learning environments. In C. M. Reigeluth (Ed.), *Instructional design theories and models: A new paradigm of instructional theory* (Vol. II, pp. 215–239). New York: Routledge.

Jonassen, D. (2011). Supporting problem solving in PBL. *Interdisciplinary Journal of Problem-Based Learning, 5*(2), 95–119.

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41*(2), 75–86.

Krajcik, J., Blumenfeld, P., Marx, R., Bass, K., Fredricks, J., & Soloway, E. (1998). Inquiry in project-based science classrooms. *Journal of the Learning Sciences, 7*(3&4), 313–351.

Kumar, R., & Refaei, B. (2017). Problem-based learning pedagogy fosters students' critical thinking about writing. *Interdisciplinary Journal of Problem-Based Learning, 11*(2). https://doi.org/10.7771/1541-5015.1670.

Means, B. (1994). Introduction: Using technology to advance educational goals. In B. Means (Ed.), Technology and education reform: The reality behind the promise. San Francisco: Jossey-Bass.

Mills, J. E., & Treagust, D. F. (2003). Engineering education—Is problem-based or project-based learning the answer. *Australasian Journal of Engineering Education, 3*(2), 2–16.

Protopsaltis, S., & Baum, S. (2019). Does online education live up to its promise? A look at the evidence and implications for federal policy. Retrieved from https://mason.gmu.edu/~sprotops/OnlineEd.pdf

Puntambekar, S., & Hübscher, R. (2005). Tools for scaffolding students in a complex learning environment: What have we gained and what have we missed? *Educational Psychologist, 40*(1), 1–12.

Quintana, C., Eng, J., Carra, A., Wu, H.-K., & Soloway, E. (1999). Symphony: A case study in extending learner-centered design through process space analysis. In M. G. Williams, M. W. Altom, K. Ehrlich, & W. Newman (Eds.), *Proceedings of CHI 99 conference on human factors in computing systems* (pp. 473–480). Reading: Addison-Wesley.

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

Savery, J. R. (2006). Overview of problem-based learning: Definitions and distinctions. *Interdisciplinary Journal of Problem-based Learning, 1*(1), 9–20.

Savery, J. R. (2009). Problem-based approach to instruction. In C. M. Reigeluth & A. A. Carr-Chellman (Eds.), *Instructional-design theories and models: Building a common knowledge base* (Vol. 3). New York: Routledge.

Saye, J. W., & Brush, T. (2002). Scaffolding critical reasoning about history and social issues in multimedia-supported learning environments. *Educational Technology Research and Development, 50*(3), 77–96.

Schmidt, H. G., Rotgans, J. I., & Yew, E. (2011). The process of problem-based learning: What works and why. *Medical Education, 45*, 792–806.

Şendağ, S., & Odabaşı, H. F. (2009). Effects of an online problem-based learning course on content knowledge acquisition and critical thinking skills. *Computers & Education, 53*(1), 132–141.

Simons, K. D., & Ertmer, P. A. (2005). Scaffolding disciplined inquiry in problem-based environments. *International Journal of Learning, 12*(6), 297–305.

Sockalingam, N., Rotgans, J., & Schmidt, H. (2011). Student and tutor perceptions on attributes of effective problems in problem-based learning. *Higher Education, 62*(1), 1–16.

Swanson, H. L., & Deshler, D. (2003). Instructing adolescents with learning disabilities: Converting a meta-analysis to practice. *Journal of Learning Disabilities, 36*(2), 124–135. https://doi.org/10.1177/002221940303600205.

Swanson, H. L., & Lussier, C. M. (2001). A selective synthesis of the experimental literature on dynamic assessment. *Review of Educational Research, 71*(2), 321–363. https://doi.org/10.3102/00346543071002321.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge: Harvard University Press.

Wang, F., & Hannafin, M. J. (2005). Design-based research and technology-enhanced learning environments. *Educational Technology Research and Development, 53*(4), 5–23.

Yew, E. H. J., & Schmidt, H. G. (2012). What students learn in problem-based learning: A process analysis. *Instructional Science, 40*(2), 371–395.

Chapter 9
Usability Evaluation of Virtual Learning Environments: A University Case Study

Attila Vertesi, Huseyin Dogan, and Angelos Stefanidis

9.1 Introduction

Information technology is an essential component of educational technology in higher education (HE). Virtual learning environment (VLE) and Learning Management System (LMS) are often used as synonyms (Paulsen 2002) to describe a complex information technology system which integrates course management tools for course administrators, online accessibility of learning materials and assignments. It also provides a communication and collaboration platform for the students and lecturers (Ryan et al. 2013). The quality and usability of a VLE are key features of a successful system, as they influence user satisfaction and acceptance (Babić 2012). Usability is the extent to which users can use a product or service to achieve specified goals efficiently and effectively while promoting feelings of satisfaction in a given context of use (ISO 1998). There are two aspects of usability in educational technology, namely, technical usability and pedagogical usability (Melis et al. 2003). Technical usability refers to human-computer interaction (HCI), while pedagogical usability is associated with supporting the learning process. Perceived usefulness and perceived ease of use are also great influential factors in the acceptability of new technology (Davis et al. 1989).

As part of this chapter, we present the case of a particular university which went through the process of procuring a new VLE through a tender process. We examine the migration of all of the pedagogical and administrative learning function from the old to the new system and carefully consider the adoption of the new system by its different stakeholders. In doing so, we examine the usability of the VLEs and capture feedback from the stakeholders.

A. Vertesi (✉) · H. Dogan · A. Stefanidis
Bournemouth University, Dorset, UK
e-mail: avertesi@bournemouth.ac.uk; hdogan@bournemouth.ac.uk; astefanidis@bournemouth.ac.uk

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_9

The university discussed in this research has various multiple VLEs which have been in operation for more than 12 years, currently used by over 20,000 students and 2000 staff. Due to EU procurement regulations, the university was required to go out to tender for a new VLE at the end of the contract with the current VLE supplier. In total, 250 students and staff, representing 10 departments from across the university, participated in the selection of the new VLE. More than 50 members of staff worked on the procuration and implementation of the new VLE for 8 months before it was introduced in September 2017. During the initial phase of the implementation, in the first 6 months, 40% of the students were transferred to the new system. The university moved towards the full rollout a year later, in September 2018. Some of the features of the new VLE system include the provision of a personalised learning experience supported by learning analytics capabilities, integrated social media, chat, video features and game-based learning, predominantly aimed at supporting students and their learning. As separate user group underpinned by a different set of requirements, the academic and administrative staff interacting with the system benefit from the customisable course development, programme management, user account management, training and end-user help desk support.

9.2 Literature Review

There is a wide range of usability evaluation methods. System Usability Scale (SUS) (Brooke 1996) is one of the most accepted and popular tools for measuring user satisfaction. SUS was utilised to carry out a general quantitative usability evaluation. The SUS scores from different user groups were analysed and compared. More detailed factor analysis was applied where the low values of the usability scores required it.

While SUS gives a reliable and comparable quantitative result (SUS score), the qualitative element of the research comprised the utilisation of an approach called Interactive Management (IM) (Broome and Keever 1986), which supports the better understanding of the dynamics of the implementation process. IM was applied to facilitate effective group communication (Dogan and Henshaw 2010) to receive detailed feedback about the usability and the implementation of the new VLE. These methods are discussed in detail in the "Research Methods" section.

A growing number of studies examine the usability of the VLE by utilising SUS as a methodology. In 2006, a web-based e-learning platform called SPIRAL was developed and evaluated (Renaut et al. 2006) at the University Claude Bernard Lyon 1. Although the SUS ratings have not been published, 72% of the professors found the system usable, according to the paper.

Three different e-learning platforms were measured using SUS by Ayad and Rigas (Ayad and Rigas 2010). User performance, learning effectiveness and satisfaction were examined to explore the usability aspects of the system. The three platforms were virtual classroom, game-based and storytelling. The SUS scores for the three platforms were 75.3, 73.4 and 64.5, respectively. The storytelling scored a little behind the other two. An SUS score above a 68 would be considered above average, and anything below 68 is below average.

An interesting comparative research article was published (Marco et al. 2013) regarding the usability enhancement of the Moodle LMS. The study examined the performance of the system in remote collaboration. The SUS score of the Moodle system in these features initially was 46.75, which indicates serious usability problems. Using a different collaborative tool called Drag&Share within Moodle, the usability of the LMS enhanced dramatically. The SUS score increased significantly, up to 89.5 after the implementation of Drag&Share, which indicates very good usability in the remote collaboration feature.

There is a very rare longitudinal study about a simulation-based learning system (Luo et al. 2014) that measured the perceived usability of the students after the first semester and after the second semester. Initially, the SUS score was 58.1, suggesting that the system needed improvement. Based on the collected data, the system had been modified, and after the second semester, the score rose to 65.9. Following another development for teachers, they evaluated the new module to 74.45, showing their satisfaction. This research also highlights the perceived usability of different user groups (e.g. teachers and students) may vary.

The above-mentioned divergence between the perceived usability of students and teachers is discussed by Emelyanova and Voronina (Emelyanova and Voronina 2014). The various aspects of the VLE and the difference between the perception of the usability should be considered when making a decision about the improvement of the system.

A comprehensive usability study was conducted in 9 European secondary schools, all using UNITE e-learning platform, with the participation of 23 teachers and 47 students (Granić and Ćukušić 2011). Teachers evaluated the system at 53.15, and students gave 59.36 on average using the SUS questionnaire. The difference between the perception of the usability is also noticeable in this study. However, in this case, the students scored the system higher than the teachers.

A new scale was developed by Onacan and Erturk (Onacan and Erturk 2016) based on the SUS (Brooke 1996), which has been tested and validated in the HE environment for 2 years. The Scale for Usability of Learning Management System (SULMS) is a 26-item, Likert-type questionnaire, which identifies five dimensions: learnability, efficiency, memorability, errors and satisfaction. In addition to SUS, SULMS tries to identify the association between the five dimensions and specific VLE-related attributes.

9.3 Research Methods

9.3.1 System Usability Scale (SUS)

SUS can provide a simple numeric result of the perceived usability of a system from different perspectives of the diverse users and user groups (Brooke 1996). The SUS scores of various systems, or the same system at different development stages, can be compared. It is easy to interpret and communicate the explicit results to the stakeholders. The evaluation is reliable even with a small sample size of 12 (Tullis and Stetson 2004). The survey is simple and short, and there is no licence fee. These features make SUS a perfect tool for quantitative research on the usability of VLEs. SUS is a 5-point Likert-type scale commonly applied in research which uses questionnaires. SUS includes ten general statements regarding the user's subjective opinion and feeling of the system. The participants ranked the statements between 1 and 5 based on how much they agree or disagree with it (Brooke 1996). Usability evaluation is linked to user satisfaction, enjoyment, effectiveness and efficiency.

The original statements (Brooke 1996) were used in the preliminary evaluation for the three VLEs (Table 9.1), and a slightly modified version was utilised during and after the implementation of the successor VLE. The first statement of the survey was rephrased from conditional tense to indicative form as the users had no option to use other VLEs for these specific tasks. For the preliminary evaluation of the three different VLEs, the original phrase was used for the first statement: "I think that I would like to use this VLE frequently". The word "system" was altered to "VLE" in every survey referring to the current system.

