Dirk Ifenthaler · Dana-Kristin Mah
Jane Yin-Kim Yau *Editors*

Utilizing Learning Analytics to Support Study Success

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Preface

Advances in educational technology have enabled opportunities to provide insight into how learners engage within the learning environment provided. The resulting availability of vast amounts of educational data can represent how students interact with higher education resources, and further analysis may provide useful insights into learning behaviour, processes, and outcomes. From a holistic point of view, learning analytics use static and dynamic educational information from digital learning environments, administrative systems, and social platforms for real-time modelling, prediction, and optimization of learning processes, learning environments, and educational decision-making. Accordingly, learning analytics are expected to provide benefits for all stakeholders (e.g. students, teachers, designers, administrators) in the higher education arena.

In particular, students may benefit from learning analytics through personalized and adaptive support of their learning journey. For example, students often enter higher education academically unprepared and with unrealistic perceptions and expectations of academic competencies for their studies. Both the inability to cope with academic requirements and unrealistic perceptions and expectations of university life, in particular with regard to academic competencies, are important factors for leaving the institution prior to degree completion.

Still, research in learning analytics and how they support students at higher education institutions is scarce. Therefore, this edited volume *Utilizing Learning Analytics to Support Study Success* aims to provide insights into how educational data and digital technologies contribute towards successful learning and teaching scenarios. We organized the chapters included in this edited volume into three major parts: (I) *Theoretical and Technological Perspectives Linking Learning Analytics and Study Success,* (II) *Issues and Challenges for Implementing Learning Analytics,* and (III) *Learning Analytics Case Studies – Practices and Evidence,* and closing with an *Epilogue.*

In Part I, the first chapter, the authors discuss how learning theories and learning analytics are important components of educational research and concludes by proposing an iterative loop for educational research employing learning analytics in which learning theories guide data collection and analyses (*Jacqueline Wong,* *Martine Baars, Björn B. de Koning, Tim van der Zee, Dan Davis, Mohammad Khalil, Geert-Jan Houben, Fred Paas*, Chap. 1). The next chapter presents a critical reflection on empirical evidence linking study success and learning analytics. Findings are reported and discussed focussing on positive evidence on the use of learning analytics to support study success, insufficient evidence on the use of learning analytics, and link between learning analytics and intervention measures to facilitate study success (*Dirk Ifenthaler, Dana-Kristin Mah, Jane Yin-Kim Yau,* Chap. 2). The next chapter describes how the Study Support Centre (SSC) at Aalen UAS assists first-year students of all faculties and, in particular, improves their mathematical skills (*Miriam Hommel, Armin Egetenmeier, Ulrike Maier,* Chap. 3). The following chapter shows how a prompting application has been implemented into an existing university environment by adding a plug-in to the local digital learning platform which injects user-centric prompts to specific objects within their digital learning environment. The solution is used to perform various educational research studies, focussing on effects of prompting for self-regulated learning (*Daniel Klasen, Dirk Ifenthaler,* Chap. 4). The final chapter of the first part explores cognitive and motivational differences between students who drop out and students who persist. From their findings, the authors consider the monitoring and analysing of error streaks as a promising way for the design of adaptive instructional interventions in courses where the students have to programme code (*Anja Hawlitschek, Till Krenz, Sebastian Zug*, Chap. 5).

In Part II, the first chapter focusses on a practical tool that can be used to identify risks and challenges that arise when implementing learning analytics initiatives and discuss how to approach these to find acceptable solutions (*Philipp Leitner, Markus Ebner, Martin Ebner*, Chap. 6). Next, the LAPS project is introduced, which is able to analyse progressions of former students and to make statements on possible risks for currently enrolled students by using machine learning techniques. The chapter provides insights into how the project is technically developed and how it can be used in consultation situations (*Mathias Hinkelmann, Tobias Jordine*, Chap. 7). The argument that precourse data could be valuable resources for learning analytics is explored in the following chapter. The authors discuss the difficulties of collecting data from open web-based learning environments, from missing data to interactions between cognitive and meta-cognitive variables (*Katja Derr, Reinhold Hübl, Mohammed Zaki Ahmed*, Chap. 8). The next chapter addresses issues and challenges for implementing writing analytics in higher education through theoretical considerations that emerge from the literature review and an example application (*Duygu Bektik*, Chap. 9). Then, a collaborative research project is presented which explores the short-term and long-term effects, risks, and benefits of the use of mobile learning analytics in students' daily life (*Luisa Seiler, Matthias Kuhnel, Dirk Ifenthaler, Andrea Honal*, Chap. 10). The following chapter reviews three categories of algorithms in light of their application to assessment and student success. The authors discuss an implementation of these algorithms through a new set of digital tools, designed to support a community of practice in problem-based instruction (*Philippe J. Giabbanelli*, Andre*w A. Tawfik, Vishrant K. Gupta*, Chap. 11). In the final chapter of the second part, the researchers studied archival data from online undergraduate course registrants through mining a dataset to determine trends and patterns of student success, as determined by the final grade earned in the online courses (*Ellina Chernobilsky, Susan Hayes*, Chap. 12).

In Part III, the authors of the first chapter present a teacher-friendly “learning analytics lifecycle” that seeks to address challenges and critically assess the adoption and impact of a unique solution in the form of an learning analytics platform that is designed to be adaptable by teachers to diverse contexts (*Natasha Arthars, Mollie Dollinger, Lorenzo Vigentini, Danny Y.-T. Liu, Elsuida Kondo, Deborah M. King*, Chap. 13). Next, the presented study identifies key predictors of persistence and achievement amongst students enrolled in an online English language course. The study is framed in Deci and Ryan’s self-determination theory (SDT) and uses data from a precourse student readiness survey, LMS log files, and a course Facebook page (*Danny Glick, Anat Cohen, Eitan Festinger, Di Xu, Qiujie Li, Mark Warschauer*, Chap. 14). The following chapter presents a study which investigates how participants in a massive open online course (MOOC) designed for working professionals interacted with various key course components of the MOOC and the usage patterns connected to participants’ profiles and perceptions (*Min Liu, Wenting Zou, ChengLu Li, Yi Shi, Zilong Pan, Xin Pan*, Chap. 15). The final chapter of this part reports a case study focussing on a capstone unit in business at a university in Western Australia. Instructors used learning analytics of average weekly eTest scores, overall average eTest scores, a benchmark assessment score, and study mode extracted from learning management system (LMS) reports to target areas where assessment integrity could be improved (*Michael Baird, Lesley Sefcik, Steve Steyn*, Chap. 16).

The edited volume closes with an *Epilogue* reflecting on the contributions of this edited volume and identifying future research and directions in learning analytics to enhance study success (*Dana-Kristin Mah, Jane Yin-Kim Yau*, *Dirk Ifenthaler,* Chap. 17).

Without the assistance of experts in the field of learning analytics, the editors would have been unable to prepare this volume for publication. We wish to thank our board of reviewers for their tremendous help with both reviewing the chapters and linguistic editing.

Mannheim, BW, Germany

Dirk Ifenthaler
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Dirk Ifenthaler is Professor and Chair of Learning, Design, and Technology at the University of Mannheim, Germany; Adjunct Professor at Deakin University, Australia; and UNESCO Deputy-Chair of Data Science in Higher Education Learning and Teaching at Curtin University, Australia. His previous roles include Professor and Director at Centre for Research in Digital Learning at Deakin University, Australia; Manager of Applied Research and Learning Analytics at Open Universities Australia, Australia; and Professor of Applied Teaching and Learning Research at the University of Potsdam, Germany. He was a 2012 Fulbright Scholar-in-Residence at the Jeannine Rainbolt College of Education at the University of Oklahoma, USA. Professor Ifenthaler's research focusses on the intersection of cognitive psychology, educational technology, learning science, data analytics, and organizational learning. He developed automated and computer-based methodologies for the assessment, analysis, and feedback of graphical and natural language representations as well as simulation and game environments for teacher education. 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. Professor Ifenthaler is the Editor-in-Chief of the Springer journal *Technology, Knowledge and Learning* (www.springer.com/10758). Dirk is the past president for the AECT (Association for Educational Communications and Technology) Design and Development Division; past chair for the AERA (American Educational Research Association) Special Interest Group Technology, Instruction, Cognition and Learning; and co-programme chair for the international conference series on Cognition and Exploratory Learning in the Digital Age (CELDA).

Dana-Kristin Mah is a researcher and consultant in the field of educational technologies and higher education. In her doctoral thesis, she concentrated on students' first-year experience in higher education with a focus on academic competencies and the potential of learning analytics and digital badges to enhance first-year student retention. She is co-editor of the edited volume *Foundations of Digital Badges and Micro-credentials: Demonstrating and Recognizing Knowledge and*

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Jane Yin-Kim Yau is a researcher in Learning Analytics and Mobile Learning at the Chair for Learning, Design and Technology in the Business School at the University of Mannheim, Germany. She is working on the BMBF-funded project "Utilising learning analytics for study success" from 2017 to 2018. She completed a PhD in computer science (mobile learning) at the University of Warwick, UK, in 2010. Her doctoral thesis was entitled "A mobile context-aware learning schedule framework with Java learning objects". She has research expertise in context awareness, personalization, and user profiling. She was awarded a postdoctoral research fellowship at the Centre for Learning and Knowledge Technologies at Linnaeus University (CeLeKT), Sweden, where she collaborated with multidisciplinary research teams in the various projects undertaken by the group. Thereafter, she was a postdoc at the School of Technology, Malmö University, Sweden, and was a co-applicant in two large successful research applications: Practice-based Experimental Learning Analytics Research Support project, PELARS (EU FP7, 2014–2017) and the Internet of Things and People Research Centre at Malmö University. She was also a visiting researcher at the German Institute for International Educational Research (DIPF) in 2016 in Frankfurt Am Main, Germany. She is a reviewer in the *IEEE Transactions in Learning Technologies*, *Educational Technology & Society*, *International Journal of Mobile and Blended Learning*, and *International Journal on Mobile Learning and Organisation*, amongst others. To date, she has published around 40 peer-reviewed articles including 16 journal articles.

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Duygu Bektik is a mixed methods researcher and currently works at the Institute of Educational Technology, Learning and Teaching Innovation's academic professional development team as a lecturer. Her research interests currently lie primarily in the fields of learning analytics, particularly writing analytics, e-assessment and automated feedback, artificial intelligence in education (AIED), successful integration of ICT into the teaching and learning process, and achieving gender equity in academia and empowering women in academia/STEM. She has worked on several European and UK research projects as a researcher with several partners.

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Vishrant K. Gupta is a graduate student supervised by Dr. Giabbanelli. His thesis focusses on the comparison of student and expert maps. His work on visualizing and recommending alignments between maps is due to appear in the proceedings of the Human Computer Interaction (HCI) conference. One of his key contributions is the ongoing development of the ITACM software, which combines technologies (e.g. Java, D3, Spring, MySQL, Neo4J) to offer a user-centric environment supporting a community of practice in assessing ill-structured problems.

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Danny Y.-T. Liu is a molecular biologist by training, programmer by night, researcher and academic developer by day, and educator at heart. A multiple national teaching award winner, he works at the confluence of learning analytics, student engagement, educational technology, and professional development and leadership to enhance the student experience.

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Part I
Theoretical and Technological Perspectives Linking Learning Analytics and Study Success

Chapter 1
Educational Theories and Learning Analytics: From Data to Knowledge

The Whole Is Greater Than the Sum of Its Parts

Jacqueline Wong, Martine Baars, Björn B. de Koning, Tim van der Zee, Dan Davis, Mohammad Khalil, Geert-Jan Houben, and Fred Paas

1 Introduction

> Without theories, people could view research findings as disorganized collections of data, because researchers and practitioners would have no overarching frameworks to which the data could be linked.
>
> Schunk (2012, p. 10)

At all levels of education, the widespread use of new technologies such as interactive learning environments, learning management systems (LMS), intelligent tutoring systems (ITS), and online learning provides access to large amounts of student data (e.g. user interaction with online course content; Gašević, Dawson, & Siemens, 2015). Despite being a rich source of information, student data automatically collected in online learning environments is typically not transformed into useful information for teaching and learning (Greller & Drachsler, 2012) and is used poorly across the educational domain (Dawson, Gašević, Siemens, & Joksimovic, 2014). In starting to transform large amounts of student data into useful information for

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learning, educational researchers recently have taken an interest in learning analytics approaches (Knight & Buckingham Shum, 2017).

Although learning analytics is an evolving discipline, it draws on research, methods, and techniques from multiple established disciplines such as data mining, information visualization, psychology, and educational sciences (Gašević et al., 2015). Learning analytics is commonly defined as "the measurement, collection, analysis, and reporting of data about the learners and their contexts for the purposes of understanding and optimizing learning and the environment in which it occurs" (Siemens & Long, 2011, p. 34). Trace data, also known as audit trails, log files, and event traces, are captured in online environments as students study the learning materials (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). By utilizing learning analytics to examine the trace data, patterns related to learning processes can be identified to deepen our understanding of how students learn and add to the development of learning theories. In turn, this will help guide the design of instructional materials to support and enhance learning.

Given that understanding learning is a highly complex issue (Phillips, 2014), many learning theories have been developed over the last century based on different views of what learning is (Murphy & Knight, 2016). Learning theories are important not only because they can help to explain the phenomenon of learning but also because design principles for learning environments, materials, and tasks can be derived from the theories (Ertmer & Newby, 1993). Moreover, learning theories can help to convert information from learning analytics into actionable knowledge for instructional and learning design.

Importantly, as expressed by Ifenthaler (2017), a synergistic relationship between instructional design and learning analytics exists. On one hand, instructional designers can better evaluate the learning environment, materials, and tasks by processing data about the learners and their complex interactions within the learning environment using learning analytics approaches. On the other hand, learning analytics require theories and principles on instructional design to guide the transformation of the information obtained from the data into useful knowledge for instructional design. Consistent with Ifenthaler's (2017) view, this chapter emphasizes the importance of taking learning theories into account when employing learning analytics in studies to support study success.

The aim of this chapter is to discuss how learning theories and learning analytics could be integrated in educational research since the whole is greater than the sum of its parts. We will first discuss the definition of learning and the role of learning theories. Then, a qualitative analysis of studies employing learning analytics to examine the current role of learning theories in research using learning analytics will be presented. Section 4 discusses the studies reviewed and proposes an iterative educational research loop to integrate both educational theories and learning analytics.