Prior to completing the surveys for the preliminary evaluation of the three VLEs, the specific user groups had to perform specific, VLE-related tasks (Table 9.2) based on the most common activities they need to accomplish using the VLE. For the evaluation of the new VLE, as the system had already been used by the participants, they did not complete predefined tasks. Instead, a list of the description of various tasks was offered to the participants to indicate which task had been completed by

Table 9.1 The original statements for SUS (Brooke 1996)

	The system usability scale standard version	Strongly disagree		Strongly agree		
		1	2	3	4	5
1	I think that I would like to use this system.	○	○	○	○	○
2	I found the system unnecessarily complex	○	○	○	○	○
3	I thought the system was easy to use.	○	○	○	○	○
4	I think that I would need the support of a technical person to be able to use this system.	○	○	○	○	○
5	I found the various functions in the system were well integrated.	○	○	○	○	○
6	I thought there was too much inconsistency in this system.	○	○	○	○	○
7	I would imagine that most people would learn to use this system very quickly.	○	○	○	○	○
8	I found the system very cumbersome to use.	○	○	○	○	○
9	I felt very confident using the system	○	○	○	○	○
10	I needed to learn a lot of things before I could got going with this system.	○	○	○	○	○

Table 9.2 Task lists

Student task list	*Administrator task list*
1. Access a unit area within the VLE	1. Navigate to a unit area
2. Review unit announcements for any notices	2. Take three word documents, and make them available to students
3. View online unit material available within the unit	3. Make a document unavailable to students
4. Open word documents made available	4. Create a link to an external website, and make it available to students
5. View embedded/linked video content	5. Post an announcement to students enrolled on the unit
6. View the unit discussion topic, and post an introductory message	6. Send an email to the students enrolled on the unit
7. View the unit blog, and post an introductory post	7. Create a group of students for the unit
8. View the unit wiki, and post an introductory page	8. View student grades and assessments
9. Complete the sample unit test	9. Access an individual Turnitin submission, view grade and feedback
10. Submit an assignment via Turnitin	10. Add a grade for a non-Turnitin student assessment
11. View your grades	11. Add grades for all students on a non-Turnitin student assessment
12. View any notifications	12. Use the grading functionality to create a calculation which sums the Turnitin and non-Turnitin
Academics and learning technologists task list	
1. Take three word documents, and make them available to students	
2. Make some text and an image available to students	
3. Create a link to an external website, and make it available to students	
4. Make a YouTube video available to students	
5. Edit one of the items created in steps 1–4	
6. Reorganise the items previously created	
7. Make one of the items created in steps 1–4 unavailable to students	
8. Post an announcement to students	
9. Send an email to the students enrolled on the unit	
10. Create a group of students for the unit	
11. Create a discussion topic, and post an introductory message	
12. Create a blog and post an introductory post	
13. Create a wiki and post an introductory page	
14. Create a test containing one multiple choice question and one multiple answer question	
15. View student grades and assessments	
16. Access an individual Turnitin submission, add a grade and feedback	
17. Add a grade for a non-Turnitin student assessment	
18. Add grades for all students on a non-Turnitin student assessment	
19. Use the grading functionality to create a calculation which sums the Turnitin and non-Turnitin assessments	

the specific user. According to Boyd et al.'s research (Boyd et al. 2019) on the memory effect and recall bias, this arrangement does not influence the result of the usability evaluation.

The calculation of the SUS scores of the survey was carried out by using spreadsheet software. The scores of items 1, 3, 5, 7 and 9 were deducted by 1 (score – 1), and the scores of items 2, 4, 6, 8 and 10 were deducted from 5 (5 – score). With this method, the positive scores given to the negative statements have been compensated by reversing the score. Now, there are ten scores ranged from 0 to 4 that gives a range of possible values from 0 to 40 in total. To extend it to a 0–100 scale, the scores were multiplied by 2.5 which gives the final SUS score of the VLE.

Experiments show (Bangor et al. 2008, 2009) that the average SUS score of more than 3000 different products is around 70. Specifically, for web pages and software with a web interface, this mean score is 68 which is used as a benchmark in this research.

9.3.2 Interactive Management (IM)

Interactive Management (IM) is a methodology designed to manage complex or new organisational or technical problems associated with multiple disciplines, involving different departments (Broome and Keever 1986). IM offers methods to facilitate effective communication and promotes consensus-based decision-making through idea generation, structuring and design. These methods can be used to gather the requirements, needs, demands and ideas of the stakeholders for a better understanding of the problem space (Dogan and Henshaw 2010). During the implementation process of a new technology, e.g. VLE, it is important to capture feedback including ideas, issues, suggestions and requirements from the users. IM can be utilised to support the qualitative part of the usability research and a better understanding of the implementation process.

In this research, IM tools are utilised to obtain feedback from the users about the implementation of the new VLE system. IM involves three phases: planning, workshop and follow-up (Warfield and Cárdenas 1994). During the workshop, trigger questions, idea writing (IW) and nominal group technique (NGT) were applied. The outcome of the workshop is a list of ranked and organised statements reflecting the implementation phase of the new VLE, addressing positive and negative usability issues.

A 3-hour meeting was organised by the authors in April 2018 at the university for academics (n = 4), administrators (n = 8) and learning technologists (n = 1). The participation was voluntary. The aim of the IM session was to collect feedback, discuss questions and problems and capture ideas in connection with the implementation and usability of the new VLE.

Idea Writing

At the beginning of the IM session, the facilitator (one of the authors) introduced the methods and the trigger questions for the idea writing (IW):

Trigger Question 1:

"What are the positive aspects of the implementation of the new VLE?"

Trigger Question 2:

"What are the negative aspects of the implementation of the new VLE?"

The participants formed two mixed groups ($n = 6$, $n = 7$), and without discussing the question, every participant, focusing on Trigger Question 1, wrote one positive aspect of the implementation of the new VLE on his/her paper and then passed the A4 sheet to the next member (on the right) of the group in the circle. After reading the previously listed statements on the new A4 sheet received from the other participant (from the left), members wrote another positive statement and circulated the A4 sheets until the original sheets arrived back. The same procedure was followed with Trigger Question 2.

Nominal Group Technique
Following the idea writing phase, the members of the two groups discussed, clarified and edited the positive and negative statements for the preliminary ranking in each group. Each participant selected the five most important statements from the whole list and ranked them by associating numbers from 1 to 5 for each statement, 5 being the most important. Single transferable vote technique was utilised to minimise discarded votes during the ranking process.

By the end of the IM session, each group produced a list of statements to each trigger questions. The statements were discussed, clarified and ranked. The results were photographed and transcribed. The categorising and structuring of the statements have not been accomplished due to the limited time. The results are satisfactory for providing meaningful feedback.

9.4 Usability Evaluation and Comparison

In this section, the System Usability Scale (SUS) scores are depicted in bar charts to support comparisons, analysis and the interpretation of the results. SUS scores are calculated based on the data collected from online and paper-based questionnaires. The mean SUS scores of the different user groups are compared and discussed. Further analysis was carried out where the results required it.

9.4.1 Preliminary Evaluation

The preliminary usability evaluation was carried out to support the selection process to single out one VLE from the three VLEs (VLE 1, VLE 2, VLE 3) remaining in contention during the final stages of the procurement process. The VLEs have been rated by different user groups including learning technologists (n = 5), academic staff (n = 32), administrator team (n = 4) and students (n = 40, postgraduate = 13, undergraduate = 22, research = 5) resulting in a total number of 81 SUS scores. The tasks for the usability evaluation were constructed to be in line with the role of the different user groups. The same tasks were carried out by the same groups on each of the three different VLEs (VLE 1, VLE 2, VLE 3). After the tasks were completed, participants filled in the Usability Questionnaire based on their experiences. The Usability Questionnaire includes the standard SUS questions tailored to the VLEs (Table 9.1). The same questionnaire was filled by every evaluator.

The Preliminary Results

The individual SUS scores were calculated according to the SUS methodology (Brooke 1996).

The total mean scores of the VLEs, including every user groups, are as follows: **VLE 1**, **54.9**; **VLE 2**, **63.1**; **VLE 3**, **55.0**

The Interpretation of the SUS Scores

Figure 9.1 shows the results with a graphical aid for interpretation and adjective rating.

The background colours of the chart (Fig. 9.1) and the letter grades (from A+ to F) are related to the well-accepted adjective scale (Fig. 9.1) based on the benchmarks set up by Bangor et al. (2009). A SUS score higher than 80 suggests a very good, highly usable system (A+, A); between 68 and 80 still refers to a good system with space for improvement (B); between 51 and 68 means “Fair” or “OK” – the system or product is still usable but should be improved (C, D); below 51 is poor (F); and below 36 is unusable.

Figure 9.1 aids to convert SUS score to percentile rank (Bangor et al. 2009) by normalising the scores based on the distribution of all scores measured in different products and systems by different users. An SUS score of 68 would be equivalent to 50% which means that the average SUS score of all the products measured with SUS method is around 68.

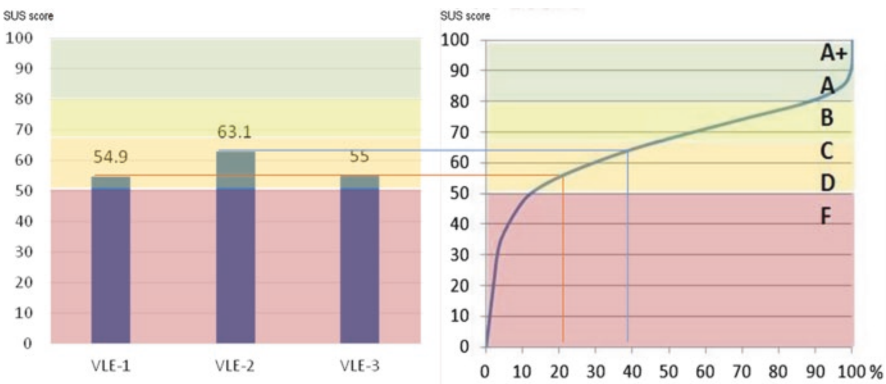


Fig. 9.1 SUS scores (mean) of the VLEs and the percentile equivalent

VLE 1 and VLE 3 scored similarly (54.9, 55) and VLE 2 has higher score (63.1), but all the three VLEs are within the 51–68 range which suggests that there are no major issues with the usability but there is space for improvement.

The Evaluation by User Groups

The following table (Table 9.3) shows the numeric results of the evaluations of the different user groups: students ($n = 40$), academics ($n = 32$), learning technologists ($n = 5$) and administrator team ($n = 4$).

The charts in Fig. 9.2 offer a more detailed insight by displaying the VLE scores of each user group.

The students did not find VLE 1 as usable as VLE 2 and VLE 3. The difference between the SUS score of VLE 1 and VLE 2 is 15 which clearly shows students' preference (VLE 1). While the academics produced more balanced SUS scores, the administrator team's evaluation demonstrates the highest deviation. Examination of the data reveals that there are only four members of the administrator team which participated in this evaluation, and the individual scores (47.5, 2.5, 27.5, 5) show high inconsistency in the case of VLE 3. A number of studies proved that the sample size below five cannot give reliable result in usability testing, although they still can unveil 80% of the system's usability problems (Virzi 1992). Therefore, the result of the administrator team should still be considered as the SUS scores are all below 50 alerting to significant usability issues in their field using VLE 3. The averages of the SUS scores given by learning technologists are more coherent. VLE 2 performed the best by most of the user groups and the majority of the participants ($n = 77$) except the administration team ($n = 4$).

Displaying the group's SUS scores grouped by the VLEs (Fig. 9.3) highlights the difference between VLE 1 and VLE 3. Even the average SUS scores were almost equal (VLE 1 = 54.9, VLE 3 = 55.0), and the standard deviation shows significant differences (VLE 1 = 4.5, VLE 3 = 18). VLE 3 carries internal tension: in the students graded to 62.9, 20.6 was given by the administrator team. In contrast, VLE 1 was valued at 63.8 by the administrator team and at 53.4 by the students which is the lowest score from those the student gave to the three VLEs. VLE 1 is still well balanced in the mean SUS scores of the groups. VLE 2 performed the best according to the students, academics and learning technologists and in mean score. Only the administrator team ranked VLE 2 below VLE 1.

The Reliability of the Evaluation

Cronbach's alpha measures reliability by calculating the internal consistency of the data (Cronbach 1951). The calculation gives a result between 0 and 1. The closer the

Table 9.3 The usability scores of different user groups

SUS scores	Students ($n = 40$)	Academics ($n = 32$)	Administrator team ($n = 4$)	Learning tech ($n = 5$)
VLE 1	53.4	55.3	63.8	57
VLE 2	68.4	57.2	56.3	64
VLE 3	62.9	49.9	20.6	52

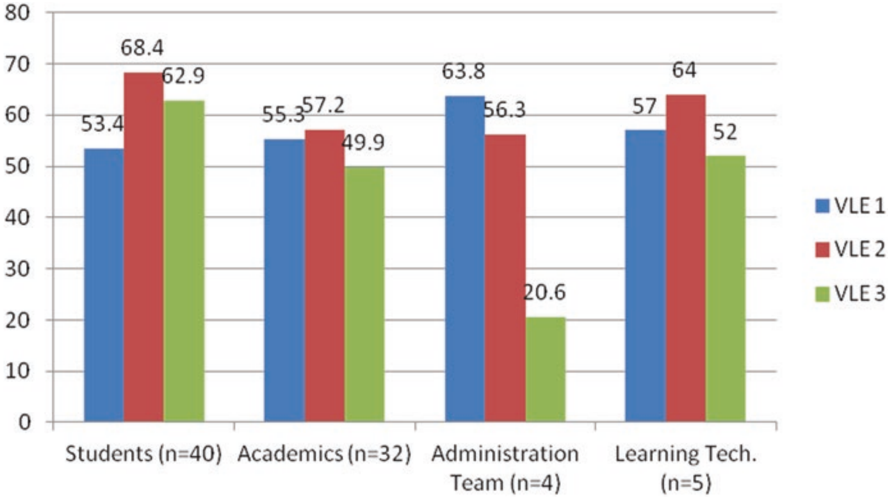


Fig. 9.2 Usability scores of different user groups chart

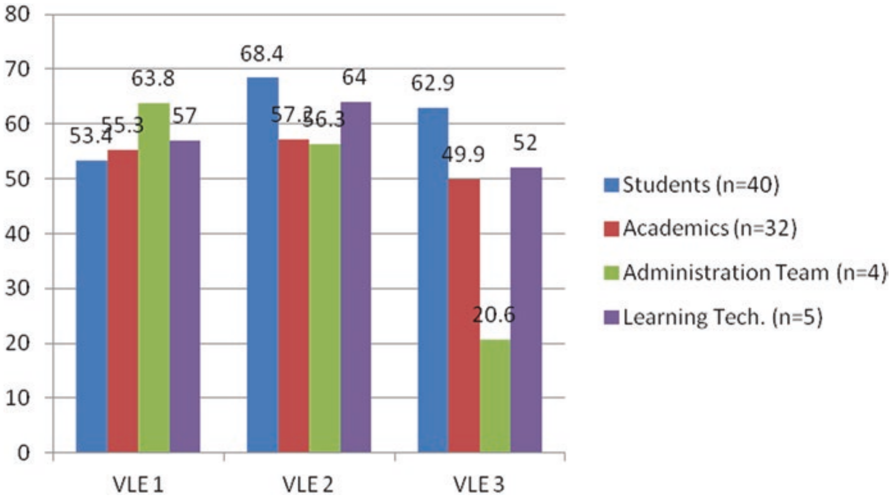


Fig. 9.3 VLE chart – user groups

α to 1, the better. SUS performs well $\alpha > 0.9$ which means the test measures what it should be, the usability. Generally, $\alpha > 0.7$ is accepted as a reliable test consistency. The standard deviation and reliability calculations have been carried out in all tests published in this paper to verify the internal consistency. The following table (Table 9.4) shows the results.