2 Understanding Learning

Building strong connections with the learning sciences was listed as one of the future directions of learning analytics by Ferguson (2012). The author reasoned that a good understanding of how learning occurs, how learning can be supported, and how student characteristics influence learning are needed if the goal of learning analytics is to understand and optimize learning. To understand the "how" of learning, one has to first define what learning is. Alexander, Schallert, and Reynolds (2009) proposed that learning can be defined as "a multidimensional process that results in a relatively enduring change in a person or persons, and consequently how that person or persons will perceive the world and reciprocally respond to its affordances physically, psychologically, and socially. The process of learning has as its foundation the systemic, dynamic, and interactive relation between the nature of the learner and the object of the learning as ecologically situated in a given time and place as well as over time" (p. 186). This definition encapsulates the many perspectives of learning that were derived from the evolution of learning theories.

2.1 Evolution of Learning Theories

Based on a recent review of papers published in *Review of Educational Research* (RER) journal over the last century, Murphy and Knight (2016) found that learning sciences have been guided by three predominant theoretical lenses: behavioural, cognitive, and contextual. The authors used the word "lenses" to analogously refer to the theories that researchers use. Just like how a certain lens may be more suitable for taking pictures in one situation than another, one learning theory may be more suitable for understanding learning in one environment than another. At the beginning of the twentieth century, learning was viewed as a change in behaviour (for an overview of learning theories, see Ormrod, 1999). Using the behavioural lens (e.g. Skinner, 1977), researchers focused on the responses of individuals to the environment and the ways to condition the desired responses. Several theories, such as classical conditioning and drive reduction theory, emerged from the behavioural viewpoint. In the middle of the twentieth century, the cognitive lens (e.g. Ausubel, 1969) was used, viewing learning as a change in the mind of an individual. The focus was on understanding the mental processes that influence the processing and storing of information in the mind. Multiple theories, such as information processing theory and cognitive constructivism, developed under the cognitive lens. Although behavioural and cognitive lenses explained changes in one's behaviour and mind, researchers were missing theories to explain social factors that influence learning that occurred in groups. The contextual lens arose to fill this gap. Under the contextual lens (e.g. Vygotsky, 1978), learning was viewed as contextually bound and a result of social interactions. Theories that developed from the contextual lens included social constructivism and social learning theory.

Murphy and Knight (2016) concluded that the shift in theoretical lens occurs when findings from new studies cannot be explained by the existing lens.

However, a shift in theoretical lens does not invalidate the prior lens. Instead, each theoretical lens offers researchers the filter to focus on different areas of learning. More importantly, multiple theories can coexist and be simultaneously used to guide instructional practice. Therefore, it is at the discretion of learning scientists and learning analysts to recognize these nuanced perspectives of learning provided by the different lenses and apply learning theories based on the learning materials, learning conditions, learning tasks, and learner characteristics.

3 Role of Educational Theories in Learning Analytics

Given that learning theories evolved to accommodate new findings from studies, one might question if there is a need for learning theories. There is no doubt that a learning theory has to be built upon collective findings from studies (Alexander, 2006). Yet, without a theory to begin with, researchers will not know what to look out for. This conundrum of not knowing what to look for is magnified in research utilizing learning analytics since studies conducted in online learning environments usually involve the collection of immense amounts of data. Therefore, a good theory is needed to guide researchers (Alexander, 2006). Using the theoretical lens of a learning theory, researchers will be better positioned to formulate their research questions, make hypotheses about what learning outcome to expect, make decisions on the research methods, and finally, make interpretations of the results derived from learning analytics approaches (Murphy & Knight, 2016).

Since one of the aims of learning analytics is to advance educational research and practice, it is of interest to take a look at how well learning theories are being referred to or investigated in studies employing learning analytics to support study success. Na and Tasir (2017) found mixed effects of the use of learning analytics interventions to support students' success. However, it is not clear whether the learning analytics interventions in the studies reviewed were based on specific learning theories or whether any learning theories were mentioned in the studies. Gaining insight into this is important to aid our understanding of how learning analytics can affect study success. Therefore, the current study extends the Na and Tasir study by investigating whether studies employing learning analytics to support study success take into account learning theories and, if so, to what extent the learning theories are guiding the studies. The main research question addressed in our review is as follows:

Which learning theories have been used in the studies examining learning analytics approaches to support study success?

3.1 Research Methodology

The review methodology consisted of four sequential steps qualifying it as a systematic qualitative review: (a) literature search based on keywords to identify relevant papers, (b) assessment of search results to select a set of primary studies, (c) categorising and integration of the results, and (d) reporting the findings (Gikandi, Morrow, & Davis, 2011).

The aim of the first step was to identify published papers examining study success using learning analytics. Given that learning analytics has been applied to examine success in different domains and at various levels of education, broad search terms (i.e. study success, student success, and achievement) were used to capture all forms of success and achievement related to study and student. The search string "learning analytics" AND ("stud* success" OR "achievement") was used to search for papers indexed in the databases of Scopus (http://www.scopus.com) and Web of Science (http://www.webofknowledge.com/wos) in December 2017. These two databases were chosen because of their multidisciplinary indexing of articles across journals and conferences. We only included papers published in journals and conferences over the last 7 years starting from 2011 when the first learning analytics and knowledge conference proceeding was published. After removing duplicates, 164 papers that were published in 46 journals and 33 conference proceedings remained.

The second step was to select a set of primary studies. Given the aim of the study was to qualitatively review the role of learning theories in studies employing learning analytics, impact factors were used to identify papers that were published in top five journals and conferences. We ranked the scientific influence of the 46 journals based on impact factors obtained from Scimago Journal and Country Rank (SJR; SCImago, 2007) and Journal Citation Reports (JCR). The two impact factors were taken into account as SJR is built on Scopus database, while JCR is built on Web of Science database. We ranked the conferences using H-index obtained from Google Scholar Metrics since conferences were not ranked by SJR or JCR. Table 1.1 shows

Table 1.1 Number of papers selected based on five highest-ranked journals according to the journal titles in alphabetical order

Publications	Number of papers	SJR	JCR
Journal titles			
Computers & Education	6	2.61	3.82
International Journal of Computer-Supported Collaborative Learning	6	1.47	3.47
Computers in Human Behaviour	1	1.60	3.44
Internet and Higher Education	4	2.83	4.24
Journal of Computer Assisted Learning	1	1.65	1.25
Soft Computing	1	.75	2.47
Conference titles		*H-index*	
Americas Conference on Information Systems (AMCIS)	1	22	
ACM Conference on International Computing Education Research (ICER)	2	19	
Conference on User Modeling, Adaptation and Personalization (UMAP)	1	21	
IEEE Global Engineering Education Conference (EDUCON)	2	19	
International Learning Analytics and Knowledge Conference (LAK)	2	32	

the distribution of papers published across the top five journals and conferences according to the SJR, JCR, and H-index. This selection process resulted in a set of 27 papers published in 6 journals and 5 conferences.

The 27 papers went through a second selection process based on the study type (i.e. experimental, correlational, student survey only, and conceptual/review). We selected only empirical papers (i.e. experimental and correlational studies) for the review, specifically papers that used learning analytics approaches to analyse trace data obtained from the online learning environments. This allowed us to examine whether the studies referred to learning theories when employing learning analytics approaches to analyse the trace data. We refer to the definition of learning analytics as "the measurement, collection, analysis, and reporting of data about the learners and their contexts for the purposes of understanding and optimizing learning and the environment in which it occurs" (Siemens & Long, 2011, p. 34). Therefore, we selected studies that collected data about the learner in online learning environment. During this selection process, papers that used student surveys only (Atif, Bilgin, & Richards, 2015; Tan, Yang, Koh, & Jonathan, 2016; Zhuhadar, Yang, & Lytras, 2013), reviews (Tlili, Essalmi, Jemni, & Chen, 2016), and conceptual papers (Kim & Moon, 2017; Wise & Schwarz, 2017; Yassine, Kadry, & Sicilia, 2016) were removed. This resulted in a final set of 20 empirical papers involving the analysis of trace data using learning analytics approaches.

In the third step, the 20 papers were read in detail and categorised according to the learning theories mentioned in the papers. Information on the studied learning environment, the learning analytics techniques/application applied, and the types of data collected were extracted from each paper. Finally, the findings of the papers were integrated and qualitatively reviewed based on the learning theories mentioned in the papers to answer the research question.

3.2 Results and Discussion

Among the set of 20 papers, there were only two (quasi)experimental papers (i.e. Rowe et al., 2017; Tabuenca, Kalz, Drachsler, & Specht, 2015) comparing different treatment conditions. Tabuenca et al. (2015) compared the effects of delivering notifications between a fixed and a random schedule to support self-regulated learning, while Rowe et al. (2017) compared the use of in-game measures of implicit science knowledge either as a bridge or as a supplement to teaching activities to enhance learning. The rest of the 18 papers were correlational studies.

3.2.1 Learning Theories and Learning Analytics Applications

After categorising the papers, 16 studies were found to mention theories related to learning, while the other four studies did not. Table 1.2 shows a summary of the learning theories mentioned in the 16 studies, the learning environments in which the studies were deployed, the learning analytics approaches used, and the types of data that were collected. Most studies tended to be situated within self-regulated learning ($n = 6$), followed by motivation ($n = 2$), and social constructivism ($n = 2$). Another six individual studies used other concepts related to learning (i.e. learner effort, feedback, deep learning, engagement, implicit knowledge, and a combination of concepts).

Self-Regulated Learning

Self-regulated learning (SRL) was the most employed theory related to learning in the selected studies. Models of SRL characterize self-regulated learners as students who actively use and adjust their learning strategies to achieve their learning goals (Bos & Brand-Gruwel, 2016; Kizilcec et al., 2017). There were six studies (i.e. Bos & Brand-Gruwel, 2016; Jovanović et al., 2017; Kizilcec et al., 2017; Siadaty et al., 2016; Tabuenca et al., 2015; You, 2016) which examined the use of learning analytics albeit in different learning environments (e.g. MOOCs and LMS). You (2016) used hierarchical regression analyses to identify events from data generated in learning management systems (LMS) to predict course achievement in e-learning courses. The results showed that students who accessed the content videos within the instructor-scheduled time and watched the full length of the video were the strongest predictor of course achievement, followed by the number of late submissions, the number of course logins, and whether the course information was downloaded.

Instead of predictive modelling, Jovanović et al. (2017) employed an exploratory learning sequence analysis to compare learning sequences of high performers and low performers in a flipped classroom. Low performers mostly focused on summative assessments that counted towards their final course scores, while high performers engaged with all the activities (i.e. formative assessment, summative assessments, reading materials, and videos) evenly. Using agglomerative hierarchical clustering based on Ward's method, the authors identified five student profiles (i.e. intensive, highly strategic, strategic, selective, and highly selective) based on the activities that students chose to engage in (e.g. focus on summative assessment or focus on course video). While the learning analytics approach helped to detect and describe differences in students' learning behaviour, it could not provide reasons as to why students' behaviour differed.

To be able to explain differences in students' behaviours, Kizilcec et al. (2017) correlated student behavioural data with student self-reports about their learning approach. The authors examined the relationship between SRL survey data, student interactions with course contents in MOOC, and personal goal attainment. The results showed that students' self-reported level of SRL was related to their intentions in completing the course. Students who scored higher on goal setting and strategic planning were more likely to attain their goals, while students who reported more help-seeking were less likely to attain their goals. In general, students with higher self-reported use of SRL strategies spent more time revisiting assessments.

Table 1.2 Learning theories identified from the selected papers

Learning theories used	Authors	Learning environment	LA technique/ application	Trace data collected	Performance-related measures
Self-regulated learning (SRL)	Bos and Brand-Gruwel (2016)	LMS, blended course	– Clustering – Multiple regression analysis	Time spent viewing recorded lectures, number of formative assessment completed and score on the formative assessment, time spent using the LMS, and number of clicks in the LMS (e.g. announcements, video files, viewing grades)	Mid-course and final course assessment, self-reported inventory of learning styles (ILS)
	Jovanović, Gašević, Dawson, Pardo, and Mirriahi (2017)	Flipped course with learner dashboard	– Learning sequence analysis – Clustering	Number of correctly and incorrectly solved summative and formative assessment items, number of solutions requested, number of videos played, number of access to content, dashboard, and schedule	Midterm and final exam scores
	Kizilcec, Pérez-Sanagustín, and Maldonado (2017)	MOOCs	– Logistic regression models – Transition graphs	Number of transitions from one interaction state type (e.g. begin a video to complete a video) and time spent on each type of learning material, number of learning materials interacted	Course goals (i.e. earning a course certificate, complete all assessments, and complete all lectures), self-reported self-regulation of learning
	Siadaty, Gašević, and Hatala (2016)	Learn-B environment	– Trace-based methodology	Number of actions performed by students in the learning environment (e.g. clicking on different competencies, choose an available learning path, rate a learning path)	Perceived usefulness of the features provided in the learning environment
	Tabuenca et al. (2015)	Online course with support from mobile application	– SQL queries to examine the distribution of study time	Students log their study time on the mobile application which in turn visualizes the summary of their recording that shows the time spent per assignment	Course grades, self-reported self-regulation of learning

	You (2016)	LMS, e-learning	– Hierarchical regression	Time spent viewing the instructional videos, number of course logins, number of late submission, students' reply to instructor's post, fulfilment of attendance, number of posting in the discussion board	Midterm and final exam scores
Motivation (achievement goal)	Lonn, Aguilar, and Teasley (2015)	Summer bridge programme	– Multiple linear regression	An early warning system that assigned students one of the three statuses (i.e. encourage, explore, engage) based on the points students earned on their coursework, difference between the course average, and number of logins	Course grades, pre- and post-measures of self-reported achievement goals (i.e. mastery and performance approach and performance-avoidance orientation)
Motivation (mastery, value beliefs, individual interest, and situational interest)	Barba, Kennedy, and Ainley (2016)	MOOC	– Structural equation modelling	Number of clicks on videos and number of quiz attempts	Final grade
Socio-constructivism (interaction types: student-content, student-instructor, student-student)	Joksimović, Gašević, Loughin, Kovanović, and Hatala (2015)	LMS	– Hierarchical linear mixed models using restricted maximum likelihood (REML) estimate	Number of time spent on four types of interaction (i.e. student-student, student-content, student-teacher, student-system)	Final course grades
Social learning theory	Carter and Hundhausen (2016)	Social programming environment	– Chi-squared test	Number of interaction types (i.e. post, reply, receive a suggestion), topic of post, progress in the course	Average grade for programming assignment and final course grade
Learner effort (distributed practice)	Zhao et al. (2017)	MOOC	– k-means clustering	Time spent watching videos and quiz score	Eligibility to earn a course certificate

(continued)

Table 1.2 (continued)

Learning theories used	Authors	Learning environment	LA technique/ application	Trace data collected	Performance-related measures
Feedback (process-oriented)	Sedrakyan, Snoeck, and de Weerdt (2014)	Conceptual modelling environment (JMermaid)	– Process model discovery and dotted chart analysis	Event log of students' group work during the modelling process (i.e. create, edit, delete, redo, and copy)	Scores on the group project's final solution
Deep learning	Romero-Zaldivar, Pardo, Burgos, and Kloos (2012)	Virtual appliance	– Multiple regression – Prediction	Time spent in the learning environment, number of times an action was performed (i.e. write a command, open a webpage, open a file with an editor, and use the C compiler, memory profiler, and C debugger), time spent performing each action	Final grades
Engagement	Junco and Clem (2015)	Digital textbooks	– Hierarchical linear regression	Number of reading days, number of reading sessions, time spent reading, number of pages read, number of highlights, number of bookmarks, number of notes	Final course grades
Implicit knowledge	Rowe et al. (2017)	Computer game	– Approach map for network clustering	Implicit knowledge measured by in-game behaviour involving specific strategic moves	Pre-/post-assessment improvement
Combination of concepts (active participation, engagement, consistent effort and awareness, interaction)	Kim, Park, Yoon, and Jo (2016)	LMS in blended course	– Random forest technique to create a prediction model	Time spent on LMS, number of LMS visits, number of discussion board visits, number of posts, post length, interval between LMS visits, interval between discussion board visits, number of replies received by a student, number of replies generated by a student	Final course grades

Based on the results, the authors suggested MOOC instructors to guide students in goal setting and strategic planning activities.

Instead of analysing temporal learning sequences, Bos and Brand-Gruwel (2016) chose a more direct method of counting the number of times an activity was done and the time spent on the activities in the learning environment. Similar to Kizilcec et al.'s (2017) study, Bos and Brand-Gruwel (2016) combined SRL survey data with data generated in a LMS platform. In the study, students were first clustered based on their scores on the administered SRL surveys. The analysis resulted in three clusters: (1) students who reported lack of regulation when external regulation is absent, (2) students who reported use of self-regulation strategies when external regulation is absent, and (3) students without a clear regulation strategy. The results showed that although students in the three clusters used the online resources to a similar extent (e.g. number of videos watched), they benefited differently from the use of the same resources. Frequencies of login and time spent in the LMS alone were found to be poor predictors of students' performance. This is not surprising given that the duration measured may not be the actual time students spent processing information on the page in an online environment.

Two studies were found to examine interventions that support SRL. Siadaty et al. (2016) examined the relationship between students' perceived usefulness of the interventions and actual use of SRL interventions. Seven SRL scaffolds were embedded in a technologically enhanced learning environment: (1) usage information, (2) social context of the workplace, (3) progress towards goal attainment, (4) peer-recommended learning goal, (5) system-recommended competencies, (6) system-recommended learning path, and (7) learning resources students own or have shared with the organization. The authors predefined activities in the online environment to measure SRL processes. For example, rating a learning path in the online environment is a measurement of self-evaluation as a SRL process. The analysis of students' activities in the online environment showed that (1) frequencies of planning activities were related to looking at usage information, social context of workplace, and system-recommended competencies and learning path, (2) frequencies related to performance phase were related to information about social context of the workplace and learning resources they own or have shared with the organization, and (3) frequencies related to reflection phase were related to competences of goals. The findings suggested that providing information on social context of the workplace had the highest impact on processes of SRL. The authors concluded that recommender system technology should be integrated in modern workplace environments to support SRL. Although this study showed that recommender system technology enhances SRL on the whole, it is not clear which factors in particular (e.g. system-recommended competencies or system-recommended learning path) influenced SRL. Moreover, a recommender system might increase students' reliance on the recommendations instead of their own regulation of learning.

In another experimental intervention study by Tabuenca et al. (2015), a within-subjects design was used to examine the effect of a mobile tool for tracking and monitoring study time on SRL. At different time points in the study, students received notifications containing tips for time management that were either generic or based on learning analytics at random time or on a fixed schedule. Students reported an increase in perceptions of time management and planning skills after the notification intervention. Students specifically preferred notifications sent early in the day with learning analytics information about their personal time management and behaviour. Activities in the time logs showed that students were more active at certain time periods and on certain days, and there were more records of study time whenever notifications were sent. However, students who had more time logs did not score higher in the final exam than students who had less time logs.

The six discussed studies exemplify the complexity of examining SRL in an online environment. SRL processes consist of a broad range of learning strategies such as time management, goal setting, and planning. The studies used different learning analytics approaches to examine the trace data. Trace data can be examined by aggregating an action in terms of frequencies and time spent on the online materials (e.g. Bos & Brand-Gruwel, 2016), action in context such as submitting an assignment on time (e.g. You, 2016), transitions of activities (e.g. Kizilcec et al., 2017), and learning sequences (e.g. Jovanović et al., 2017). The learning analytics approaches provide insights into what students do in the online environment that might relate to SRL. However, trace data alone are insufficient to explain students' behaviour. Among the selected studies, four studies attempted to shed more light on this by relating trace data to self-report data. The combination of trace data and self-reports enables a deeper understanding on the relationship between SRL and students' behaviour. For example, students who reported higher levels of SRL also spent more time revisiting assessments (Kizilcec et al., 2017). It should be noted that these studies involved primarily correlational analyses, so causality cannot be inferred from these studies. Therefore, there is a need for more experimental studies such as the Tabuenca et al.'s (2015) study. Together, the selected studies suggest that SRL is a promising area in which learning theories and learning analytics converge. The fact that SRL turned out to be the most investigated learning theory in learning analytics research is understandable given that SRL has been shown to be crucial to academic success in online learning environments (Broadbent & Poon, 2015).

Motivation

Two studies (i.e. Barba et al., 2016; Lonn et al., 2015) examined motivation, each with a different theoretical approach. Barba et al. (2016) examined the impact of general motivation (i.e. individual interest, mastery approach, utility value beliefs) and state-level motivation (i.e. situational interest). Motivation in this study was defined as systems of beliefs that can be activated by contextual and personal factors. Using structural equation modelling, they investigated the relationship between motivation, participation, and study success in MOOCs. The different types of motivation were measured by surveys, whereas participation in MOOC activities was measured by the number of videos viewed and the number of quizzes attempted. The results showed that students who reported a mastery approach towards learning attempted more quizzes. Students' report of higher situational interest was related to larger number of videos watched. The strongest predictor of final grades in the MOOCs was the number of quizzes attempted followed by situational interest. These results suggest that it is important for MOOC designers to focus on supporting situational interest.

The study by Lonn et al. (2015) focused on achievement goal theory to measure the effects of a learning analytics intervention in a summer bridge programme. Achievement goal theory was used to conceptualize students' two types of motivation orientation: mastery goals focus on the development of personal competencies, while performance goals focus on showing competence compared to others. The intervention in Lonn et al.'s (2015) study consisted of an early alert system that tracked students' progress to identify whether they were at risk. Student advisors in the course could then look at the information provided by the early alert system and act accordingly. Results of the study showed that the mastery approach decreased over time, suggesting that the learning analytics intervention is negatively correlated to mastery approach. Therefore, the study suggested that this learning analytics intervention should be implemented with caution as it may have a negative influence on student motivation.

Both discussed studies used surveys to measure motivation instead of predefining student activities in the log data as proxies of motivation (as was, e.g. done in the SRL study by Siadaty et al., 2016). This could be due to the fact that motivation is a cognitive process related to goal-directed behaviour (Schunk, 2012). The two studies exemplify the important relationship between learning theories and learning analytics. Barba et al. (2016) linked student motivation to participation, providing insights to how motivation can be manifested in learning behaviours. This suggests that learning analytics can help to quantify learning behaviours to deepen our understanding of motivation—what behaviours are related to motivation. Lonn et al.'s (2015) study showed that learning analytics interventions can affect motivation. This suggests that learning theories can help guide the implementation of learning analytics interventions—how can motivation be supported to enhance study success.

Social Constructivism

Two studies (i.e. Carter & Hundhausen, 2016; Joksimović et al., 2015) were categorised under the theoretical framework of social constructivism. As discussed in Sect. 2, social constructivism can be viewed from a contextual lens. Under this view, learning does not occur only within the learner but is contextualized and dependent on the environment. These studies examined the interactions in online learning environments and related the interactions to theory of social constructivism. Carter and Hundhausen (2016) examined peer interactions using trace data generated in a programming environment where students could pose and answer questions. The results showed that students who asked a question, received a suggestion, and acknowledge the suggestion were more likely to make progress in the course and achieve better final grades.

Joksimović et al. (2015) not only examined student-student interaction but also interaction between student and instructor, student and content, and student and system in an online course. The analytical approach involved identifying the interactions, classifying them into interaction types, calculating the frequency and time spent on each interaction type, and statistically analysing the relationship between interaction types and final grades. The results showed that student-system interactions were positively related to final grades, while student-content interactions were negatively related to final grades. Also, student-instructor interactions were negatively correlated to final grades in core courses only. Based on these results, the authors suggested that the different courses (i.e. core, elective, and foundational courses) require different forms of interactions to support the learning process.

The discussed studies demonstrate that using learning analytics enables researchers to examine the effect of actual interactions instead of relying on only perceived interactions. The results from the two studies showed that interactions such as student-student interactions (Carter & Hundhausen, 2016) or student-system interactions (Joksimović et al., 2015) can differentially affect grades. Future studies can build on these two studies to further compare different properties of interactions (e.g. asynchronous, synchronous, virtual, augmented). In addition, learning analytics can also be used to help students monitor their interactions. To conclude, there is a reciprocal relationship between learning analytics and social constructivism. Learning analytics provide evidence for learning from a social constructivist perspective, while social constructivism helps to make sense of interaction data provided by learning analytics.

Studies Using Specific Learning Concepts

In this section, other specific learning concepts mentioned in individual papers are discussed. What stands out is that the extent to which the learning theories were discussed in the studies as well as the moment at which they were introduced varied. Most studies introduced the learning theories at the beginning but failed to link the patterns or clusters obtained back to the learning theories. In some studies, certain concepts related to learning were mentioned although no clear learning theories were stated.

Zhao et al. (2017) investigated the link between assessment and learner effort within a MOOC. Educational researchers suggest that learner effort should be distributed evenly across topics and course weeks. This appears to be related to the concept of distributed practice (Dunlosky & Rawson, 2015). Results of the study showed that MOOC students behaved differently after meeting the minimum passing requirement. Some students reduced their engagement with videos and quizzes after passing, suggesting that students who passed did not necessarily have complete mastery of all course content. The authors concluded that differences in post-passing behaviours may be related to students' motivation for taking the course. However, student motivation was not actually measured in this study.

The role of feedback is mentioned in Sedrakyan et al.'s (2014) study. Feedback can be linked to several learning theories depending on the focus of the feedback (Thurlings, Vermeulen, Bastiaens, & Stijnen, 2013). Feedback is also viewed as an important component of self-regulated learning (Butler & Winne, 1995). Sedrakyan et al. (2014) examined whether quality of work can be predicted by differences in students' learning patterns. Based on a three-dimensional analysis (i.e. hierarchical, modelling, and time trend), the results showed that the quality of work can be predicted by students' learning pattern. This suggested that instructors can identify poor-performing students and provide process-oriented feedback during the task to enhance their quality of work. The potential of feedback to support learning is proposed but not investigated in the study.

Romero-Zaldivar et al. (2012) employed the concept of deep learning (Webb, 1997) to evaluate the effectiveness of a virtual appliance where students interact with the tools from a pre-installed application on the computer. Based on the assumption of deep learning, learning is enhanced when students have high level of interactions with the learning tools. Predictive modelling based on the frequency and time spent with the tools in the learning environment showed that students' final grades can be predicted by the use of two out of the six tools available. However, the authors did not relate the activities back to the concept of deep learning.

Likewise, predictive modelling was used in Junco and Clem's (2015) study in which theory of engagement was mentioned. The authors gave a brief background on the theory on engagement by Astin (1984) which suggested that amount of learning is related to the amount of time and effort that students invest. Course outcomes were predicted based on the usage data generated from a digital textbook. The results showed that time spent reading was significantly related to course grades. Also, students in the top tenth percentile used more highlights than students in the lower 90th percentile. The study did not further examine the texts that were highlighted, as such, it is not clear how students were using the highlights to support their reading.

Rowe et al. (2017) examined the assessment of implicit science knowledge in digital games. Implicit knowledge is defined as what learners are able to do given their existing understanding. In-game measures of implicit learning were first developed using educational data mining technique. The digital games were then either used as a bridge for science class or as an extra activity outside of class or not used at all in an experimental study. Using hierarchical linear models, the results showed that the in-game measures of implicit knowledge correlated to external measures of learning (i.e. post-assessment). Moreover, students did better in the course when teachers use information about students' implicit knowledge for explicit teaching.

Kim et al. (2016) constructed proxy variables in an asynchronous online discussion environment to measure various concepts related to learning: active participation in the course, engagement with discussion topics, consistent effort and awareness, and interaction. Psychological and behavioural characteristics of high-performing students were then identified for each concept. For instance, psychological and behavioural characteristics of consistent effort and awareness were responsibility, punctuality, time management, and intrinsic motivation.

These characteristics were further operationalized by proxy variables that can be measured by the log file data such as interval regularity of visit to the online environment, total time spent, number of LMS visits, number of discussion board visits, and number of posts. To evaluate how well the proxy variables were able to predict good and poor performers, the authors used random forest technique to develop the prediction model. The results indicated that, using the proxy variables, the prediction model was highly accurate. The authors suggested that for whole-class discussions, students can be encouraged to reply to others and be supported to work towards more in-depth discussion. For team-based discussion, the authors suggested employing support for cognitive engagement at the beginning and sustain engagement throughout the course.