Table 9.4 Reliability of the preliminary surveys

	SUS score	Cronbach's alpha	Standard deviation
VLE 1	54.9	0.91	22.34
VLE 2	63.1	0.92	23.34
VLE 3	55.0	0.94	25.27

9.4.2 The Subsequent Evaluation of the New VLE

The quantitative part of the usability evaluation (Vertesi et al. 2018) was conducted on the new VLE by utilising SUS methodology the same way as in the case of the preliminary evaluation. The total number of participants is n = 182 including students (n = 137), academics (n = 23), learning technologists (n = 3) and administrator team (n = 19). Printed (paper) and online questionnaires were offered. N = 13 SUS evaluations arrived on paper evaluated by learning technologists (n = 1), academics (n = 4) and administrators (n = 8). Students did not participate in this session. The online questionnaire was submitted by 169 users including learning technologists (n = 2), students (n = 137), academics (n = 19) and administrators (n = 11).

In this case, the participants were not asked to complete any task prior to the questionnaire, but a list of features was attached to the paper questionnaires enabling the participant to indicate which tasks have been carried out by them. The user evaluation was based on the general experience gained during the first phase of the implementation (from September 2017 to April 2018) of the new VLE by using the features needed for the different user groups. This approach does not influence the outcome of the evaluation (Boyd et al. 2019).

The SUS questions were intended to be the same as the preliminary questions based on the original SUS questions (Brooke 1996) with a slight change in the wording. Unfortunately, a small error slipped into the online student questionnaire. Question 5 (Table 9.2) was repeated twice, and as a result, the last question (Q 10) was left out. This small discrepancy does not affect the result significantly as the structure of the SUS questions and the methodology make the evaluation robust and resilient to small errors and changes (Sauro and Lewis 2011). The standard error is within 0.25 regarding the final SUS score. The accuracy is higher than 99.5%.

The Result

The overall SUS score of the adopted VLE is 58.6 out of 100 measured 6 months after the first phase of the implementation in April 2018. This is the result of the evaluation of n = 182 users including students (n = 137), administrators (n = 19), academics (n = 23) and learning technologists (n = 3).

The final score does not differ significantly from the SUS scores in the preliminary evaluation. It is still in the range of 51–68 being below the average usability expectation (68) but still envisions a usable system with a scope for improvement.

Comparisons of User Groups' Evaluations

A more differentiated picture can be seen by examining and comparing the evaluation of the different user groups. The largest number of users which participated in

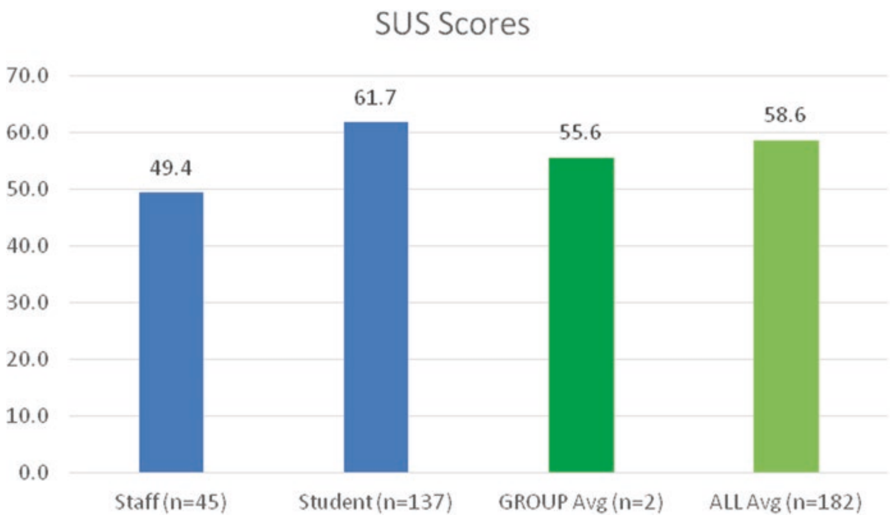


Fig. 9.4 SUS scores of students and staff

this evaluation is the students (n = 137) which scored 61.1 opposed to all members of staff (n = 45) 49.4. As a result, students' SUS score weighted more in the overall score and scored 58.6 for the total average. If the two user groups formed by the students and the staff are weighted equally, the mean SUS score is 55.6, lower than the average score 58.6 calculated with all users as one group. The following chart (Fig. 9.4) displays the SUS score in respect to the two main user groups, the group average and the total average.

Students' Evaluations

Starting the analysis with the largest user group, the students (n = 137), it is interesting to see the comparison of the SUS scores of the different subgroups within the students.

Student Groups by Years

Undergraduate (n = 127) and postgraduate (n = 10) students filled in the online form.

There is a falling trend which can be seen in the graph (Fig. 9.5) by the undergraduate student groups from 71.4 (Level 4, Year 1) through 59.7 (Level 5, Year 2) to 48.9 (Level 6, Year 3). Year 1 (Level 4) students evaluated the new VLE slightly above the average expectation. They seem to be more satisfied with the new system, unlike Year 3 (Level 6) students who expressed higher expectations. The postgraduate students (Level 7), however, gave 69.6 for usability (Fig. 9.5) which is above the generally accepted average (68) for SUS scores.

Student Groups by Frameworks/Courses

The results of six different groups of students can be seen in Fig. 9.6. The groups were formed based on curriculum areas and courses. The students participated from every year and level in each group. The largest group is the nursing students (n = 66).

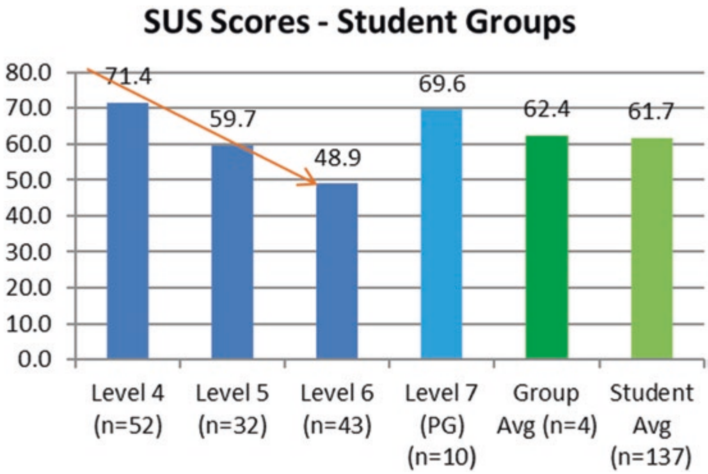


Fig. 9.5 SUS scores of student groups by levels

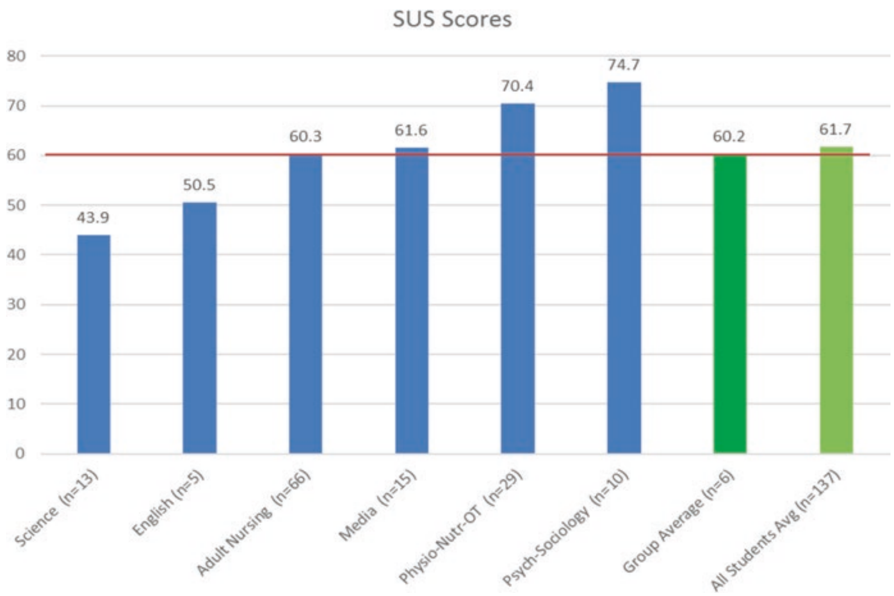


Fig. 9.6 SUS scores of student groups by frameworks/courses

Their average SUS score is 60.3 which is very close to the average score of the six groups (60.2) indicated by the red line in Fig. 9.6. The difference between the lowest (43.9) and highest SUS score (74.7) is more than 30 (30.8).

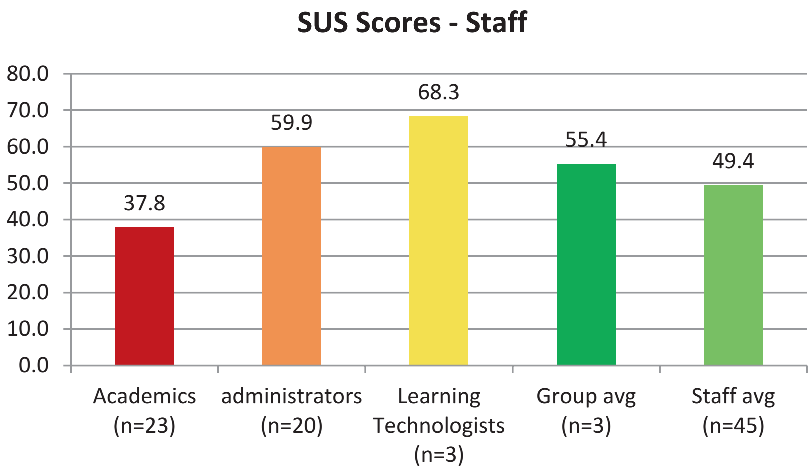


Fig. 9.7 SUS scores of staff groups

Staff Evaluation

N = 45 evaluation arrived from staff members either online (*n* = 32) or on paper (*n* = 13). The following groups are created: academics (*n* = 23), administrators (*n* = 20) and learning technologists (*n* = 3).

Figure 9.7 shows the results graphically. It is noticeable that academics gave very low usability score (37.8) to the new VLE since the evaluation of administrators (59.9) and learning technologists (68.3) suggests that the VLE is closer to an average system with respect to the usability. The mean value of the groups' SUS scores is 55.4 which is acceptable, but the total average falls slightly below 50 (49.4) which is the minimum usability requirement of any system.

The result of the academics (SUS = 37.8) draws attention to some significant usability issues. For further analysis, the chart in Fig. 9.8 shows the individual scores in the academics group (*n* = 23). Blue bars (*n* = 19) show the online result; yellow bars (*n* = 4) relate to the paper-based questionnaire.

Half of the group of academics (*n* = 12) evaluated the new VLE below 38 which indicates serious usability issues. Interestingly, the paper-based results (*n* = 4) are significantly higher (SUS avg. = 64) than the online scores (SUS avg. = 32). Although the overall standard deviation is not high (21), the range and distribution of the scores are unusual.

Factor Analysis

SUS is not a diagnostic tool; it is an evaluation method. SUS reveals but does not specify the usability problem. However, more detailed analysis can give some hints about the weak areas of the new VLE.