The studies mentioned above suggest that learning analytics have the potential to provide information on various learning-related concepts. Learning analytics add value to educational research through the collection of different sources of data (e.g. trace data) and measuring and analysing the data in ways that can be related to learning theories (e.g. predictive models and clustering). However, for learning analytics to achieve the potential of providing deeper insights to learning, it is important to first clearly determine which learning theories are being investigated so that decisions can be made on which data to be collected and which analytical method to be used.

3.2.2 Absence of Learning Theories

Out of the 20 empirical studies that used correlational and experimental design, 16 studies were found to mention certain learning theories or concepts related to learning. The four studies that did not mention any learning theories were mainly focused on using exploratory approaches to identify student behaviours predictive of academic achievement. Studies by Brooks, Erickson, Greer, and Gutwin (2014) and Liu and d'Aquin (2017) used clustering methods to identify groups of learners that were most likely to be successful. The third study by Carter, Hundhausen, and Adesope (2015) argued that theories in learning research lacked the ability to predict "student performance that are dynamic, robust, and continuously updated throughout a course". Therefore, they proposed a normalized programming state model that explained how removing compilation errors from a programme is related to better achievement. Finally, Marbouti, Diefes-Dux, and Madhavan (2016) compared seven prediction methods to evaluate the models' accuracy in identifying at-risk students: (1) Logistic Regression, (2) Support Vector Machine, (3) Decision Tree, (4) Multi-Layer Perceptron, (5) Naive Bayes Classifier, (6) K-Nearest Neighbour, and (7) ensemble model. The accuracy of the models depends on the performance data collected which can be affected by quality and reliability of the grading. This suggests that there is no one prediction method that is the most accurate. Together, while the studies using various learning analytics methodologies without mentioning learning theories do provide insights into factors influencing student success, we argue that more direct links with learning theories would help to advance the conversation from "what are the factors that influence learning?" to "how and why do these factors influence learning?".

4 Conclusion and Suggestions for Future Research

The aim of the current review was to investigate which theories have been used in studies employing learning analytics to support study success. We searched for studies in two major databases and selected 20 empirical papers for the final review. Based on the studies reviewed, self-regulated learning (SRL) appears to be widely referenced in studies employing learning analytics (i.e. Bos & Brand-Gruwel, 2016; Jovanović et al., 2017; Kizilcec et al., 2017; Siadaty et al., 2016; Tabuenca et al., 2015; You, 2016). There are also two studies related to theories about motivation (i.e. Barba et al., 2016; Lonn et al., 2015) and two studies related to theories on social constructivism (i.e. Carter & Hundhausen, 2016; Joksimović et al., 2015). There are several single studies on different concepts related to learning such as learner effort (i.e. Zhao et al., 2017), feedback (i.e. Sedrakyan et al., 2014), deep learning (i.e. Romero-Zaldivar et al., 2012), engagement (i.e. Junco & Clem, 2015), and implicit knowledge (i.e. Rowe et al., 2017). Kim et al.'s (2016) study is the only exception that examined multiple concepts related to learning (i.e. active participation, engagement, consistent effort and awareness, interaction).

All of these studies are examples of how learning theories are used in studies that employed learning analytics to examine student behaviours in online learning environments. We observed that, at present, learning theories have been used in studies employing learning analytics in two ways. First, learning theories help to guide decisions on the types of data to be collected and the learning analytics approaches to take. From the studies, it is noted that similar data points (e.g. time spent on an activity) can be used as proxies related to different learning theories (e.g. SRL and engagement). Therefore, learning theories play an important role in explaining the concept of learning that is being measured. For example, researchers examining SRL may focus on learning sequences (e.g. Jovanović et al., 2017), while researchers taking the perspectives of socio-constructivism may focus on students' interactions with instructors and other students. Second, learning theories help researchers to explain why students might behave in certain ways and why behaving in certain ways might lead to study success. For example, students who are better at SRL are more inclined to revisit assessments and, hence, more likely to be successful learners (Kizilcec et al., 2017).

Although this chapter has identified several learning theories mentioned in studies employing learning analytics approaches to support study success, a trend that we observed is that learning theories are often briefly mentioned or introduced at the beginning of the articles but rarely circled back to contextualize the results with the learning theory mentioned (e.g. Romero-Zaldivar et al., 2012). While the first part (introducing the theory) is certainly a step in the right direction, we contend that a robust, thorough employment of learning theory in learning analytics should use the results obtained from the various analyses to make direct inferences about the applicability of the theory on the learning behaviour observed (and also, perhaps, the method applied, as learning analytics borrows from a very wide variety of methodologies). As learning analytics is a young, blossoming, interdisciplinary field, it is comprised of researchers from a plethora of other fields, each bringing with them various levels of expertise in different topics. And, as is often the case in interdisciplinary research, knowledge from some fields will inevitably be more prominent than others. For example, a large part of learning analytics research comes from computer science departments (Dawson et al., 2014). To move forward within the learning analytics field, it is imperative that learning analytics researchers, regardless of their base discipline, go beyond a surface-level understanding of the learning theory or theories they are employing. Instead of having it merely as a framing at the beginning of a paper, the learning theories should be integral to the research narrative and provide explanations at every stage about how the theory informed each decision along the way.

Learning theories play an important role in transforming results obtained from learning analytics into insights about learning. While learning analytics can help to identify patterns of student behaviours and add new understanding to the field of educational research, it alone does not provide explanations for underlying mechanism. The analysis of trace data in Jovanović et al.'s (2017) study helped to detect series of student actions corresponding to the unfolding of learning strategies used by the students, yet the results fall short in explaining what underlying factors could have accounted for the differences in the use of learning strategies between different groups of students. In accordance with learning theory related to self-regulated learning in Zimmerman's model (Zimmerman & Campillo, 2003), the use of learning strategies is preceded by self-motivational beliefs and processes of task analysis. By adopting Zimmerman's model in their study, Jovanović et al.'s (2017) could examine whether motivational beliefs influence students' use of learning strategies manifested in the different series of student actions. When using learning theories, researchers should recognize that a theory may have a number of constructs, for instance motivational beliefs can include self-efficacy beliefs, goal orientation, and task interest. Therefore, discussions among researchers are needed to discern learning theories that may align better with learning analytics. The potential of learning analytics can only be realized when the nuances of learning theories are aligned with the nuances of the data.

Another trend that we observed was the considerable overlap in the analytical techniques found in several studies. For instance, regression was mostly used as the analytical method in the first stage followed by clustering in the second stage (Bos & Brand-Gruwel, 2016; You, 2016; Lonn et al., 2015; Romero-Zaldivar et al., 2012; and Junco & Clem, 2015). There were also studies that explore novel analytics approaches such as trace-based methodology (Siadaty et al., 2016) and process model discovery (Sedrakyan et al., 2014). The multiple analytics approaches used in the studies demonstrate the ability of learning analytics to deep dive into rich data sources of log files, discussion forums, time spent on tasks, and number of interactions to extrapolate learning as a holistic and social process based on students' behaviours. However, as noted by Gašević et al. (2015), the interpretation of students' behaviours can change depending on the understanding of the students' internal conditions (e.g. cognitive load, self-efficacy, achievement goal orientation, and interest) as well as external conditions (e.g. instructional design and previous experience with using the tool). Therefore, future studies should include multiple sources of data that can be derived from learning theories (e.g. prior knowledge, self-report of motivation) to supplement the analysis of student data generated in the online environments.

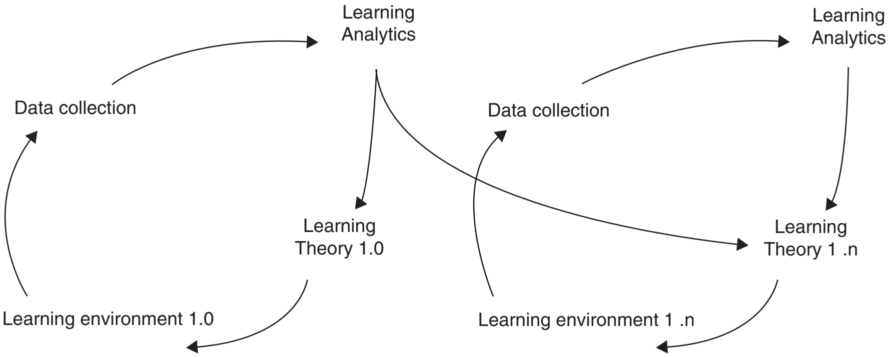

Fig. 1.1 Propose iterative loop in which learning theory is integral to study employing learning analytics

We propose an iterative loop as illustrated in Fig. 1.1 to guide future educational research employing learning analytics. The iterative loop starts with a theory of learning (learning theory 1.0) that is used to examine how students learn in a learning environment. This is followed by theory-guided data collection so that a predefined set of data is collected. Subsequently, theory-guided selection of learning analytics methods is used to analyse the data. The analysis based on learning analytics can either provide evidence to support the hypotheses derived from learning theory 1.0 or suggest how the theory can be developed (learning theory 1.n). The process is iterative until the findings fit a theory. Rowe et al.'s (2017) study is an example of a study which already fits well with what we proposed. Based on theory of implicit knowledge, data were collected in a digital game environment to detect student actions related to implicit knowledge based on learning analytics approaches. Hypotheses were derived to examine whether students whose teachers used the digital game to assess implicit knowledge as a bridge in class would perform better than students whose teachers use the digital game as a supplementary activity and students whose teachers did not use the digital game at all. New data are collected in the digital game environment along with course grade to understand how assessing implicit knowledge can support the teacher and ultimately enhance learning.

Beside the iterative loop, we also suggest three ways in which learning theories can and should be used. First, learning theories can guide decisions on which research questions to investigate or not to investigate. By keeping abreast of the development of learning theories, future studies employing learning analytics can focus on research questions that are not yet answered instead of running the risk of claiming new discoveries that are perhaps long-established findings. For example, in digital learning environments, it is typically easy to collect data about students' levels of activity, which is commonly found to be a great predictor of study success (e.g. You, 2016). This mirrors the finding that in higher education, class attendance is one of the strongest predictors of study success (Credé, Roch, & Kieszczynka, 2010).

Second, learning theories can guide the operationalization of research questions into testable hypotheses, which is a critical step in designing an empirical test. Knowledge from educational research helps to sidestep collection of problematic or inappropriate variables. For example, researchers might be tempted to rely on students' evaluations of online courses and educational technologies to infer about better or more effective approaches. However, student evaluations of courses and/or teachers are only minimally related to learning outcomes and should not be used as a proxy of learning (Clayson, 2009).

Finally, learning theories can guide the design and evaluation of tools and interventions. In the learning analytics literature, dashboards and other educational technologies are a popular subject of research. Learning theories provide highly relevant frameworks to guide the process of creating as well as evaluating dashboards and other educational technologies. For example, the added, or possibly detrimental, value of visualizations in dashboards can and should be empirically assessed, for example, by using cognitive load theory (Sweller, 2011) and the cognitive-affective theory of multimedia learning (Mayer, 2011). Similarly, these large fields of research are invaluable to design and create dashboards and other tools based on decades of relevant empirical research.

In conclusion, the current study shows that learning theories are often mentioned without much depth in the studies employing learning analytics. While learning analyst may be proficient with analytical approaches, they may be less familiar with the nuances of learning. Similarly, learning scientist may be apt at recognizing the nuances of learning but not equipped with skills to perform the analytics using trace data. Therefore, the study of learning can benefit from the joint effort of learning scientists and learning analysts in conducting research that integrate learning theories and learning analytics. This will help to achieve an understanding of learning of which the whole is greater than the sum of its parts.

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Chapter 2
Utilising Learning Analytics for Study Success: Reflections on Current Empirical Findings

Dirk Ifenthaler, Dana-Kristin Mah, and Jane Yin-Kim Yau

1 Introduction

Study success includes the successful completion of a first degree in higher education to the largest extent and the successful completion of individual learning tasks to the smallest extent (Sarrico, 2018). The essence here is to capture any positive learning satisfaction, improvement or experience during learning. As some of the more common and broader definitions of study success include terms such as retention, persistence and graduation rate, the opposing terms include withdrawal, dropout, noncompletion, attrition and failure (Mah, 2016).

Learning analytics (LA) show promise to enhance study success in higher education (Pistilli & Arnold, 2010). For example, students often enter higher education academically unprepared and with unrealistic perceptions and expectations of academic competencies for their studies. Both the inability to cope with academic requirements and unrealistic perceptions and expectations of university life, in particular with regard to academic competencies, are important factors for leaving the institution prior to degree completion (Mah, 2016). Yet Sclater and Mullan (2017) reported on the difficulty to isolate the influence of the use of LA, as often they are used in addition to wider initiatives to improve student retention and academic achievement.

However, the success of LA in improving higher education students' learning has yet to be proven systematically and based on rigorous empirical findings.

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Only a few works have tried to address this but limited evidence is shown (Suchithra, Vaidhehi, & Iyer, 2015). This chapter aims to form a critical reflection on empirical evidence demonstrating how LA have been successful in facilitating study success in continuation and completion of students' university courses.

2 Current Empirical Findings on Learning Analytics and Study Success

There have been a number of research efforts, some of which focussed on various LA tools and some focussed on practices and policies relating to learning analytics system adoption at school level, higher education and national level. Still, significant evidence on the successful usage of LA for improving students' learning in higher education is lacking for large-scale adoption of LA (Buckingham Shum & McKay, 2018).

An extensive systematic literature review of empirical evidence on the benefits of LA as well as the related field of educational data mining (EDM) was conducted by Papamitsiou and Economides (2014). They classified the findings from case studies focussing on student behaviour modelling, prediction of performance, increase self-reflection and self-awareness, prediction of dropout as well as retention. Their findings suggest that large volumes of educational data are available and that pre-existing algorithmic methods are applied. Further, LA enable the development of precise learner models for guiding adaptive and personalised interventions. Additional strengths of LA include the identification of critical instances of learning, learning strategies, navigation behaviours and patterns of learning (Papamitsiou & Economides, 2014). Another related systematic review on LA was conducted by Kilis and Gülbahar (2016). They conclude from the reviewed studies that log data of student's behaviour needs to be enriched with additional information (e.g. actual time spent for learning, semantic-rich information) for better supporting learning processes. Hence, LA for supporting study success requires rich data about students' efforts and performance as well as detailed information about psychological, behavioural and emotional states.