The system was graded less than or equal to 40 according to 15 academics that brings our attention to this area for further analysis. Figure 9.9 shows the result of each factor (the scores given to each question) of the evaluations which have the

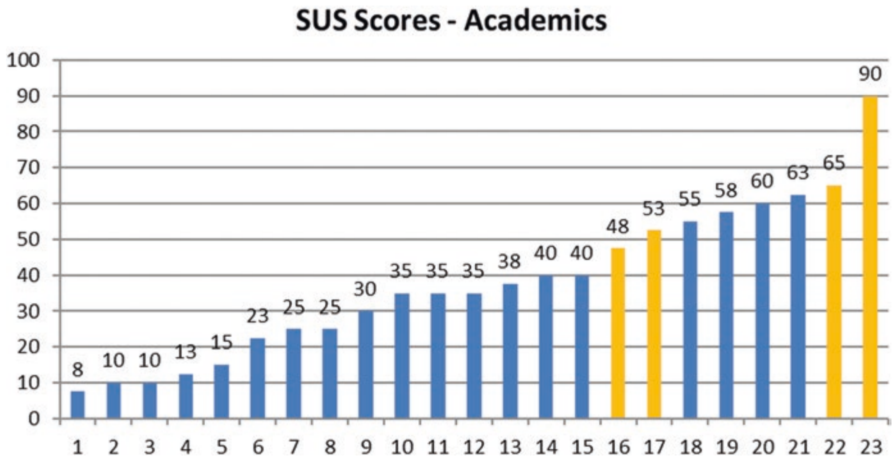


Fig. 9.8 SUS scores of academics

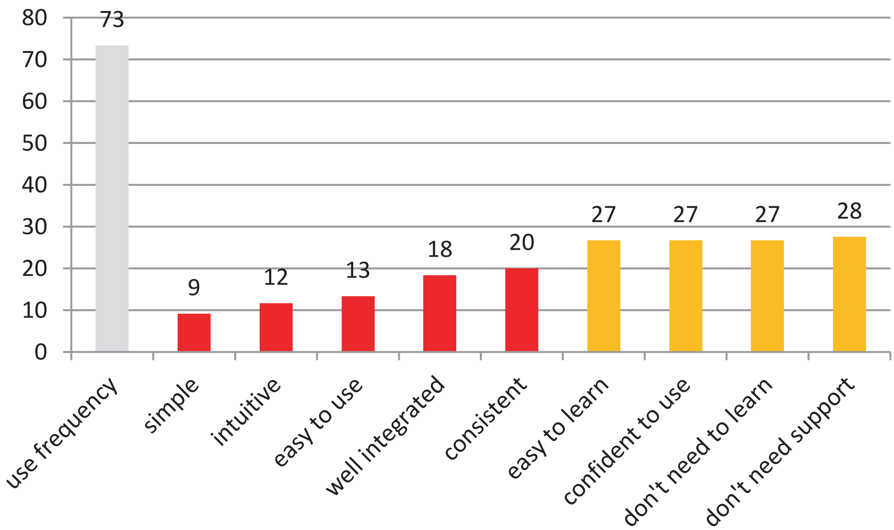


Fig. 9.9 Factor analysis of the weakest evaluations (SUS ≤ 40)

total SUS score under 41. These are the first 15 scores from the left on the previous bar chart in Fig. 9.8.

The weakest areas are highlighted in red on the bar chart (Fig. 9.8). These academics (n = 15 out of 23) found the VLE underperforming in the following factors: "simple", "intuitive", "easy-to-use", "well-integrated", "consistent". The high value of the "frequency of the use" is an outlier and can be misleading as there is no

Table 9.5 Reliability of the new VLE surveys

Reliability	SUS score	Cronbach's alpha	Standard deviation
Students	61.66	0.89	20.80
Staff	49.43	0.88	21.62
All (students + staff)	58.61	0.90	21.65

alternative VLE to use at this stage. That is why it is colour-coded with grey indicating the insignificance of that value.

The Reliability of the Test

The following results in the table (Table 9.5) show the mean SUS score, the reliability and the standard deviation of the scores. Cronbach's alpha relates to the internal consistency of the answers. The range of the reliability score can be from 0 to 1. The closer to 1, the more reliable the result. Although the interpretation of the reliability depends on the system, usually, above 0.7 is acceptable, 0.8 is good, and 0.9 refers to a highly reliable set of results. The results in the table (Table 9.5) suggest very good internal consistency. The standard deviation shows consistent result as well.

9.5 Interactive Management Session

9.5.1 Idea Writing and Rating

By the end of the IM session, four lists of ranked statements were produced by the two groups in response to the two trigger questions (Vertesi et al. 2018). The two positive and two negative lists were merged into one positive and one negative list. The merged list can be seen in Table 9.6 of the positive and Table 9.7 of the negative statements. The wording follows the original transcript. The scores in the tables are the sum of the individual scores given by the participants. They show the importance of the statements according to the participants.

Tables 9.6 and 9.7 show the prioritised list with the total scores summed from the individual ranking scores.

9.5.2 Categories

The positive and negative statements are grouped into categories based on similarities which makes the problem domain clearer and easier to recognise structure and pattern.

The following groups (Tables 9.8 and 9.9) are created form the lists in Tables 9.6 and 9.7. The order of the statements follows the scores in ranking. The list starts

Table 9.6 Ranked list of positive statements

	All positives – merged	Score
1	Clean and fresh, works good, better user interface	23
2	On-demand help from learning tech, contact directly	19
3	Able to contact trainers	18
4	Functionalities for staff/students	18
5	Programme support help area now a lot cleaner	17
6	Access to sandbox to mess around without worrying about breaking the system	16
7	Learning technologists were very helpful above expectations	15
8	Allows students to hand in late submissions in same area, lateness is clearly marked	14
9	Impersonating a student doesn't log you out	11
10	Training organised and run in plenty of time	10
11	Advantage in piloting is confidence in Year 2	9
12	Not having to log in	9
13	Lots of training available/given	8
14	Clear	5
15	Help section divided for academics/professional support	5
16	Opens more than one screen at a time without needing to log out	5
17	Quick, intuitive meaning mistakes by others are easy to correct	5
18	Drag and drop files	2
19	Similar concepts to the previous VLE in terms of content structure	2

Table 9.7 Ranked list of negative statements

	All negatives – merged	Score
1	Trainers had limited time to learn themselves	34
2	Implementation rushed meaning having to deal with issues that now arise	23
3	No LT support	15
4	Current VLE and new VLE not always linked up	13
5	Systems not talking to each other as well as advertised	12
6	Who was consulted regarding large file submission?	11
7	Lack of info prior to rollout	10
8	Training too general	8
9	Learning tech team restructured during launch	8
10	Training for Turnitin not available at the time of implementation – given too early – academics need to be reminded to read help pages	8
11	A lot of things shown were not useful in terms of usability for teaching	6
12	Anticipating members of staff to be able to sort IT-related issues due to incompatibility of videos, documents and live streaming apps	6
13	No personal training for unique faculty needs	5
14	More communication required about implementation	5
15	No template for structure of unit	5
16	LT consultation at same time as everything new meant lack of support	5
17	Too many ways of accessing the same thing	4

(continued)

Table 9.7 (continued)

	All negatives – merged	Score
18	Sandbox can't simulate everything	4
19	Grader app not supported	3
20	Too many courses in initial rollout	3
21	Help and guidance very lengthy and difficult to follow	3
22	Learning "how to" at same time as LTs who often don't know how to do things	3
23	Did not have choice	2
24	Software lacks consistency in interface	2
25	Interface too "flat" – How do you know where you are?	2
26	No confidence in software	2
27	Lack of updates when a process changes	2
28	Signposting students to new VLE – need much more	2
29	Student support and academics are not in the same training	1

Table 9.8 Positive statements grouped by categories

Positive statements grouped by categories
Usability
Clean and fresh, works good, better user interface
Functionalities for staff/students
Programme support help area now a lot cleaner
Allows students to hand in late submissions in same area, lateness is clearly marked
Impersonating a student doesn't log you out
Not having to log in
Open more than one screen at a time without needing to log out
Quick, intuitive meaning mistakes by others are easy to correct
Similar concepts to the previous VLE in terms of content structure
Drag and drop files
Learnability
Access to sandbox to mess around without worrying about breaking the system
Training organised and run in plenty of time
Advantage in piloting is confidence in Year 2
Help section divided for academics/professional support
Support
Able to contact trainers
On-demand help from learning tech, contact directly
Programme support help area now a lot cleaner
Learning technologists were very helpful (HSS + FMC but not FM) above expectations
Training organised and run in plenty of time
Lots of training available/given
Help section divided for academics/professional support

Table 9.9 Negative statements grouped by categories

Negative statements grouped by categories
Time (time pressure)
Trainers had limited time to learn themselves
Implementation rushed meaning having to deal with issues that now arise
Training for Turnitin not available at the time of implementation – given too early – academics need to be reminded to read help pages
LT consultation at same time as everything new meant lack of support
Structural and organisation
Learning tech team restructured during launch
LT consultation at same time as everything new meant lack of support
Too many courses in initial rollout
Who was consulted regarding large file submission?
Support
No LT support
Training too general
Training for Turnitin not available at the time of implementation – given too early – academics need to be reminded to read help pages
No personal training for unique faculty needs
Too many ways of accessing the same thing
Sandbox can't simulate everything
Help and guidance very lengthy and difficult to follow
Learning "how to" at same time as LTs who often don't know how to do things
Usability
Current VLE and new VLE not always linked up
Systems not talking to each other as well as advertised
A lot of things shown were not useful in terms of usability for teaching
Anticipating members of staff to be able to sort IT-related issues due to incompatibility of videos, documents and live streaming apps
No template for structure of unit
Software lacks consistency in interface
Who was consulted regarding large file submission?
Communication
Systems not talking to each other as well as advertised
Who was consulted regarding large file submission?
Lack of info prior to rolling out
Training for Turnitin not available at the time of implementation – given too early – academics need to be reminded to read help pages
More communication required about implementation
Lack of updates when a process changes
Who was consulted regarding large file submission?

with the most important statements. Some statements are listed in more than one category if it was required.

The categories refer to usability, learnability, support and communication. The individual statements specify the area and nature of the usability issues. IM offers valuable feedback by supporting the general evaluation of the SUS with specific comments.

9.6 Discussion

9.6.1 Preliminary Results

The results show that regarding the usability, there are no big differences between the three VLEs. VLE 1 and VLE 3 reach almost identical SUS scores (54.9 and 55.0), while VLE 2 received 8 points higher score (63). The average, normalised usability score generally for web-based systems is 68. All three VLEs performed under the average expectation. There are differences in the perceived usability of the different user groups. The influential factors that could cause differences in the results are not researched in this study. The students seem to be more satisfied with the VLEs than members of staff.

9.6.2 The New VLE

The usability evaluation of the new VLE at this stage provided reliable and meaningful feedback. The overall SUS score (58.6) suggests a usable system in general but also indicates some usability issues in particular areas. As the implementation is in its early stage (phase 1), this score should not be considered as a final SUS score of the fully implemented and fine-tuned system. The analysis of the evaluation of the different user groups and individual users discloses more details and differences within and between the usability perception of the user groups. The VLE is a complex system with numerous features. Each user group evaluates a slightly or significantly different part of the VLE. The divergence between the SUS scores hints that (a) the system is not uniform regarding the usability and (b) the expectation and perception are different. The detailed analysis of the low SUS scores (37.8) given by the academics identified five problematic areas: simplicity, intuitiveness, ease of use, integration and consistency. Students are mostly satisfied with the new VLE, although interesting trends can be seen in the undergraduate results (Fig. 9.5). Academics and administrators are not always fully satisfied.

9.6.3 Interactive Management Workshop

The IM workshop offered a valuable opportunity to identify, communicate and resolve some serious usability issues. The feedback captured during the workshop was useful for the team that administer the implementation.

The feedback captured in the IM session suggests some explanation for low SUS scores. There are more negative statements ($n = 29$) in the ranked lists than positive ones ($n = 19$). The categories refer to areas that need attention either from the usability perspective or regarding the implementation process. The high importance of providing support, offering training and maintaining good communication is well recognised by the team that manages the implementation and confirmed by the result of this study as well.

9.6.4 Limitation

The research has the following limitations. The different user groups were not represented in equal number. Three times more student completed the online evaluation, but no students participated in the IM session. The SUS score comparison of the user groups gives an equal weighting to every user group.

The phrasing of the first question was modified from “I think that I would like to use this system frequently” to “I use this VLE frequently”. The reason behind this change is that there was no choice of using other VLEs for these users. The impact of this change is that the SUS scores given to the first question are relatively high compared to the average scores. It slightly raises the mean SUS score.