As further research is conducted in the field of LA, the overriding research question of this chapter remains: Is it possible to identify a link between LA and related prevention and intervention measures to increase study success in international empirical studies?

2.1 Research Methodology

Our critical reflection on empirical evidence linking study success and LA was conducted in 2017. Literature review contributions to LA were first analysed, followed by individual experimental case studies containing research findings and empirical conclusions as well as evidence. Search terms included "learning analytics" in combination with "study success", "retention", "dropout", "prevention", "course completion" and "attrition". We searched international databases including Google Scholar, ACM Digital Library, Web of Science, ScienceDirect, ERIC and DBLP. Additionally, we searched articles published in journals such as *Journal of Learning Analytics*, *Computers in Human Behaviour*, *Computers & Education*, *Australasian Journal of Educational Technology* and *British Journal of Educational Technology*. 6220 articles were located, and after duplicated papers were removed, 3163 were remaining. All of these abstracts of papers were screened and were included in our critical reflection on empirical evidence according to our inclusion criteria as follows: (a) were situated in the higher education context, (b) were published between 2013 and 2017, (c) were published in English, (d) presented either qualitative or quantitative analyses and findings and (e) were peer-reviewed. The number of key studies identified was 374 (in the first round) then limited to 46 (due to substantiality of empirical evidence); an elaboration of the identified empirical evidence from the limited studies will form our upcoming work. In this paper, we provide a general overview of the identified empirical evidence.

2.2 *Results of the Critical Reflection*

This section is divided into (1) positive evidence on the use of LA to support study success, (2) insufficient evidence on the use of LA to support study success and (3) link between LA and intervention measures to facilitate study success.

2.2.1 Positive Evidence on the Use of Learning Analytics to Support Study Success

Some of the positive empirical evidence presented by Sclater and Mullan (2017) include the following: At the University of Nebraska-Lincoln after LA was adopted, their 4-year graduation rate increased by 3.8% in 4 years. At Columbus State University College, Georgia, course completion rates rose 4.2%. Similarly, at the University of New England, South Wales, the dropout rate decreased from 18% to 12%. Control group studies yield the following results: there was a significant improvement in final grade (6%) at Marist College; at Strayer University, Virginia, the identified at-risk students were given intervention and resulted in 5% increase in attendance, 12% increase in passing and 8% decrease in dropout. At the University of South Australia, 549 of 730 at-risk students were contacted; 66% passed with average GPA of 4.29. Fifty-two percent of un-contacted at-risk students passed with average GPA of 3.14. At Purdue University, Indiana, it was found that using the university's predictive analytics system (Course Signal), there were consistently higher levels of Bs and Cs grades obtained than Ds and Fs grades in two semesters of courses. A 15% increase in recruitment and a 15% increase in retention as a result was reported (Tickle, 2015).

We also identified positive evidence on the use of LA to support study success through the use of assessment data, engagement indicators, online platform data and the use of personalised feedback, as follows.

Predictive Analytics Using Assessment Data It was found on average that there was a 95% probability if a student had not submitted their assignment and that they will not finish the course (Hlosta, Zdrahal, & Zendulka, 2017). Here, assessment description referred to (1) students' demographic information (e.g. age, gender, etc.), (2) students' interactions with the VLE system, (3) information about students' date of registration and (4) a flag indicating student assignment submission. This information is used to extract learning patterns from the students where their progress of the course can be predicted. The assessment of the first assignment provides a critical indicator for the remainder of the course. The conducted experiments showed this method can successfully predict at-risk students.

Predictive Analytics Using Engagement Indicators Information about students' behaviour that is made available during the course can be used to predict the decrease of engagement indicators at the end of a learning sequence. Three main tasks that students conducted in a MOOC environment were able to yield good results in the prediction if there would be a decrease in engagement in the course as signalled by engagement indicators (Bote-Lorenzo & Gomez-Sanchez, 2017). The authors found that three engagement indicators derived from tasks being carried out in a MOOC were very successful in predicting study success—watching lectures, solving finger exercises and submitting assignments. It was suggested that their predictive method would be useful to detect disengaging students in digital learning environments.

Predictive Analytics Using Digital Platform Data Self-report and digital learning system information (i.e. trace data) can be used to identify students at risk and in need of support as demonstrated by a study conducted by Manai, Yamada, and Thorn (2016). For example, some self-report survey items measure non-cognitive factors such as indicative predictors of student outcomes allowing one to inform actionable insights with only a few items' data. Certain formulas were used in their study such as (1) if students showing higher levels of fixed mindset and to be at risk, a growth mindset is promoted to them by engaging them in growth mindset activities and also giving feedback to students that establishes high standards and assuring that the student is capable of meeting them; (2) if students showing higher levels of belonging uncertainty, group activities that facilitate building a learning community for all students in the classroom are provided; and (3) if students showing low levels of math conceptual knowledge, scaffolding for students is provided during the use of the online learning platform. Similarly, Robinson, Yeomans, Reich, Hulleman, and Gehlbach (2016) utilised natural language processing, and their experiment showed promising predictions from unstructured text which students would successfully complete an online course.

Personalised Feedback Leading to Learning Gains Feedback can be tailored based on the student's affective state in the intelligent support system. The affective state is derived from speech and interaction, which is then used to determine the type of appropriate feedback and its presentation (interruptive or non-interruptive) (Grawemeyer et al., 2016). Their results showed that students using the environment were less bored and less off-task showing that students had higher learning gains and there is a potential and positive impact affect-aware intelligent support.

2.2.2 Insufficient Evidence on the Use of LA to Support Study Success

The most recent review of learning analytics published in 2017 from Sclater and Mullan (2017) described the use of LA to be most concentrated in the United States, Australia and England; most institutional initiatives on LA are at an early stage and lacking sufficient time to find concrete empirical evidence of their effectiveness (Ifenthaler, 2017a). However, some of the most successful projects were in the US for-profit sector, and these findings are unpublished. In the review conducted by Ferguson et al. (2016), the state of the art in the implementation of LA for education and training in Europe, United States and Australia was presented which is still scarce. Specifically, it was noticed that there are relatively scarce information on whether LA improves teaching and learners' support at universities, and problems with the evidence include lack of geographical spread, gaps in our knowledge (informal learning, workplace learning, ethical practice, lack of negative evidence), little evaluation of commercially available tools and lack of attention to the learning analytics cycle (Ferguson & Clow, 2017).

Threats deriving from LA include ethical issues, data privacy and danger of over-analysis, which do not bring any benefits and overconsumption of resources (Slade & Prinsloo, 2013). Accordingly, several principles for privacy and ethics in LA have been proposed. They highlight the active role of students in their learning process, the temporary character of data, the incompleteness of data on which learning analytics are executed, the transparency regarding data use as well as the purpose, analyses, access, control and ownership of the data (Ifenthaler & Schumacher, 2016; West, Huijser, & Heath, 2016). In order to overcome concerns over privacy issues while adopting LA, an eight-point checklist based on expert workshops has been developed that can be applied by teachers, researchers, policymakers and institutional managers to facilitate a trusted implementation of LA (Drachsler & Greller, 2016). The DELICATE checklist focusses on Determination, Explain, Legitimate, Involve, Consent, Anonymise, Technical aspects and External partners. However, empirical evidence towards student perceptions of privacy principles related to learning analytics is still in its infancy and requires further investigation and best practice examples (Ifenthaler & Tracey, 2016).

Ferguson et al. (2016) documented a number of tools that have been implemented for education and training and raised a number of important points—(a) most LA tools are provided on the supply side from education institutions and not on the demand side required by students and learners; (b) data visualisation tools are available, however do not provide much help in advising steps that learners should take in order to advance their studies/increase study success; and (c) especially evidence is lacking on formal validation and evaluation of LA tools of the impact and success, although national policies in some European countries such as Denmark, the Netherlands and Norway and universities such as Nottingham Trent University, Open University UK and Dublin City University have commenced to create an infrastructure to support and enable policies of utilisation of LA or implementation/incorporation of LA systems. Hence, the evidence on successful implementation and institution-wide practice is still limited (Buckingham Shum & McKay, 2018). Current policies for learning and teaching practices include developing LA that are supported through pedagogical models and accepted assessment and feedback practices. It is further suggested that policies for quality assessment and assurance practices include the development of robust quality assurance processes to ensure the validity and reliability of LA tools as well as developing evaluation benchmarks for LA tools (Ferguson et al., 2016).

2.2.3 Link between Learning Analytics and Intervention Measures to Facilitate Study Success

Different LA methods are used to predict student dropout such as predictive models and student engagement with the virtual learning environment (VLE) (more reliable indicator than gender, race and income) (Carvalho da Silva, Hobbs, & Graf, 2014; Ifenthaler & Widanapathirana, 2014). Some of the significant predictors of dropout used in these methods can be indicated and include the following: posting behaviour in forums, social network behaviour (Yang, Sinha, Adamson, & Rose, 2013), percentage of activities delivered, average grades, percentage of resources viewed and attendance (85% accuracy of at-risk student identification) (Carvalho da Silva et al., 2014). Similarly, different factors are used at Nottingham Trent University to signal student engagement: library use, card swipes into buildings, VLE use and electronic submission of coursework, analyses the progression and attainment in particular groups (Tickle, 2015). An example technique is as follows: if there is no student engagement for 2 weeks, tutors will get an automatic email notification, and they are encouraged to open up a dialogue with the at-risk student. Their LA system intends to help increase not only study retention but also to increase study performance. Prevention measures include pedagogical monitoring. The timeliness of the institution or university's intervention is very important including noticing signs of trouble and responding immediately to these (Tickle, 2015). A question concerning ethics may be "do students want an algorithm applied to their data to show they are at risk of dropping out?" causing intervention from respective tutors to take place (West et al., 2016).

LA are often discussed and linked with regard to self-regulated learning. Self-regulated learning can be seen as a cyclical process, starting with a forethought phase including task analysis, goal setting, planning and motivational aspects (Ifenthaler, 2012). The actual learning occurs in the performance phase, i.e. focussing, applying task strategies, self-instruction and self-monitoring. The last phase contains self-reflection, as learners evaluate their outcomes versus their prior set goals. To close the loop, results from the third phase will influence future learning activities (Zimmerman, 2002). Current findings show that self-regulated learning capabilities, especially revision, coherence, concentration and goal setting, are related to students' expected support of LA systems (Gašević, Dawson, & Siemens, 2015; Schumacher & Ifenthaler, 2018b). For example, LA facilitate students through adaptive and personalised recommendations to better plan their learning towards specific goals (McLoughlin & Lee, 2010; Schumacher & Ifenthaler, 2018a). Other findings show that many LA systems focus on visualisations and outline descriptive information, such as time spent online, the progress towards the completion of a course and comparisons with other students (Verbert, Manouselis, Drachsler, & Duval, 2012). Such LA features help in terms of monitoring. However, to plan upcoming learning activities or to adapt current strategies, further recommendations based on dispositions of students, previous learning behaviour, self-assessment results and learning goals are important (McLoughlin & Lee, 2010; Schumacher & Ifenthaler, 2018b). In sum, students may benefit from LA through personalised and adaptive support of their learning journey; however, further longitudinal and large-scale evidence is required to demonstrate the effectiveness of LA.

3 Conclusion

This critical reflection of current empirical findings indicates that a wider adoption of LA systems is needed as well as work towards standards for LA which can be integrated into any learning environment providing reliable at-risk student prediction as well as personalised prevention and intervention strategies for supporting study success. In particular, personalised learning environments are increasingly demanded and valued in higher education institutions to create a tailored learning package optimised for each individual learner based on their personal profile which could contain information such as their geo-social demographic backgrounds, their previous qualifications, how they engaged in the recruitment journey, their learning activities and strategies, affective states and individual dispositions, as well as tracking information on their searches and interactions with digital learning platforms (Ifenthaler, 2015). Still, more work on ethical and privacy guidelines supporting LA is required to support the implementation at higher education institutions (Ifenthaler & Tracey, 2016), and there are still many open questions how LA can support learning, teaching as well as the design of learning environments (Ifenthaler, 2017b; Ifenthaler, Gibson, & Dobozy, 2018). Another field requiring rigorous empirical research and precise theoretical foundations is the link between data analytics and assessment (Ifenthaler, Greiff, & Gibson, 2018). Further, as LA are of growing interest for higher education institutions, it is important to understand students' expectations of LA features (Schumacher & Ifenthaler, 2018a) to be able to align them with learning theory and technical possibilities before implementing them

(Marzouk et al., 2016). As higher education institutions are moving towards adoption of LA systems, change management strategies and questions of capabilities are key for successful implementations (Ifenthaler, 2017a). The preliminary findings obtained in this critical reflection suggest that there are a considerable number of sophisticated LA tools which utilise effective techniques in predicting study success and at-risk students of dropping out.

Limitations of this study include the difficulty in comparing results of different studies as various techniques and algorithms, research questions and aims were used. Although much empirical evidence is documented in these papers, many studies are still works-in-progress, experimental studies and at very small scale. The papers discuss how LA can work to predict study success, and the steps following this to the discussions with the students and the approaches that teachers can take to address to at-risk students are under-documented. The questions raised concerning this are, for example: (a) Will students be able to respond positively and proactively when informed that their learning progress is hindered or inactivated? (b) Will instructors be able to influence the at-risk students positively so that they will re-engage with the studies? (c) In addition, ethical dimensions regarding descriptive, predictive and prescriptive learning analytics need to be addressed with further empirical studies and linked to study success indicators.

However, evidence on a large scale to support the effectiveness of LA actually retaining students onto courses are still lacking, and we are currently examining the remainder of the key studies thoroughly to obtain a clearer and more exact picture of how much empirical evidence there is that LA can support study success. Methods and advice also can be used as a guide in helping students to stay on the course after they have been identified as at-risk students. One suggestion is to leverage existing learning theory by clearly designing studies with clear theoretical frameworks and connect LA research with decades of previous research in education. Further documented evidence on LA include that LA cannot be used as a one-size-fits-all approach, i.e. requiring personalisation, customisation and adaption (Gašević, Dawson, Rogers, & Gašević, 2016; Ifenthaler, 2015).