9.6.5 Future Work

There are only a few longitudinal studies that measure the usability periodically during the whole life cycle of the product. Even fewer usability research can be found on VLEs (Luo et al. 2014). Even if any kind of usability evaluation is involved, usually, it is limited to the development phase only. This could suggest the assumption that the users’ perceived usability does not change after a product, e.g. a VLE is installed and works properly. Even if the system does not change, the users are changing.

It would be beneficial to get feedback on a regular basis regarding the user acceptance and perceived usability of the new VLE. Valuable information can be collected regarding the whole educational technology system including users and developers. A simple usability evaluation such as SUS can measure the impact of any changes on the VLE. As the perceived usability is influenced by the user’s attitude and other social changes, it would be even more interesting to see the effect of the pedagogical and social intervention on the SUS scores.

9.6.6 Conclusion

The usability evaluation provided meaningful, easy to understand and comparable results to support the decision-making during and after the procurement process regarding the three VLEs. The adopted VLE has been reevaluated 6 months after the introduction of the new system, at the first stage of the implementation. More detailed research comprising IM methodologies offered a realistic, specific and accurate picture about the adopted VLE at the end of the first phase of the implementation. The case study also demonstrated an example of a feasible, quantitative and qualitative usability evaluation of a VLE combining SUS and IM methodologies.

Acknowledgements The research team would like to express gratitude to the Centre for Excellence of Learning (CEL) and Visual for Learning (V4L) team of the university, especially to Ms. Wendy Drake and Mr. Giles Ashton for the contribution of the research by organising surveys and providing data for the research.

References

Ayad, K., & Rigas, D. (2010). Comparing virtual classroom, game-based learning and storytelling teachings in e-learning. *International Journal of Education and Information Technologies, 4*(1), 15–23.

Babić, S. (2012). Factors that influence academic teacher's acceptance of e-learning technology in blended learning environment. In *E-learning-organizational infrastructure and tools for specific areas* (pp. 3–18). Rijeka: InTech.

Bangor, A., Kortum, P. T., & Miller, J. T. (2008). An empirical evaluation of the system usability scale. *International Journal of Human-Computer Interaction, 24*(6), 574–594.

Bangor, A., Kortum, P., & Miller, J. (2009). Determining what individual SUS scores mean: Adding an adjective rating scale. *Journal of Usability Studies, 4*(3), 114–123.

Boyd, K., Bond, R., Vertesi, A., Dogan, H., & Magee, J. (2019). How people judge the usability of a desktop graphic user interface at different time points: Is there evidence for memory decay, recall bias or temporal bias? *Interacting with Computers, 31*(2), 221–230.

Brooke, J. (1996). SUS-A quick and dirty usability scale. *Usability Evaluation in Industry, 189*(194), 4–7.

Broome, B. J., & Keever, D. B. (1986). *Facilitating group communication: The interactive management approach*.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003.

Dogan, H., & Henshaw, M. J. D. (2010, April). *Transition from soft systems to an enterprise knowledge management architecture*. In International conference on Contemporary Ergonomics and Human Factors, pp. 13–15.

Emelyanova, N., & Voronina, E. (2014). Introducing a learning management system at a Russian university: Students' and teachers' perceptions. *The International Review of Research in Open and Distributed Learning, 15*(1).

Granić, A., & Ćukušić, M. (2011). Usability testing and expert inspections complemented by educational evaluation: A case study of an e-learning platform. *Journal of Educational Technology & Society, 14*(2), 107–123.

ISO. (1998). 9241-11. Ergonomic requirements for office work with visual display terminals (VDTs). *The International Organization for Standardization, 45*(9).

Luo, G. H., Liu, E. Z. F., Kuo, H. W., & Yuan, S. M. (2014). Design and implementation of a simulation-based learning system for international trade. *The International Review of Research in Open and Distributed Learning, 15*(1).

Marco, F. A., Penichet, V. M. R., & Gallud, J. A. (2013). Collaborative e-learning through Drag & Share in synchronous shared workspaces. *Journal of Universal Computer Science, 19*(7), 894–911.

Melis, E., Weber, M., & Andrès, E. (2003). Lessons for (pedagogic) usability of eLearning systems. In *E-learn: World conference on E-learning in corporate, government, healthcare, and higher education* (pp. 281–284). Norfolk: Association for the Advancement of Computing in Education (AACE).

Onacan, M. B. K., & Erturk, A. (2016, October). *Usability evaluation of learning management system in higher education institution: A scale development study*. In International conference on Leadership, Technology, Innovation and Business Management (ICLTIBM-2016), Antalya, Turkiye.

Paulsen, M. F. (2002). Online education systems: Discussion and definition of terms. *NKI distance education*, 202.

Renaut, C., Batier, C., Flory, L., & Heyde, M. (2006). Improving web site usability for a better e-learning experience. *Current developments in technology-assisted education*, 891–896.

Ryan, S., Scott, B., Freeman, H., & Patel, D. (2013). *The virtual university: The internet and resource-based learning*. Routledge.

Sauro, J., & Lewis, J. R. (2011, May). When designing usability questionnaires, does it hurt to be positive? In *CHI* (pp. 2215–2224).

Tullis, T. S., & Stetson, J. N. (2004, June). *A comparison of questionnaires for assessing website usability*. In Usability Professional Association conference (Vol. 1).

Virzi, R. A. (1992). Refining the test phase of usability evaluation: How many subjects is enough? *Human Factors, 34*(4), 457–468.

Vertesi, A., Dogan, H., Stefanidis, A., Ashton, G., & Drake, W. (2018). Usability evaluation of a virtual learning environment: a university case study. In: 15th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA), Budapest, Hungary.

Warfield, J. N., & Cárdenas, A. R. (1994). *A handbook of interactive management* (p. 338). Ames: Iowa State University Press.

Chapter 10
Reciprocal Learning Assistance Systems in Smart Manufacturing: Transformation from Unidirectional to Bidirectional Learning Technology in Manufacturing Enterprises

Fazel Ansari and Walter Mayrhofer

10.1 Introduction: Learning in Highly Automated Environments

A current topic in the research area of human-technology interaction at the workplace is job automation and its impact on the learning process. The vision of Industry 4.0 and digital transformation in manufacturing enterprises lead to higher automation and a decreasing number of direct personnel in factories. However, the recent European skills and job survey (Cedefop 2018), which comprises a large body of studies, doubts the significance of the predictions with regard to the robotization of the labor market. The main reason for imperfect predictions is grounded in the market, industry sector, or technology specificity of the underlying hypotheses (e.g., full robotization of human jobs), which affects the formulation of theory and accordingly proper explanation and interpretation of a set of phenomena. At the same time, the survey reveals that technological progress may widen inequality, e.g., with regard to wages, and contribute to the polarization of jobs in the labor market (Cedefop 2018). According to the International Federation of Robotics (IFR), the reliance of European companies on robots in average is significantly different than other regions. In particular, the average number of installed industrial robots per 10,000 employees in European manufacturing industry in 2017 is estimated 106, comparing to the world average 85 (IFR 2018). Although it is worth noting that South Korea stands in the first rank by 710 installed robots per 10,000 employees (IFR 2018). However, especially Western European "high-wage countries" are catching up, although when it comes to the application of robots in manufacturing,

F. Ansari (✉) · W. Mayrhofer
Vienna University of Technology, Vienna, Austria
e-mail: fazel.ansari@tuwien.ac.at; walter.mayrhofer@tuwien.ac.at

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2_10

there is also a distinctly higher automation rate of larger companies in comparison to small- and medium-sized companies (Mayrhofer et al. 2019c).

Over the past decades, industrial robots have primarily replaced low-medium-skilled workers carrying out manual and repetitive tasks rather than critical, non-routine, or decision-making tasks. However, it is not only robots but increasingly automated or autonomous machinery that are replacing human operators and supervising personnel. As a result, there is less opportunity for human learning, in particular for low-medium-skilled workers, resulting in decreasing tacit knowledge about processes and systems. Furthermore, the scientific challenge increases with regard to the human-machine learning process and their cognitive dependencies, where machine refers to a range of technological entities and intelligent systems such as robots, artificial intelligence (AI) agents, algorithms, smart devices, and utilities.

This effect was already described 35 years ago as one of the "ironies of automation" (Bainbridge 1983) and "recent technological developments may have some new ironies in store for us" (Baxter et al. 2012). Such recent technological developments include robotics and (intelligent) assistance systems as well as the possibilities of distributed Internet of Things (IoT) applications, AI, and machine learning, which are some of the driving forces and enabling technologies behind Industry 4.0 (Ganschar et al. 2013; Schlund and Pokorni 2016).

However, in all the excitement about the new technological potential with respect to automation and digitalization, human capabilities are often considered as a given, almost static, variable. In an extension of the "human-in-the-loop" approach, the following chapters present a reciprocal learning methodology to human-machine learning with the goal to improve the capabilities of both humans and machines simultaneously in order to raise their "collective intelligence" (Levy 1994; Glenn 2013).

Reframing the risks of automation as an opportunity, the key challenge today is "How to build an integrated human-machine collaboration framework for reciprocal learning in smart factories?", based on the definition of reciprocal learning (also known as human-machine mutual learning) given by Ansari, Erol, and Sihn (2018a).

Foresight involves future-oriented awareness in order to enable today's smart factories to transform into human-centered self-learning factories, in which not only humans and machines think but also the factory could think and innovate new products or processes. To this end, Sect. 10.2 discusses learning in smart factories and learning assistance under consideration of background terminologies, challenges, and requirements from both technological and non-technological perspectives. Furthermore, it discusses the concept of reciprocal learning and introduces related terms such as "human and machine as a learner" in smart factories. Subsequently, Sect. 10.3 presents the AUTODIDACT concept for building a reciprocal learning platform in TU Wien's Pilot Factory Industry 4.0. Finally, Sect. 10.4 concludes the discussion and elaborates on a future research agenda.

10.2 Requirements and Challenges for Learning in Smart Factories

10.2.1 Human Learning and the Development of Learning Assistance Systems: A Brief Overview

Human learning has been considered a subject in the field of education, pedagogy and cognitive psychology describing and modelling human learning processes, in order to better understand how humans acquire, store and demonstrate knowledge and competence, and thus how they continuously support and improve the learning process and pertained outcomes (i.e. knowledge and competence). Learning theories have evolved (e.g., behaviorism, cognitivism, constructivism, and humanism) over the past centuries, considering a range of role (from passive to proactive) for a learner. A passive learner is only a recipient of learning content, whereas an (pro) active or self-regulated participant in the learning process actively constructs meanings and experiences learning (Illeris 2018; Hetzner et al. 2011; Ertmer and Newby 1993). Learning processes referring to employees and work environments have been subject to ongoing changes over time, especially influenced by the emergence and application of technology-assisted learning (Abele et al. 2019; Boud and Garrick 1999).

Over the last 25 years, technology-assisted learning (aka e-learning, computer-based training, etc.) has been one of the major trends in education. While early forms of technology-assisted learning just provided electronic versions of books and other educational materials, later developments included multi-media content and increased interaction. However, such systems often used a "one-size-fits-all" approach to content and curriculum although a modular structure allowed for variations evolving into "adaptive learning systems" (aka personal learning environment (PLE), learning management system (LMS), etc.) that respond to the needs and already mastered knowledge of the individual learner (Brusilovsky 1999; Stoyanov and Kirschner 2004; Nuri and Nese 2013). A core element of such adaptive learning systems is a distinct learning path for each individual learner (Janssen et al. 2018).

Increasing immersion and interaction with the surrounding physical environment leads to so-called smart learning environments. In this context, smart learning environments (SLE) are defined as "physical environments that are enriched with digital, context-aware and adaptive devices, to promote better and faster learning" (Koper 2014).According to Koper (2014), a SLE is a learning environment in which:

1. "one or more digital devices are added to the physical locations of the learner;
2. the digital devices are aware of the learners location, context and culture;
3. the digital devices add learning functions to the locations, context and culture, such as the provision of (augmented) information, assessments, remote collaboration, feedforward, feedback, etc.;
4. digital devices are monitoring the progress of learners and provides appropriate information to relevant stakeholders."

The last item in the above list, the monitoring of learning progress, often is referred to as "learning analytics" and has become a distinct area of research (Duval 2011; Siemens 2013; Gasevic et al. 2015). Due to the collection, monitoring, measurement, and analysis of learning, related data (content, context, individual and collective performance, etc.) allows dynamic personalization of content, monitoring of learning performance and intervention and individualized motivation, and an approach that could be called "evidence-based curriculum development." Although certain problematic issues with respect to privacy and ethics remain, learning analytics is one of the most promising fields in technology-assisted learning.

Technological advances, namely, IoT, robotics, human-machine interaction, human-centered AI, big data, and knowledge intelligence, and embedded systems enable technology-enhanced learning solutions such as adaptive and ubiquitous learning scenarios (Freigang et al. 2014). In extension of the notion of ubiquitous learning, such learning environments can be integrated into people's workstations or even be morphed with the equipment they use on an everyday basis (comp. Haase 2015).

The approach for an "on-the-job learning assistance system" presented in this chapter strives to take the notion of ubiquitous learning and workplace integration one step further, especially by focusing on undergoing transformation in manufacturing enterprises to smart factories (cf. Sect. 10.2.2). By integrating learning and teaching functionality into traditional worker assistance systems and utilizing existing physical and IoT infrastructure, daily human-machine interactions become learning experiences for both humans and machines. Thus, the vision of "learning by doing" or vice versa "doing by learning" finally comes one step closer to reality at the shared human-machine workplace.

10.2.2 Smart Factories: Terminology and Background

The increasing permeation of physical equipment with digital technologies and advances in collaborative robotics and data science is expected to lift factory automation to a new level (IFR 2017; Bauer et al. 2016; Monostori et al. 2016). In combination with the widespread use of IoT technologies within manufacturing facilities, their implementation is widely referred to as "smart factory" (Zühlke 2008; Kagermann et al. 2013; Wagner et al. 2017). The vision of Industry 4.0 advocates the realization of smart factory technologies to connect humans, machines, and intelligent objects in order to create high-performance processes and products (Spath et al. 2013; Liao et al. 2017).

Traditionally, automation and Industry 4.0 give emphasis to technological opportunities and focus less on the organizational setting and socio-technical environment. In order to tap the full potential of Industry 4.0 and to create a conducive environment to test new approaches in human-machine learning, it is necessary to employ a comprehensive approach that takes well-known interdependencies of factories, as socio-technical entities with strong linkages between technological and organizational changes, into account (Schlund et al. 2018).

The transformation with regard to the integration of new technologies and its effects on the way manufacturing is organized are already visible. The increasing degree of autonomy of intelligent robots and assistance systems poses a major challenge to the traditional organization of factories. Collaborative and mobile robotics will carry out manual routine tasks, while digital assistance systems take over cognitive routine tasks and provide support in non-routine situations. Thus, the organization of work will inevitably change and autonomous systems increasingly require human work that is more flexible. The required competences of factory workers as well as those of support functions such as maintenance and quality assurance staff are expected to change significantly (Jäger et al. 2012; Erol et al. 2016; Lanza et al. 2016). Section 10.2.3 gives an outline in what directions those changes are most likely to lead.

10.2.3 Learning Matters in Smart Factories

As the expected changes in competency development due to Industry 4.0 are widely discussed, there is a need to adapt learning in factory environments to those changes, to retain and improve learning curves for blue-collar and white-collar employees. Due to increased automation in smart factories, the challenges of learning grow on various levels (Schlund and Pokorni 2016). The barriers (challenges) to learning in smart factories comprise the following:

- *Larger scope*: Due to higher automation and increasingly autonomous technical systems, the average staffing per machine decreases. Hence, the number of processes, to be monitored and controlled by the remaining employees, is increasing.
- *Fewer learning opportunities*: Since machines take over routine tasks and the resulting focus of humans is put on non-routine tasks, less learning opportunities with respect to routine processes exist for human operators (Baxter et al. 2012).
- *Uncertain role of human work in hybrid (human-machine) settings*: Due to collaborative tasks with machines and algorithms, additional requirements in terms of learning emerge. Especially the "reciprocal learning approach" will become necessary in hybrid (man-machine) settings in a smart factory. This approach uses human experience and tacit knowledge to train machine data sets (machines learn from humans) and on the other hand employs data-based learning that is guided by smart algorithms (humans learn from machines) (Goldberg 2017).

Besides the challenges mentioned above, learning in a smart factory also changes its perspective with regard to different periodicity.

- *Short-term*: Process optimization, operational excellence, and quick results usually drive learning in the short-term. To learn to carry out one or several work tasks more efficiently usually follows a learning curve (Zangwill and Kantor 1998), and short-term learning goals translate into a steepening of the learning curve during the ramp-up phase.

- *Mid-term*: The emergence of hybrid settings of mixed man-machine teams necessitates an optimal assignment of tasks to a good fit with the team members. The assignment of tasks depends on individual capabilities and the needed effort to train each team member for a specific task. Moreover, task assignment is most likely not static and will change over time as the capability level of workers and machines evolves. Hence, there is a constant need for training and retraining. The assignment of tasks will be evaluated with respect to relevant parameters such as economic and organizational goals but also regarding competency development and learning.
- *Long-term*: Learning about and gaining an understanding of a complicated manufacturing process usually contributes to process and product innovations. Mistakes, mishandling, and unplanned events regularly offer room for small improvements or even novel ideas. Furthermore, the tacit knowledge of processes and their interconnections and eventual impacts provide a competitive advantage that is often hard to copy by rivaling companies. Therefore, the optimal ratio of automated and human decision-making is essential in maintaining an organization's ability to improve and adapt to unplanned and to some extent unforeseeable changes.

10.2.4 Evolution of Reciprocal Learning in Smart Factories

From an ontological point of view, reciprocal learning is derived from the theory of "reciprocal altruistic behavior," which occurs between members of different species (Trivers 1971). In human societies reciprocal altruistic behavior takes place in various contexts and cultures. However, five typical types of reciprocal altruistic behavior could be summarized according to Trivers (Trivers 1971) as "1) helping in times of danger, 2) sharing food, 3) helping the sick, the wounded, or the very young and old, 4) sharing implements and workplace; and 5) sharing knowledge." Reciprocal learning, therefore, can be a motive and may occur as a result of an altruistic behavior, in particular sharing knowledge and sharing workplace between members of different species, especially when in a long run they benefit by cooperating.

The concept of reciprocal learning could be extended to the context of human-machine interaction, where the division of tasks between human workforces and machines is changing from distinctive roles and tasks into hybrid (collaborative) roles and task schemes. The latter divides the entire pool of tasks into three clusters, namely:

(i) Tasks assigned to the human workforce
(ii) Tasks assigned to (intelligent) machines
(iii) Shared tasks assigned to both human workforce and intelligent machines (incl. robots, markedly collaborative robots (cobots), virtual assistance systems, etc.) (cf. Fig. 10.1)

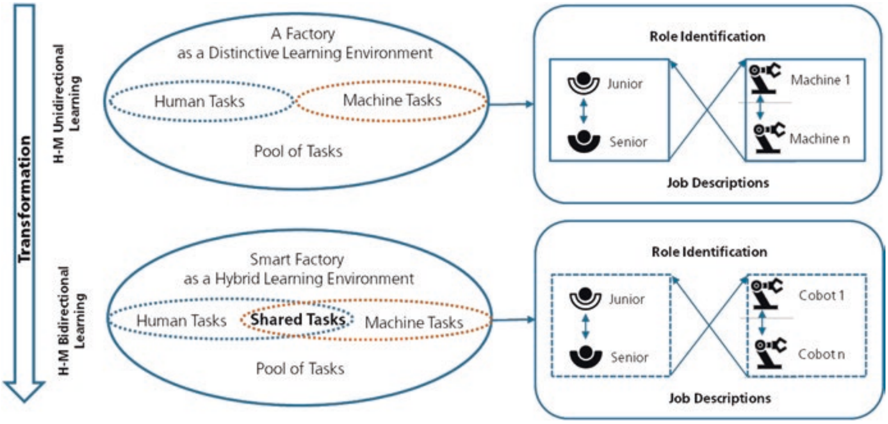


Fig. 10.1 Division of tasks and its impact on human-machine learning. (Reprinted from Ansari et al. 2018c)

Participation in the shared tasks (Michalos et al. 2018) necessitates the learning capabilities of the human workforce and machines (i.e., humans and machines as a learner) and further combines them into a new boundary system in which mutual learning takes place. Henceforth, the definition of human-machine reciprocal learning (aka mutual learning) given earlier by Ansari, Erol, and Sihn (2018a) is modified as follows: *Reciprocal (mutual) learning is a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating a new meaning or concept, enriching the existing ones or improving skills and abilities in (symmetric or asymmetric) associated with each group of learners*.

Creating digital profiles of the aforementioned group of learners facilitates modeling, estimating, and evaluating of the magnitude and significance of the learning effectiveness and outcomes resulting from reciprocal learning in smart factories. Furthermore, digital profiles of human workforces and machines provide possibilities to collect data, construct distinct learning profiles, and identify reciprocal learning in a consistent, dynamic, and realistic way.

A digital profile typically comprises all basic information, i.e., personal or professional information of the human workforce or the technical specifications of a machine. It also contains on-the-job performance data collected by means of sensors and condition monitoring systems for the target human workforce or machine. Furthermore, it encompasses feedback collected, e.g., via a 360° feedback (multi-source feedback) approach or via a customer or end-user questionnaire survey. Such a continuously growing database provides opportunities for identification and prediction of learning trajectories for both human and machine workforces over time.

The machine's digital profile can be quantified based upon the determination of the degree of autonomy of the individual machine functions. The degree of autonomy of a machine specifies its technical ability to autonomously adapt to dynamically changing production conditions, without endangering the efficiency and effectiveness of the production process. In order to define the degree of autonomy of a machine, a descriptive basis for a corresponding comparison must first be determined. There are various possibilities for this corresponding comparison, e.g., as proposed by Gronau and Theuer (2016):

(iv) Number of autonomous functions/number of all functions
(v) Number of autonomous controlling systems/number of all controlling systems
(vi) Number of autonomous actuator systems/number of all controlling actuators
(vii) Number of autonomous resource supply systems/number of all resource supply systems
(viii) Number of autonomous mobility systems/number of all mobility systems
(ix) Autonomous quantity of data/total quantity of data

The degree of autonomy shall be determined for each machine function. A summation of the corresponding quantified degrees via Likert scale enables the definition of a specific machine's digital profile, which can be described in the form of a vector representation.

Further, the concept of a machine's digital profile may resemble the virtual representation, monitoring, and configuration of a machine's components and functions in a dynamic manner. Therefore, the term digital twin is defined as an evolving digital profile of a production system (Brenner and Hummel 2017). It establishes an interface between the physical and digital world through streaming and linking the status data of all physical objects in the production system to their virtual models (Uhlemann et al. 2017). Using intelligent data analytic methods, learning accomplishments can be recorded, and corresponding implementation decisions can be directed to operators and technical systems (Mussomeli et al. 2017).

In the proposed concept of AUTODIDACT, the term machine digital twin is used to address the digital profile of a machine workforce (cf. Sect. 10.3). The definition and characteristics of the human digital profile are based on descriptive parameters consisting of different determinants, which enable a human workforce to perform a task in a work system.According to Schlick, Bruder, and Luczak (2010), these determinants include:

1. Human constituent characteristics
2. Human disposition characteristics
3. Human qualification and competency characteristics
4. Human adaptation characteristics

Employing "Performance Shape Factors 3" (PSF 3) introduced by Bubb (2005), it is possible to build a quantified human digital profile as discussed in Ansari, Hold, and Sihn (2018b). Human and machine's digital profiles are the core building blocks for realizing an integrated human-machine collaborative framework for reciprocal learning in smart factories, which is discussed in Sect. 10.3.

10.3 Autodidact: Toward Reciprocal Learning in TU Wien's Pilot Factory Industry 4.0

The TU Wien Pilot Factory Industry 4.0 (PFI4.0) is a research lab and demonstration factory promoting the realization of smart factory technologies – tailored to future-oriented solutions for manufacturing industries (PFI40 2018; Ansari et al. 2018a). Human-technology collaboration is one of the main working areas in which the current focus is on realizing innovative solutions for human and technology interactions, including human-robot collaboration, digital assistance systems, etc. The developed solutions aim at enhancing workplace productivity and efficiency while also improving working conditions, ergonomics, safety, and education (Mayrhofer et al. 2019a). As discussed earlier, learning is one of the key areas to innovation, and reciprocal learning is essential to develop and enhance synergistic innovation capability in the PFI4.0.

Hence, in order to implement and demonstrate such a next-generation reciprocal learning assistance system, the concept of "AUTODIDACT" is developed. It envisages an integrated human-machine collaboration framework for reciprocal learning in the PFI4.0 and aims at realizing an "on-the-job" learning approach for reciprocal learning, to improve both the autonomous systems and humans that collaboratively work with them (cf. Fig. 10.2).