Our future work also includes locating learning theories onto LA (which is currently lacking)—there is missing literature on variables as key indicators of interaction and study success in digital learning environments. Hence, while the field of learning analytics produces ever more diverse perspectives, solutions and definitions, we expect *analytics for learning* to form a novel approach for guiding the implementation of data- and analytics-driven educational support systems based on thorough educational and psychological models of learning as well as producing rigorous empirical research with a specific focus on the processes of learning and the complex interactions and idiosyncrasies within learning environments.

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Chapter 3
Supporting Stakeholders with Learning Analytics to Increase Study Success

A Case Study

Miriam Hommel, Armin Egetenmeier, and Ulrike Maier

1 Introduction

More and more students are entering the universities with different types of university entrance qualifications (UEQ). This implies a high degree of first-year diversity, heterogeneous university preparation, and a wide range of skills, especially in mathematics. Heterogeneity has, therefore, become a ubiquitous issue and challenge in higher education institutes (HEIs) (Bebermeier & Nussbeck, 2014; Reinmann, 2015).

It has been known for some time that underachievement is a major cause of dropout at HEIs in Germany (Heublein, Richter, Schmelzer, & Sommer, 2012, 2014; Heublein & Wolter, 2011). Heublein et al. (2017a) recently published results from a nationwide survey investigating motives and causes of dropout in German HEIs. They found that especially in the study entry phase (first year) at Universities of Applied Sciences (UAS) in the federal state of Baden-Wuerttemberg, almost 50% of the students decide to quit university without a degree (Heublein et al., 2017b, p. 281). Based on their research, Heublein et al. (2017a) formulated recommendations for various fields of action to lower dropout rates. Suggestions are, e.g., a comprehensive range of support measures and the introduction of a control system that enables HEIs to take preventive or intervention measures (Heublein et al., 2017a, pp. 20–21).

Most universities already offer support such as tutorials or preparatory courses (Biehler, Hochmuth, Fischer, & Wassong, 2011; Hoppenbrock, Biehler, Hochmuth, & Rück, 2016). In order to strengthen these supporting structures with regard to the challenges in the study entry phase, the German Federal Government has initiated a nationwide funding program for HEIs (Deutsches Zentrum für Luft- und Raumfahrt e. V. [DLR], 2014; DLR, 2015).

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With the proliferation of many different supportive structures, there is a growing interest in analyzing their effectiveness. Due to the governmental funding, reporting is mandatory. A detailed analysis of the impact of the supporting measures may also be beneficial for similar projects as their outcomes are important for both institutions and policy-makers. Investigations concerning preparatory courses (prep courses) can be found in Derr, Hübl, and Podgayetskaya (2015) or Heiss and Embacher (2016). A study on tutorials is presented in Bebermeier and Nussbeck (2014). Even though a data-driven approach may bring new insights, mostly qualitative methods (e.g., surveys) are used for the analyses. For estimating the effectiveness of the supportive measures more realistically, there is a necessity to analyze corresponding data also *quantitatively* to prevent study-dropouts and to ensure high teaching quality and study success.

Despite the fact that study success is a key aspect of many higher education studies, there is no universally accepted definition of "study success." One reason may be the different perspectives of "success" by students, lecturers, or society (Erdel, 2010, p. 12). In the absence of a consistent and clear definition of "study success," different characteristics are used to include as many relevant aspects as possible. This begins with a simple but obvious definition, such as "achieving a degree" (Dell'mour & Landler, 2002, p. 43), to a more advanced version that includes criteria like "time to completion" or "final grade." More subjective criteria such as "study satisfaction," "relevant competences," or "employability" are also used as characteristics for "study success" (Rindermann & Oubaid, 1999).

In educational policy in Germany, "study success" is often defined as the opposite of "study failure" (Erdmann & Mauermeister, 2016). In this sense, avoiding dropping out can be considered as "success" which explains the close link between research on "study success" and "study failure" (study-dropout). Assuming that the support measures of a university can influence the (individual) decision to continue studying, a "student success" is also an "institutional success."

In our study, we use a working definition of "study success" based on the academic achievement of students in the first year. This includes the impact of the support measures on their intended purpose (in our case the improvement of mathematical skills of freshmen). Dropouts are often caused by performance problems, and insufficient math skills increase the risk of quitting (Heublein, Hutzsch, Schreiber, Sommer, & Besuch, 2010, pp. 68–70). Therefore, currently our main criterion to quantify "study success" is the passing of the first math exam as it marks an important step toward graduation (compare Sect. 2.2.4). This offers the opportunity to evaluate the effects of supportive actions on study success at an early stage.

1.1 Learning Analytics

In recent years, new technology-enriched methods and digital offerings have been developed to improve teaching and increase students' learning outcomes. By using digital learning material, large amounts of data can be analyzed. In this environment, new fields of research such as Educational Data Mining (EDM) and Learning Analytics (LA) were established. A major difference between both fields is that while EDM focuses on automation by the computer, the goal of LA is to empower stakeholders to make decisions based on data rather than relying only on “gut instinct” or experiences (Long & Siemens, 2011, p. 32). Our contribution focuses on LA.

Since the first Conference on Learning Analytics and Knowledge (LAK) in 2011, a commonly accepted definition for LA is “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Long & Siemens, 2011, p. 34). Brown (2011, p. 1) supplements this definition by “The purpose of LA is to observe and understand learning behaviors in order to enable appropriate interventions.”

1.2 Benefits and Issues of Learning Analytics

A benefit of LA is the ability to promote learners on electronic platforms through help systems and personalized feedback in their personal learning habits. It offers the opportunity to track individual learning outcomes and learning progresses of students (regardless of group size). On the other hand, data can be grouped and related as desired. Thus, LA can assist teachers in identifying students at risk and intervene in the learning process in a timely manner with the help of feedback.

In addition, the observation of learning processes enables HEIs to further develop and improve the quality of teaching in the long term. This can lead to curriculum developments and the introduction of new supportive measures. The use of data already available at universities can facilitate the evaluation of the effectiveness of these measures. This can also influence the knowledge on education processes and thus lead to an improvement of educational research. “Theoretically, LA has the potential to dramatically influence existing education models and gain new insights into what works and what does not work in teaching and learning” (Siemens, 2012, p. 7).

In contrast to the hype of recent years, there has been a slowdown in the introduction and use of LA, in particular due to ethical, privacy, and legal concerns (Drachsler & Greller, 2016). Especially ethical aspects like data protection often remain unaddressed by institutional review boards (Willis, Slade, & Prinsloo, 2016). Besides these aspects, the data itself includes issues. It is still not clear what type of data really matters to generate incontrovertible evidence about what makes successful learning (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006; Macfadyen & Dawson, 2012). Although technology-enhanced learning is becoming more relevant, most HEIs (especially in Germany) are still using “traditional” (face-to-face) learning environments (Romero & Ventura, 2013, p. 16). Nevertheless, data collection mostly takes place in centralized educational systems like learning management systems (LMS) or web-based systems (Chatti et al., 2014; Papamitsiou & Economides, 2014).

On closer examination of the study success, “appropriate intervention” is an integral part of Learning Analytics. In an effective LA cycle, a key step is “‘closing the loop’ by feeding back this product [e.g., analytics] to learners through one or more interventions” (Clow, 2012, p. 134). Since the effect of feedback depends on individual factors such as prior knowledge or self-efficacy (Kluger & DeNisi, 1996; Narciss, 2013), the interpretations of LA results require some level of expertise. Possible misinterpretations may lead to unintended behavior of the students (Corrin & Barba, 2014). In order to avoid such behavior, it is useful to include pedagogical considerations (Tempelaar, Rienties, & Nguyen, 2017; Wise, 2014) that can also increase the quality of the LA application.

Overviews of benefits and issues of LA are given, for example, in Long and Siemens (2011); Papamitsiou and Economides (2014); Avella, Kebritchi, Nunn, and Kanai (2016); and Leitner, Khalil, and Ebner (2017).

1.3 Stakeholders of Learning Analytics

The obvious group of users of an LA framework are students and teaching staff. Brown (2011, p. 1) stresses: “The reports that an LA application generates can be very helpful for instructors (about student activities and progress), for students (feedback on their progress), and for administrators (e.g., aggregations of course and degree completion data).” Thus, to unfold the full potential of an LA framework, it is necessary and lucid to address several stakeholders. Taking into account politics/government as a superordinate extension, four stakeholder levels can be identified (Greller & Drachsler, 2012). Embedded in an institutional framework, these groups can be distributed hierarchically to mega-, macro-, meso-, and micro-level.

Ifenthaler (2015) presents a matrix that shows how all levels of stakeholders benefit from LA. Figure 3.1 shows an adaptation of a graphic by Ifenthaler (2015) illustrating the actors and their influences within the education system and the possible recipients of an LA support. In contrast to the original figure, the learning environment includes not only teacher and learner (as main recipients of information) but also parts of the LA system. Research within an LA framework seems to be a good way to self-evaluate (and constantly improve) provided support or reports. Regarded as an additional group, researchers act across all LA levels and thus can hardly be associated to a specific stakeholder level (cf. Greller & Drachsler, 2012; Romero & Ventura, 2013).

In order to support students’ success, various approaches are pursued at HEIs. This led to many models and tools in the field of LA addressing different stakeholders. Most of the large-scale, systematic implementations of LA are located at Colleges and HEIs in the United States of America, Canada, and Australia (Sclater, Peasgood, & Mullan, 2016, A21). One of the best-known implementations in the field is “Course Signals” (CS) of Purdue University (Arnold & Pistilli, 2012). Based on a prediction model, the CS system visualizes the students’ chances of success for

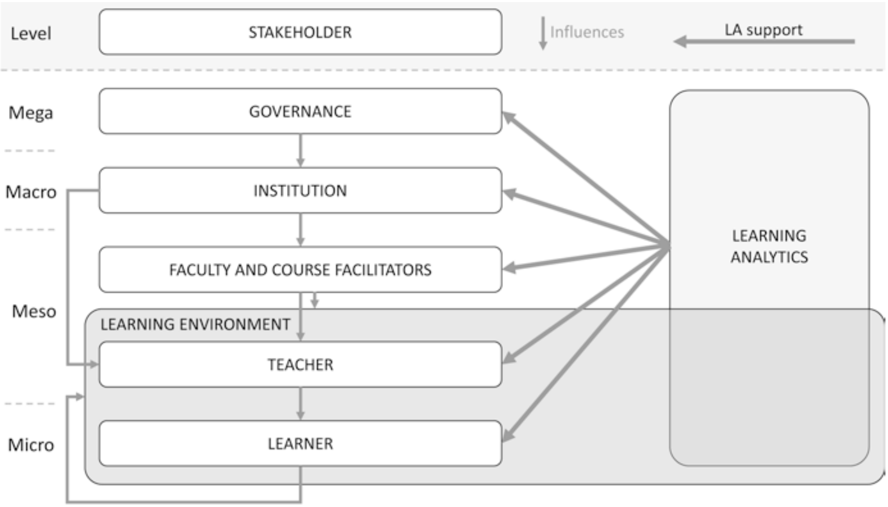

Fig. 3.1 Learning Analytics associated with stakeholder levels (inspired by Ifenthaler, 2015)

teachers and learners via "status traffic lights." Other tools like the "Student Activity Meter" (SAM) (Govaerts, Duval, Verbert, & Pardo, 2012) support students' self-reflection and awareness of, for example, resource usage and expenditure of time. This type of feedback has been developed for learners and teachers alike.

In Australia, the University of Sydney has developed the "Student Relationship Engagement System" (SRES) and has deployed it at several Australian universities (Vigentini et al., 2017). SRES is an educator-driven, web-based LA system supporting student success with personalized feedback. To provide students with appropriate information, various types of data (e.g., attendance, grades, personal information) can be collected, filtered, and analyzed in the system. This pedagogically oriented system is specifically designed to meet the needs of the teaching staff.

As student advisors contribute to student success, they can also benefit from LA implementations. For instance, the "Learning dashboard for Insights and Support during Study Advice" (LISSA) (Charleer, Vande Moere, Klerkx, Verbert, & Laet, 2017) has been developed to provide insight into grade data of students to be counseled. The tool is suitable as a starting point for advisory sessions based on facts which can stimulate the dialogue between student and advisor.

A growing adoption of LA can also be found in some European countries due to national education initiatives like JISC in the United Kingdom (cf. Sclater et al., 2016) or SURFnet in the Netherlands (cf. Baas et al., 2015). These initiatives build a nationwide collaborative network to address common existing and upcoming issues in the field. This paves the way for further LA implementations. An overview of case studies and, in particular, LA applications is presented in a paper by Wong (2017) which also includes a list of LA implementations sorted by different goals and uses (e.g., improving student retention, supporting decision-makers, or giving timely feedback).

Documented case studies in Germany are rare, partly due to strict data protection legislation. Another reason may be that HEIs in Germany are still in an early stage of adopting LA, and thus, there are only few LA systems, e.g., to identify at-risk students (Ifenthaler, Mah, & Yau, 2017). Examples are LeMo (Fortenbacher et al., 2013) and eLAT (Dyckhoff, Zielke, Bültmann, Chatti, & Schröder, 2012) supporting teaching staff, or the tool LAPS, formerly S-BEAT (Hinkelmann, Maucher, & Seidl, 2016), which was developed to support student counseling. It is noticeable that the results mostly still address a small number of stakeholders. This is regrettable because a limited access to the results may cause disadvantages for stakeholders and decision-makers involved (Ifenthaler & Widanapathirana, 2014). Due to the different interpretation of analytics results, informing more stakeholders (on different levels) can provide various insights and, therefore, cause different interventions.

In the following sections, we describe how we provide information about the learning process of the first-year students and their success to stakeholders of all LA levels (compare Fig. 3.1). Section 2 first introduces the Study Support Center (SSC) of Aalen UAS. Subsequently, its evidence-oriented research (as a basis for LA) with study design, research questions, and research method is described. Afterward, some results of our analyses are exemplified. Section 3 presents how our results affect different levels of stakeholders. Our contribution ends with a short summary and conclusion (Sect. 4).