From a design perspective, AUTODIDACT consists of four functional layers, excluding the factory layer, consisting of representative use-cases in manufacturing and assembly units. These layers are introduced in the following:

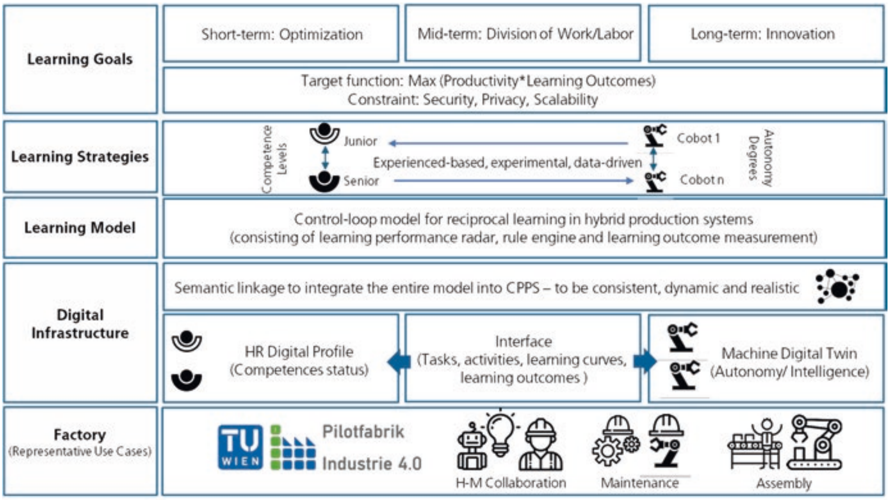


Fig. 10.2 AUTODIDACT – An integrated human-machine collaboration framework for reciprocal learning. (Reprinted from Ansari et al. 2018c)

- *Digital infrastructure* consists of the human workforce's and machine's digital profiles, known as HR digital profile and machine digital twin, respectively. In addition, it features taxonomies of tasks, domain ontologies, and associated statistical models and indicators for estimating learning curves and measuring learning outcomes. The entire digital profiles are semantically linked to the existing cyber-physical production systems (CPPS) for dynamic acquisition and exchange of knowledge.
- *Learning model* is a control loop model that assists in building learning profiles and trajectories for each group of learners as well as identifying and measuring the mutual learning outcomes. It includes a learning performance radar and rule engine to facilitate monitoring and assessing the learning outcomes.
- *Learning strategies* refer to experience-based, experimental, and data-driven strategies enhanced by machine learning and statistical learning methods for both groups of learners, i.e., human or cobots, in various competency and autonomy levels, respectively. It mainly deals with various learning strategies to improve not only unidirectional learning but also bidirectional (cf. Fig. 10.3).
- *Learning goals* feature the target function that should link productivity to learning outcomes under certain constraints and boundary conditions such as security, privacy, scalability, etc. The outcome is used for progressing toward the factory goals, i.e.:

  1. Short-term: optimization of tasks and processes
  2. Mid-term: new division of works between human and machine workforce
  3. Long-term: innovation in products and services

Human-robot collaboration (cf. Fig. 10.4) is one of the typical use-cases in smart factories, which represents certain characteristics of reciprocal learning, i.e., participation of two groups of learners in performing tasks, including shared tasks, and at the same time the acquisition of (new) knowledge within a dynamic and changeable environment. In this case, the teacher and learner role (i.e., senior and junior) can be identified depending on the human competences and performance determinants (e.g., constitutional, disposition, adaptation, qualification, and competence characteristics) as well as the machine's (robot's) intelligence and technical functions/conditions represented by the associated digital profiles, respectively (Hold et al. 2016; Ansari et al. 2018b).

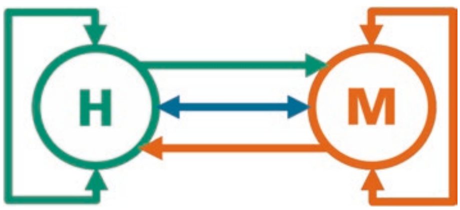


Fig. 10.3 Schematic sketch of unidirectional and bidirectional learning modes (Unidirectional Modes: $\text{Human}_i \rightarrow \text{Machine}_j$, $\text{Machine}_j \rightarrow \text{Human}_i$, $\text{Human}_i \rightarrow \text{Human}_h$, $\text{Machine}_j \rightarrow \text{Machine}_k$ & Bidirectional Modes: $\text{Human}_i \leftrightarrow \text{Human}_h$, $\text{Machine}_j \leftrightarrow \text{Machine}_k$, $\text{Human}_i \leftrightarrow \text{Machine}_j$)

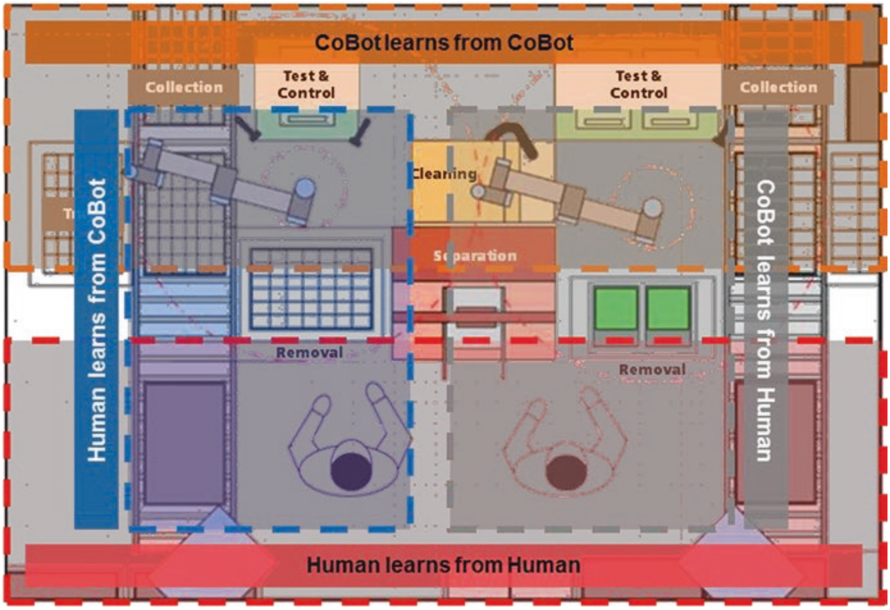


Fig. 10.4 Schematic representation of human-robot collaboration. (Reprinted from Ansari et al. 2018c)

Figure 10.4 schematically represents the human-robot collaboration in an assembly cell, consisting of two human workforces and two cobots. The mutual learning between human workforce (e.g., operator) and cobot occurs by fulfilling the four steps of a so-called questioning, controlling and summarizing, clarification, and prediction, as originally proposed by Hacker and Tenent (Hacker and Tenent 2002) in the context of reciprocal teaching. The four steps are as follows:

(a) To check the counterpart with regard to learning success (questioning)
(b) To change the execution of the activity among them (controlling and summarizing)
(c) To experimentally transfer the performance of a similar activity to each other (clarification)
(d) To allow the other party to make a prediction for the execution of a new task and finally to perform the predicted task execution (prediction)

For this purpose, the control loop model of reciprocal learning illustrated in Fig. 10.2 is set into direct interaction with the human workforces and cobots. Based on a fundamental and prospectively planned task distribution between the human workforces and cobots, the success of a corresponding task execution along a learning process is measured (questioning) via different sensor systems.

The task execution between the human workforce and cobots is changeable and comparable with regard to the learning success (summarizing) via different control logics. Corresponding decisions for a new distribution of activities between them

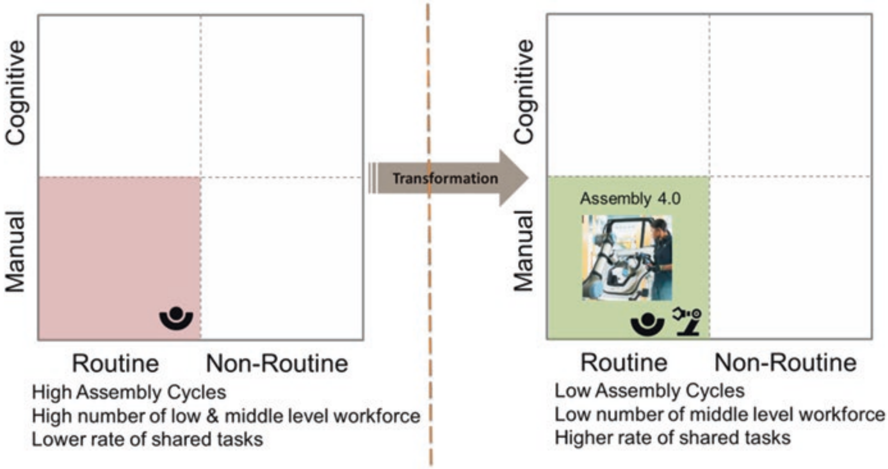


Fig. 10.5 Transitional path of cyber-physical assembly systems. (adapted from Mayrhofer et al. 2019b)

can be carried out by means of data analysis (clarification). This provides possibilities to dynamically switch between human workforces and cobots in relation to comparable activities (prediction). In this way, new types of learning logic are identified and will be taken into account with regard to an improved distribution of tasks in the forthcoming planning period.

The application of such cyber-physical assembly systems will have certain effects on the way tasks are divided between humans and machines (Mayrhofer et al. 2019). Figure 10.5 depicts likely transitional path of cyber-physical assembly systems, where robots will increasingly take over quality-critical, repetitive manual routine tasks from employees with a low to medium skill level, while humans focus on complex, manual routine tasks. For common tasks a focus will be on the task sharing in dealing with disturbances between assembly workers (junior and senior) and collaborative robots (Bauer et al. 2014).

Socio-technical challenges cover learning strategies, objectives, and measure for modeling and measuring learning impacts in four reciprocal learning situations, when:

1. Junior assembly worker learns from senior assembly worker how to handle an error (human learns from human)
2. Junior worker learns from cobot how to handle an error (human learns from cobot)
3. Senior assembly worker teaches a cobot how to handle an error (cobot learns from human)
4. A cobot teaches another cobot how to handle an error (cobot learns from cobot)

Measuring learning impact in the abovementioned situations requires not only competence-based human learning approaches but also knowledge-based and explainable AI algorithms.

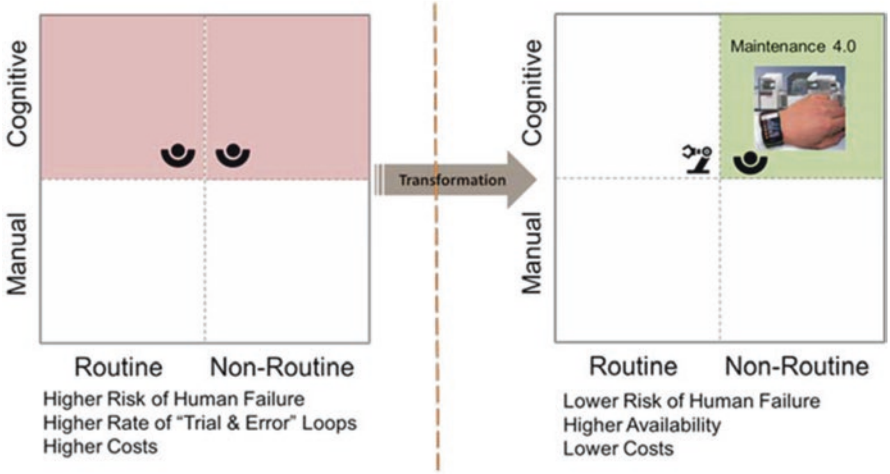


Fig. 10.6 Transitional path of maintenance 4.0. (Adapted from Mayrhofer et al. 2019b)

Figure 10.6 illustrates a similar transitional path for maintenance tasks, which dominantly deals with cognitive tasks. In this case, the share of non-routine activities is expected to increase at the expense of cognitive routine tasks and represents a paradigm shift toward predictive and prospective maintenance strategies, which utilize optimal selection of sensor data in order to derive recommendations for maintenance measures (Ansari et al. 2019).

In this case, machine learning and artificial intelligence might be able to deal with many of the routine tasks, increasing the share of non-routine tasks for maintenance workers. Challenges for learning cover the following:

- Continuously teach and train personnel about maturity, experience level, and specific shortcomings of machine learning support.
- Create awareness for expected human action and interference (initialization, verification) and interfaces for hybrid actions.
- Transfer experience-based knowledge in readable machine learning algorithms.