2 Evidence-Oriented Accompanying Research at Aalen University of Applied Sciences

2.1 Study Support Center

As introduced in Sect. 1, high dropout rates as a result of missing basic mathematical prerequisites are a challenge at many universities. At Aalen UAS, a university offering degrees in the fields of technology and economics, the SSC was set up as part of the quality pact teaching project "AkaMikon" (see Acknowledgments) in 2011 to support students of all study courses in the introductory phase. The overall objective of the SSC is to reduce the number of subject-related study-dropouts. With mathematical prep courses, lecture-accompanying tutorials, as well as measures to level the heterogeneity in the initial mathematical knowledge (e.g., by pilot projects for continuous learning and extracurricular offers at selected schools), the SSC team pursues the goal to facilitate the study entry for the new students (Nagengast, Hommel, & Löffler, 2013; Nagengast, Hommel, Maier, Egetenmeier, & Löffler, 2017). In addition to these support measures in traditional classroom teaching, digital learning environments, e.g., a mathematics online course, are being developed to complement traditional supportive measures (Krieg, Egetenmeier, Maier, & Löffler, 2017).

Figure 3.2 illustrates the time frame of the SSC support. A three-stage test concept (pretest at the first prep course day, posttest at the end of the prep course, follow-up test 4–6 weeks after the end of the prep course) forms the basis for our research on the impact of the prep course.

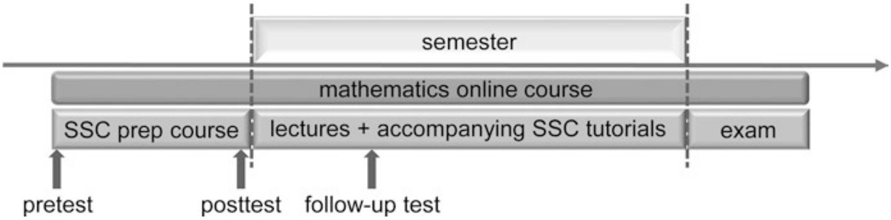

Fig. 3.2 Time frame of SSC support measures

One goal of the SSC is to ensure high teaching quality, which for us means that students are able to follow the lecture and that they are motivated (ideally intrinsically) to work independently and to internalize the content. Consequently, students should not only learn for the exam but also be able to recall the content of the lecture even at a later point in time.

Concerning the SSC support, a prerequisite for high teaching quality is a scientific background (mostly mathematics) of its members, which in particular ensures their professional competence. In addition, each team member has completed training in the field of didactics and gained experience in teaching underperforming students for several semesters.

The quality of lessons is usually subjective and difficult to quantify. Therefore, it seems more appropriate to agree on effective teaching methods. The SSC prefers teaching methods focusing on practicing in order to encourage the students to actively engage with the mathematical content. Hence, activating exercises are integrated into the lecture part of the prep course to keep the students' attention high and to motivate them to practice and apply the course contents directly as suggested by Heublein et al. (2017a, 2017b). The prep course groups usually have a size of 50–70 students and are arranged according to study courses to encourage fellow students to get to know each other and to form study groups from the beginning. After the lecture part of the prep course, tutorials are offered where each group is conducted by specially trained students of higher semesters from the respective study course. This and the comparatively small group size lowers the threshold to ask questions about mathematical contents and studying. Thus, the prep course also includes social components.

In lecture-accompanying tutorials, the members of the SSC teach in various fields of study (engineering, computer sciences, business administration, health management). Subjects are (economics) mathematics as well as physics and engineering mechanics. Again, the focus lies on the active practice of the mathematical content.

2.2 Study Design

Since evaluation of study and teaching is an important instrument for ensuring (didactic) quality, the SSC has been carrying out a scientific accompanying research since the beginning. The aim of this research is to especially monitor the effectiveness of the supportive measures in order to adapt them efficiently. Furthermore, the analysis of the learning outcomes and progresses should provide insights into the learning behavior and performance of first-year students. A long-term study should also disclose trends. As the results of this research can support different stakeholders in decision-making (learners, teachers, faculty and course facilitators, institution, governance), they are used as a basis for the LA framework of Aalen UAS (see Sect. 3).

The following subsections describe the data captured and analyzed by the SSC regularly since 2013, some research questions as well as the research method and some exemplary evaluation results.

2.2.1 Database and Data Protection

In order to analyze the students' learning behavior and performance as well as to check the effectiveness of the supporting measures, the following data is collected each semester.

- In the prep course and in the semester-accompanying tutorials, attendance lists are kept to record the participation frequency of the students in the measures.
- At various times, paper and pencil tests (pretest, posttest, follow-up test) of the mathematical foundations that are covered by the prep course are carried out to capture the specific level of knowledge of the students (compare time frame in Fig. 3.2).
- Prior to the tests, a self-assessment of the new students on the course topics is queried in order to examine how students assess their own basic mathematical knowledge. The self-assessments are compared with the actual test results.

The collected data (about 4000–4500 test sheets per year) is entered manually into standardized Excel spreadsheets. Therefore, the evaluations are far from being "real time." To gain further insight, the data is supplemented by electronically available data records from the student information system (SIS, known in Germany generally as the HIS management system of the university administration) and linked to it. The SIS contains, e.g., sociodemographic data such as the type and grade of the higher education entrance qualification and examination results. Unlike common data collection on sociodemographic data using questionnaires, SIS provides a consistent and reliable source of information.

The evaluation of personal data requires a data protection safeguarding. For the database of the project described above, this safeguarding has already taken place. This means, especially, that the individual linkage of the collected data to SIS data is permitted (Egetenmeier et al., 2016). For the online course in mathematics, the process of data protection safeguarding is still in process.

The students' participation in the support measures and the prep course tests is optional. *Note*: Data is only evaluated for those students who have signed a data privacy statement developed for the SSC (SSC DPS), i.e., only the data of part of the students in the study entry phase are analyzed. That accounts for about 50–60% of the first-year students (representing a statistically relevant subgroup).

2.2.2 Research Questions

A better understanding of learning behavior, learning progress, and the impact of support measures can lead to appropriate interventions to improve learning as well as learning environments if the insights are fed back to the different stakeholders. The identification of groups of students who are particularly at risk of dropping out and may require special support is also of great interest to stakeholders of all levels. Moreover, understanding long-term trends can help stakeholders of the meso- and macro-level to develop curricula and supportive measures.

To gain such insights on first-year students of all faculties in the field of mathematics, the following research questions were examined:

1. With which level of knowledge of the individual basic mathematical topics do students start their degrees, and how is their self-assessment on these topics?
2. Is there a way to directly measure learning outcome of the "prep course" and does the attendance of the course change the students' self-assessment?
3. Do the measures "prep course" and "lecture-accompanying tutorials" have an influence on the success in the exams of basic subjects in the study entry phase?
4. Students of which sociodemographic background use the SSC measures "prep course" and "tutorials" and with what frequency do the respective groups use the measures?
5. Which participants show special deficits in the initial mathematical knowledge that is indispensable for the chosen subject?
6. Which groups of students are at particular risk of changing the course or even dropping out? Is it possible to identify characteristic features in the personal data (e.g., UEQ, test results in the prep course, but also ECTS credits, non-taking of examinations, failed attempts) that already at an early-stage point toward a problematic study process?
7. What effects do SSC measures have on the study process or the long-term success of first-year students?
8. Is it possible to disclose trends or developments from the collected and analyzed data of the first-year students?

2.2.3 Research Method

The following list explains how the data described in Sect. 2.2.1 is used in order to answer the questions in Sect. 2.2.2. The numbering coincides with the order of the research questions.

1. An unannounced pretest together with a self-assessment to the content of the prep course is taken directly before starting the prep course. The results indicate the level of initial math knowledge of the freshmen as well as their self-assessment.
2. The comparison of the post- and follow-up test results with the pretest results determines the learning progress achieved by the measure "prep course."

The learning progress of basic mathematical knowledge through the prep course can thus be made visible. The prep course follow-up tests are written in selected lectures during the semester to provide a comparison group of students who did not attend the prep course.

3. Based on the individual marks in math exams (from the SIS), it can be examined whether a regular participation in the prep course or in the lecture-accompanying tutorials favors the examination success.
4. Analyzing the data from the SIS sheds light on how the groups of participants are composed (e.g., UEQ type and final school grade – FSG) and whether there are differences in the use of support.
5. Group-specific analyses (e.g., according to sociodemographic characteristics) help to identify students with a particular need for support.
6. In addition to the answers given to questions 3–5, an in-depth analysis of the test results is planned. Postponing exams, multiple exam attempts, or multiple changes of study courses may indicate that a student is at risk of quitting his or her studies.
7. The analysis and comparison of individual courses of SSC participants can provide an answer to question 7. The SSC is allowed to conduct these investigations based on the data privacy statement.
8. Long-term studies aim to identify trends and developments. For this, data has been collected since summer semester 2013.

The algorithm used to analyze the data consists of several steps (pseudonymizing, merging, filtering/clustering, evaluating, visualizing). Figure 3.3 illustrates the different steps.

In order to comply with data protection, the data is prepared in a *pseudonymizing* step, i.e., in each file, the typical student matriculation number is replaced by an automatically generated pseudo number (Egetenmeier et al., 2016). All evaluations are carried out with the modified data. Since the matriculation number at a university is assigned uniquely, the students' individual learning process can be followed throughout the semesters. In accordance with data protection, decoding of the pseudo-numbers and, thus, individual identification of students is very difficult.

Subsequently, the data obtained from the support measures are linked with sociodemographic data in a *merging* step using the pseudo numbers as key. *Filtering*

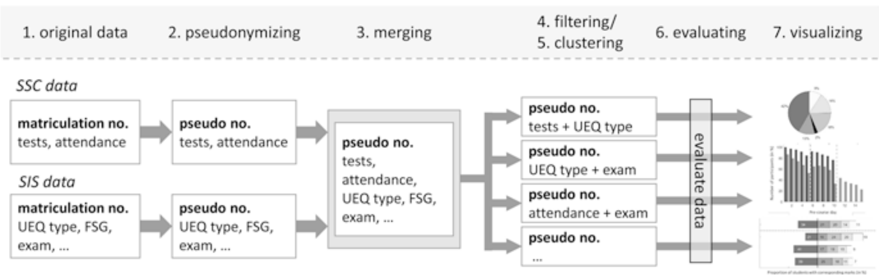

Fig. 3.3 Data preprocessing and analyzing steps

the relevant data for a particular rating, i.e., selecting only the data that is really needed for the particular evaluation (e.g., pseudo number + participation in the prep course + mark in the first math exam), keeps the data analysis short and functional. In the *clustering* step, some data (e.g., the type of UEQ or the attribute of having passed or failed an exam) are used to group the dataset into a few relevant groups. This allows the identification of group-specific features in the data. The *evaluating* step is the main step of the analysis. Here, methods of descriptive statistics are used. Finally, in a *visualization* step, the results of the evaluations are displayed according to the target group (stakeholder).

The above steps of the data analysis are realized using separate MATLAB routines developed at SSC. It should be noted that each of the SSC's data analyses must consist of at least seven people to protect students' privacy. This corresponds to the evaluation statute of Aalen UAS.

2.2.4 Exemplary Analyses

This section contains some exemplary data analyses of the SSC answering several of the research questions described above. Analyses answering research questions 1 and 2 are presented in Nagengast et al. (2013). It could be shown that the prep course significantly improves the entry-level competences in mathematics (development from pre- to posttest). Unfortunately, the improvement is not permanent. Question 5 is investigated in Nagengast et al. (2017). It turned out that the educational biography has an important impact on the initial mathematical knowledge of first-year students. Questions 6–8 are subject of future research.

This contribution concentrates on questions 3 and 4, i.e., the impact of SSC measures on math exams and in addition UEQ grouping and prep course participation for first-year students who passed or failed the first math exam.

The influence of the SSC prep course and the tutorials on the first mathematics exam of the degree has been evaluated since the beginning of the accompanying research. Figures 3.4, 3.5, and 3.6 show results for the winter semester (WS) 2016.

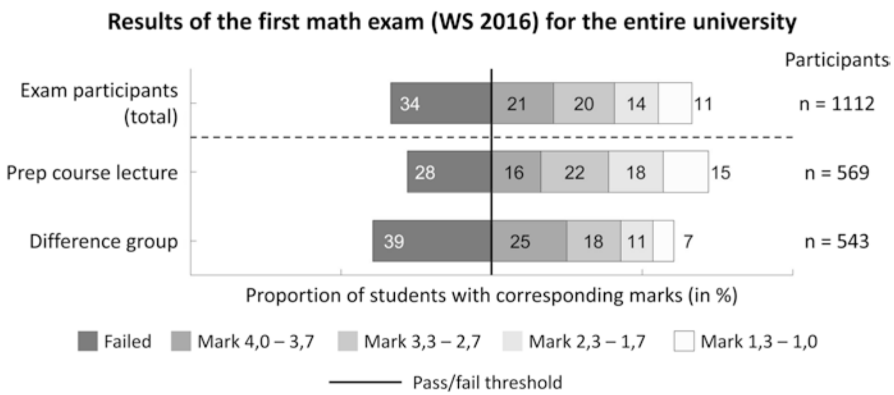

Fig. 3.4 Impact of participation in prep course lectures on the success at the first math exam

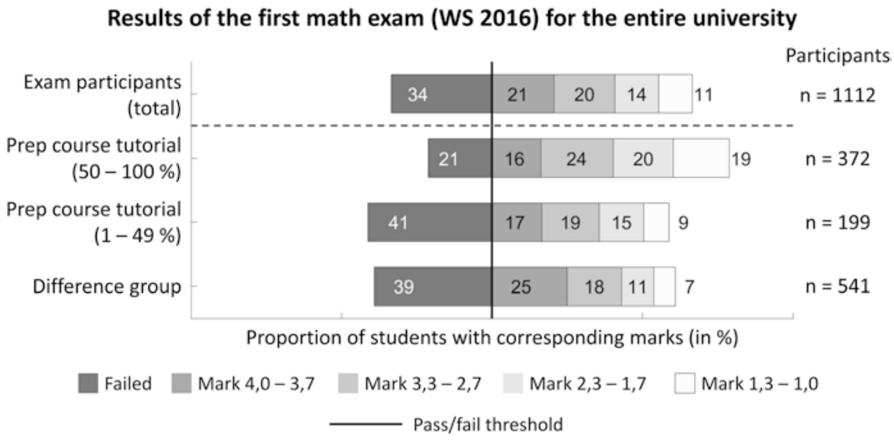

Fig. 3.5 Impact of participation in prep course tutorials on the success at the first math exam

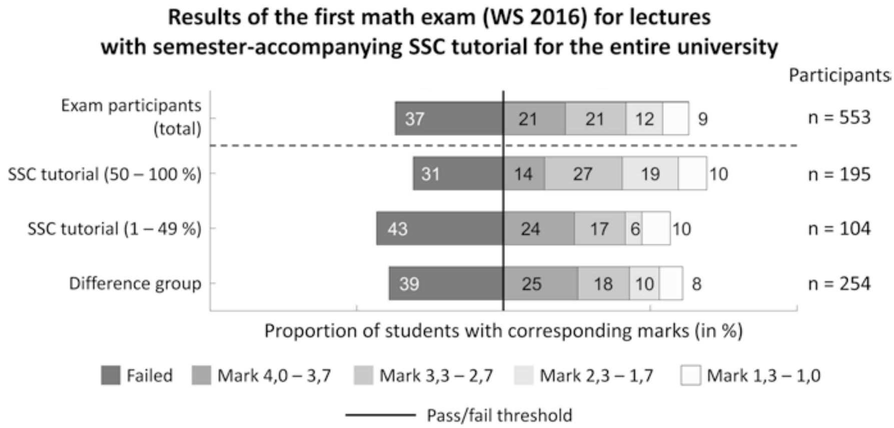

Fig. 3.6 Impact of participation in semester-accompanying tutorials on the success at the first math exam

Other semesters show comparable results. Figures 3.4 and 3.5 present the influence of the prep course participation on the success at the math exam. At the top of the figures, the results of all participants at the first math exam are visualized (*exam participants (total)*). In the middle, the results for those students who participated in the *prep course lecture* (Fig. 3.4) and the *prep course tutorial* (Fig. 3.5) are shown. The *difference group*, whose results are displayed at the bottom, includes all students who did not participate in the respective support measure or did not sign the SSC data privacy statement (SSC DPS). Figure 3.5 also distinguishes between those attending more (*50–100%*) or less (*1–49%*) than half of the prep course tutorials.