10.4 Future Research Agenda

The proposed concept of reciprocal learning features a dual character affected by human and machine collective intelligence. Hence, building AUTODIDACT in various smart factories is tied to theoretical and application-oriented research in both human- and machine-specific learning domains. In particular, the following topic areas should be further investigated, namely:

1. Learning profiles and trajectories for both human and machine workforce, e.g., in TU Wien's Pilot Factory Industry 4.0, considering specific use-cases in three areas of human-robot collaboration, maintenance, and assembly
2. AUTODIDACT's system specifications for modeling and measuring reciprocal learning, including technological and non-technological requirements and constraints
3. AUTODIDACT's ontological knowledge base, which specifies the shared conceptualization of tasks and associated domain knowledge between human and machine workforce
4. AUTODIDACT's control loop, consisting of a dynamic rule engine (set of rules) for inferring optimal task sharing and measuring learning outcomes in relation to key performance indicators (KPIs) used in production management
5. AUTODIDACT's application-specific parameters in manufacturing enterprises characterized by different properties associated with (1) variation of product specifications, product types, production technologies, manufacturing or assembly tasks, and task sequences; (2) context specificity, e.g., maintenance, quality control, intralogistics, etc.; (3) job holder profiles and task descriptions as well as types of tasks and related learning requirements, addressing several challenges such as multiplicity of actors, e.g., two human operators and two robots in an assembly cell; and (4) emergence of new automatable tasks, e.g., in quality control and documentation, and emergence of new learning modes, e.g., "robot-to-robot bidirectional learning" or "human-to-robot shared bidirectional learning via task sharing in addition to workplace sharing"

Last but not least, it is worth noting that the abovementioned topic areas shape the pathways for future research, in which the requirements of reciprocal learning should be empirically investigated and proof-of-concept physical demonstrators are developed for human-robot assembly and maintenance systems.

Acknowledgment The authors would like to express their sincere gratitude to the Austrian Research Promotion Agency (FFG) and several private industrial firms that co-finance the TU Wien Pilot Factory Industry 4.0.

Furthermore, it is also noted that some of the activities covered in this chapter were financed through the bmvit-endowed chair for Industry 4.0 at TU Wien.

References

Abele, E., Metternich, J., & Tisch, M. (2019). *Learning factories: Concepts, guidelines, best-practice examples*. Cham: Springer.

Ansari, F., Erol, S., & Sihn, W. (2018a). Rethinking human-machine learning in industry 4.0: How does the paradigm shift treat the role of human learning? *Procedia Manufacturing, 23C*, 117–122.

Ansari, F., Hold, P., & Sihn, W. (2018b). *Human-centered cyber physical production system: How does industry 4.0. Impact on decision-making tasks?* In 2018 IEEE Technology and Engineering Management Society conference, 27 June-1 July 2018, IL, USA.

Ansari, F., Hold, P., Mayrhofer, W., Schlund S., & Sihn, W. (2018c). *AUTODIDACT: Introducing the concept of mutual learning into a smart factory industry 4.0*. In Proceedings of 15th international conference on Cognition and Exploratory Learning in Digital Age (CELDA 2018), October 21–23, Budapest, Hungary, pp.61–68.

Ansari, F., Glawar, R., & Nemeth, T. (2019). PriMa: A prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing, 32*(4–5), 482–503.

Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*, 775–780.

Bauer, W., Schlund, S., Ganschar, O., & Pokorni, B. (2014). *Concept of a failures management assistance system for the reaction on unforeseeable events during the ramp-up*. In 8th international conference on Digital Enterprise Technology (DET 2014), March 25th – March 28th 2014, Stuttgart, Procedia CIRP 25. Amsterdam: Elsevier, pp. 420–425.

Bauer, W., Bender, M., Braun, M., Rally, P., & Scholtz, O. (2016). *Lightweight robots in manual assembly – Best to start simply*. Examining companies' initial experiences with lightweight robots, Stuttgart, pp. 1–32.

Baxter, G., Rooksby, J., Wang, Y., & Khajeh-Hosseini, A. (2012). The ironies of automation … still going strong at 30? In P. Turner & S. Turner (Eds.), *Proceedings of the 30th European conference on Cognitive Ergonomics* (pp. 65–71). New York: ACM.

Boud, D., & Garrick, J. (1999). Understanding of workplace learning. In *Understanding learning at work* (pp. 1–12). London: Routledge.

Brenner, B., & Hummel, V. (2017). Digital twin as enabler for an innovative digital shopfloor management system in the ESB logistics learning factory at Reutlingen – University. *Procedia Manufacturing, 9*, 198–205.

Brusilovsky, P., 1999. Adaptive and intelligent technologies for web-based education. In C. Rollinger &C. Peylo (Eds.), *Special issue on intelligent systems and teleteaching* (Künstliche Intelligenz, 4, pp. 19–25).

Bubb, H. (2005). Human reliability: A key to improved quality in manufacturing. *Human Factors and Ergonomics in Manufacturing, 15*(4), 353–368.

Cedefop. (2018). *Insights into skill shortages and skill mismatch: Learning from Cedefop's European skills and jobs survey* (Cedefop Reference Series, No 106). Luxembourg: Publications Office of the European Union.

Duval, E. (2011). *Attention please! Learning analytics for visualization and recommendation*. In Proceedings of the 1st international conference on Learning Analytics and Knowledge, LAK 2011, February 27–March 01, 2011, Banff, AB, Canada.

Erol, S., Jäger, A., Hold, P., Ott, K., & Sihn, W. (2016). *Tangible Industry 4.0: a scenario-based approach to learning for the future of production*. In Procedia CIRP 54, 6th CIRP conference on Learning Factories, Gjøvik, Norway, pp. 13–18.

Ertmer, P. A., & Newby, T. J. (1993). Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. *Performance Improvement Quarterly, 6*(4), 50–72. (Reprinted in: *26*(2), 43–71, 2013).

Freigang, S., Schlenker, L., & Köhler, T. (2014). A conceptual framework for designing smart learning environments. *Smart Learning Environments, 5*, 27. Springer (2018).

Ganschar, O., Gerlach, S., Hämmerle, M., Krause, T., Schlund, S., & Spath, D. (Hrsg.). (2013). *Produktionsarbeit der Zukunft – Industrie 4.0*. Stuttgart: Fraunhofer Verlag. ISBN:978-3-8396-0570-7, 150 S.

Gasevic, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 51*(1), 64–71.

Glenn, J. C. (2013). Collective intelligence and an application by the millennium project. *World Futures Review, 5*(3), 235–243.

Goldberg, J., (2017, June 11). The robot-human alliance: Call it multiplicity: Diverse groups of people and machines working together. *The Wall Street Journal*.

Gronau, N., & Theuer, H. (2016). Determination of the optimal degree of autonomy in a cyber-physical production system. *Procedia CIRP, 57*, 110–115.

Haase, T., (2015). Technologiebasierte Qualifizierung – Weiterbildung und Wissenstransfer der Zukunft mit neuen Methoden des Digital Engineering and Operation. In Schenk. M. (Hrsg.), *Produktion und Logistik mit Zukunft, Digital Engineering and Operation* (pp. 337–364). Springer.

Hacker, D. J., & Tenent, A. (2002). Implementing reciprocal teaching in the classroom: Overcoming obstacles and making modifications. *Journal of Education & Psychology, 94*(4), 699–718.

Hetzner, S., Steiner, C. M., Dimitrova, V., Brna, P., & Conlan, O. (2011, September). Adult self-regulated learning through linking experience in simulated and real world: A holistic approach. In European conference on Technology Enhanced Learning 166-180). Springer, Berlin/Heidelberg.

Hold, P., Ranz, F., Sihn, W., & Hummel, V. (2016). Planning operator support in cyber-physical assembly systems. *IFAC PapersOnLine, 49*(32), 60–65.

Illeris, K. (2018). An overview of the history of learning theory. *European Journal of Education, 53*(1), 86–101.

International Federation of Robotics (IFR). (2017). *How robots conquer industry worldwide*. In Presentation IFR Press conference, September 27, 2017.

International Federation of Robotics (IFR). (2018). *World robotics report 2018*. IFR Press. https://ifr.org/free-downloads. Accessed on: 17.09.2019.

Jäger, A., Mayrhofer, W., Kuhlang, P., Matyas, K., & Sihn, W. (2012). Total immersion: Hands and heads-on training in a learning factory for comprehensive industrial engineering education. *International Journal of Engineering Education, 29*(1), 23–32.

Janssen, J., Berlanga, A. J., Vogten, H., & Koper, R. (2018). Towards a learning path specification. *International Journal of Continuing Engineering Education and Lifelong Learning, 18*(1), 77–97.

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Recommendations for implementing the strategic initiative INDUSTRIE 4.0*. Final report of the Industrie 4.0 Working Group, Ed. By Forschungsunion Wirtschaft – Wissenschaft und acatech – Deutsche Akademie der Technikwissenschaften e.V.

Koper, R. (2014). Conditions for effective smart learning environments. *Smart Learning Environments, 1*, 5. Springer.

Lanza, G., Minges, S., Stoll, J., Moser, E., & Haefner, B. (2016). *Integrated and modular didactic and methodological concept for a learning factory*. In Procedia CIRP 54, 6th CIRP conference on Learning Factories, Gjøvik, Norway, pp. 136–140.

Levy, P. (1994). *L'intelligence collective. Pour une anthropologie du cyberspace*. Paris: La De'couverte.

Liao, Y., Deschamps, F., Rocha Loures, E. F., & Ramos, L. P. P. (2017). Past, present and future of industry 4.0 – A systematic literature review and research agenda proposal. *International Journal of Production Research, 55*(12), 3609–3629.

Mayrhofer, W., Rupprecht, P., & Schlund, S. (2019a). *One-fits-all vs. tailor-made: User-centered workstations for field assembly with an application in aircraft parts manufacturing (forthcoming)*. In Proceedings of the 25th ICPR – Manufacturing Innovation: Cyber Physical Manufacturing, August 9–14, 2019, Chicago, IL.

Mayrhofer, W., Ansari, F., Sihn, W., & Schlund, S. (2019b). Konzept für ein Assistenzsystem für arbeitsplatznahes, reziprokes Lernen in hochautomatisierten Produktionsumgebungen, GfA Frühjahrskongress 2019, Arbeit interdisziplinär analysieren – bewerten – gestalten, Dresden, February 27–March 1, 2019.

Mayrhofer, W., Kames, D., & Schlund, S.. (2019c). Made in Austria: Produktionsarbeit in Österreich 2019, Studie, Technische Universität Wien. ISBN:978-3-9504856-0-8.

Michalos, G., Spiliotopoulos, J., Makris, S., & Chryssolouris, G. (2018). A method for planning human robot shared tasks. *CIRP Journal of Manufacturing Science and Technology, 22*, 76.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., & Ueda, K. (2016). Cyber-physical systems in manufacturing. *CIRP Annals – Manufacturing Technology, 65*(2), 621–641.

Mussomeli, A., Cotteleer, M., & Parrott, A.. (2017). *Industry 4.0 and the digital twin – Manufacturing meets its match*. Deloitte University Press.

Nuri, K., & Nese, S. (2013). Adaptive learning systems: Beyond teaching machines. *Contemporary Educational Technology, 4*(2), 108–120.

PFI40. (2018). *Website of TU Wien Pilot Factory Industrie 4.0*. Retrieved from: http://pilotfabrik.tuwien.ac.at. Accessed on 17.09.2019.

Schlick, C. M., Bruder, R., & Luczak, H. (2010). *Arbeitswissenschaft*. Berlin/Heidelberg: Springer.

Schlund, S., & Pokorni, B. (2016). *Industrie 4.0 – Wo steht die Revolution der Arbeitsgestaltung?* Stuttgart/Ulm: Ingenics AG, p. 35.

Schlund, S., Mayrhofer, W., & Rupprecht, P. (2018). Möglichkeiten der Gestaltung individualisierbarer Montagearbeitsplätze vor dem Hintergrund aktueller technologischer Entwicklungen. *Zeitschrift für Arbeitswissenschaft, 72*, 276–286.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400.

Spath, D., Ganschar, O., Gerlach, S., Hämmerle, M., Krause, T., & Schlund, S. (Eds.). (2013). *Produktionsarbeit der Zukunft – Industrie 4.0*. Stuttgart: Fraunhofer-Verlag.

Stoyanov, S., & Kirschner, P. (2004). Expert concept mapping method for defining the characteristics of adaptive E-learning: ALFANET project case. *Educational Technology, Research & Developement, 52*(2), 41–56.

Trivers, R. L. (1971). The evolution of reciprocal altruism. *The Quarterly Review of Biology, 46*(1), 35–57.

Uhlemann, T. H.-J., Lehmann, C., & Steinhilper, R. (2017). The digital twin: Realizing the cyber-physical production system for industry 4.0. *Procedia CIRP, 61*, 335–340.

Wagner, T., Herrmann, C., & Thiede, S. (2017). *Industry 4.0 impacts on lean production systems*. In Procedia CIRP 63, 50th CIRP conference on, Taichung City, Taiwan, pp. 125–131.

Zangwill, W. I., & Kantor, P. B. (1998). Toward a theory of continuous improvement and the learning curve. *Management Science, 44*(7), 910–920.

Zühlke, D. (2008). *SmartFactory – A Vision becomes Reality*. In: Proceedings of the 17th World Congress IFAC'08, pp. 14101–14108.

Index

P. Isaias et al. (eds.), *Online Teaching and Learning in Higher Education*, Cognition and Exploratory Learning in the Digital Age,
https://doi.org/10.1007/978-3-030-48190-2