It has turned out that a regular participation in the prep course lecture (Fig. 3.4) and especially in the tutorials (Fig. 3.5) on more than half of the offered dates significantly correlates with better exam results. Note the low rate of 21% for failed exams in this group (Fig. 3.5).

Figure 3.6 displays the influence of a regular participation in lecture-accompanying tutorials during the semester. As not every mathematics lecture in the first semester can be supported by a tutorial held by the SSC for reasons of capacity, the total number of exam participants ($n = 553$) is lower than in Figs. 3.4 and 3.5. In Fig. 3.6 it contains only those students who had the possibility to attend a SSC tutorial. In this case, the difference group consists of all students having written the first math exam but never attended the SSC tutorial or did not sign the SSC DPS. It is also possible that students of this group took part in alternative tutorials that are held by students from higher semesters.

Figure 3.6 shows that a regular participation in semester-accompanying tutorials also correlates with the chance to pass the exam significantly. Of course, there are also students who do not make use of the measures and still perform well (see results of the difference group), as they master their mathematical content well.

For getting deeper insights, the sociodemographic background of the students is considered in the analyses (Nagengast et al., 2017). Figure 3.7 compares the distribution of the educational biographies (UEQ-types) of all *first-semester students* having signed the SSC DPS and the *participants of the first math exam* having signed the SSC DPS. For an explanation of the different UEQ-types and the German education system in general, see Eckhardt (2017).

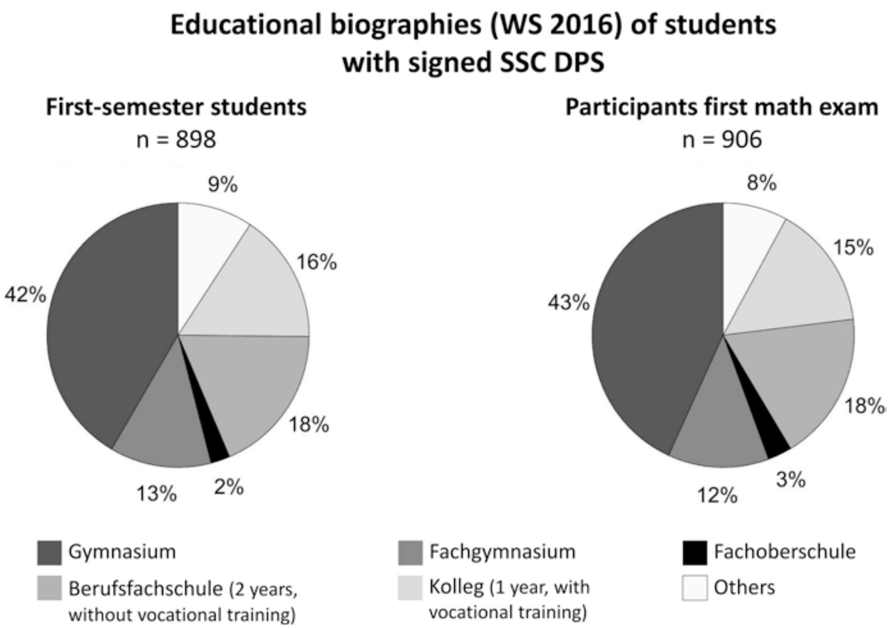

Fig. 3.7 Proportion of students with different educational biographies (types of UEQ) for all first-semester students (left-hand side) and all participants in the first math exam (right-hand side)

The diagrams in Fig. 3.7 show similar distributions of the educational biographies for all first-semester students (left-hand side) and for all exam participants (right-hand side). Furthermore, both groups consist of a similar number of students: The diagram on the left-hand side contains the educational biographies of 898 students, whereas the educational biographies of 906 exam participants (72 of them repeated the exam) were analyzed in the diagram on the right-hand side.

For further analysis of the relationship between the educational biography and the exam results, the group of participants in the first math exam (right-hand side of Fig. 3.7) is divided into students who passed the exam and those who failed it. Figure 3.8 shows that the group of students passing the exam contains a higher proportion of students with a general higher education entrance qualification gained at the "Gymnasium" (50%) or "Fachgymnasium" (12%) than the group of failing students (29% and 13%, respectively). This shows that it might be harder for students with specific educational biographies (e.g., "Berufsfachschule" or "Kolleg") to pass the exam and, therefore, specific support measures could be useful.

Table 3.1 shows for different groups the proportions of students having signed the SSC DPS in comparison to all students of the respective group. In the WS 2016, 85% of the students having passed the first mathematics exam have signed the SSC DPS. This means that 85% of the exam passers participated in the measures of the

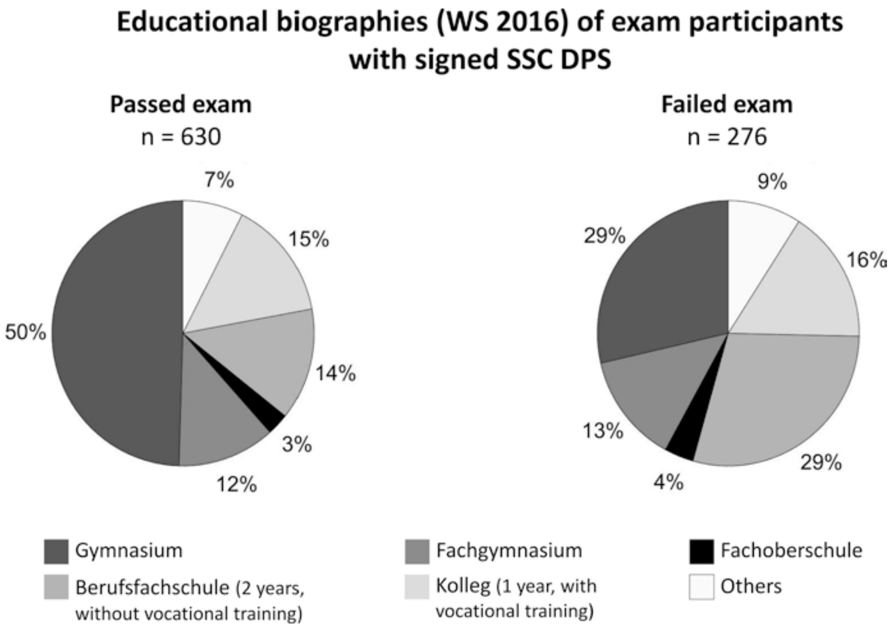

Fig. 3.8 Proportion of students with different educational biographies (types of UEQ) for the participants in the first mathematics exam having passed it (left-hand side) and having failed it (right-hand side)

Table 3.1 Overview over the numbers of first-semester students and participants at the first math exam and the respective number with signed SSC data privacy statement (SSC DPS) for the WS 2016

	Total number	Number with signed SSC DPS	Relative proportion of signed SSC DPS to total number
First-semester students	1326	898	68%
Exam participants	1112	906	82%
Passed exam	739	630	85%
Failed exam	373	276	74%

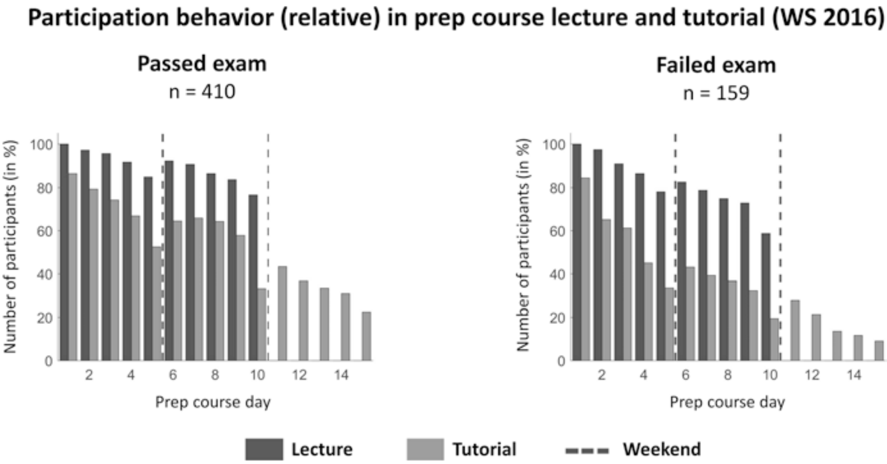

Fig. 3.9 Participation behavior in the prep course of students who passed the first math exam (left-hand side) and those who failed it (right-hand side)

SSC, e.g., by visiting the prep course or a semester-accompanying tutorial. In contrary, only 74% of the students who failed the exam took part in the SSC measures. Thus, the SSC reaches a larger share of students who pass the exam than those who fail. This also shows that participation in the SSC measures increases the chances of success in the first mathematics exam.

For a better understanding of bad exam results, further analyses can be helpful. Therefore, the participation behavior in the prep course (lecture as well as tutorial) was analyzed for the passing and the failing group. Figure 3.9 shows the relative participation numbers for each of the 15 prep course days for both groups, separated for lecture and tutorial. It should be mentioned that the third week of the prep course consists of tutorials only.

Figure 3.9 shows that students who passed the exam had a higher attendance rate at the lecture and especially at the tutorials than students who failed. This implicates that the revision of the mathematical basics and particularly the active practicing during the tutorials help to get better exam results. Additionally, it should be noted that the second prep course week contains also topics relevant to the first math exam which could also lead to better results for the participants.

The exemplary results presented give an idea of how LA can help to understand learning outcomes. At Aalen UAS such results are used to inform various stakeholders through a feedback system about first-year students, their in-depth knowledge of mathematics, and possible developments. The following section describes the levels to which this feedback system is directed.

3 Benefits of Learning Analytics at Aalen UAS for Different Stakeholders

This section presents the LA framework of Aalen UAS with its benefits for the four different stakeholder levels (cf. Fig. 3.1 or Ifenthaler, 2015). Figure 3.10 as an adaptation of Fig. 3.1 summarizes this LA framework graphically. It shows that the results of the analyses of the SSC's accompanying research are forwarded to the various stakeholders via a feedback system (feedback emails and reports). The LA engine on the right-hand side of Fig. 3.10 consists of two parts: the SSC and the mathematics online course. Both support the stakeholders. It should be noted that the SSC also uses its own analysis to reflect the impact of its support measures and to adapt and refine them according to the conclusions drawn. One of these adjustments was the development and installation of an online course for basic mathematics, which now also provides LA support (directly in form of a hint system and indirectly in form of user data). First analyses of the user data captured via the online course are presented in Egetenmeier, Krieg, Hommel, Maier, and Löffler (2018). The following subsections describe this feedback system for the stakeholder levels that are addressed at Aalen UAS.

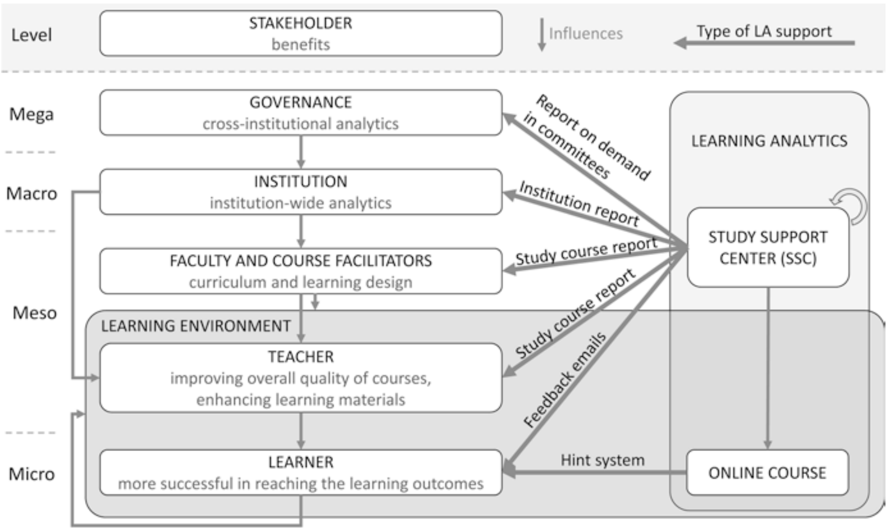

Fig. 3.10 Learning Analytics at Aalen UAS associated with stakeholder levels

3.1 Micro-Level

The intention of the micro-level analytics is to help the learner to achieve the learning outcomes more successfully. At Aalen UAS there are two types of LA micro-level support designed to improve students' basic mathematical skills. The first is the three-step hint system in the mathematics online course (Krieg et al., 2017), which gives hints to solve the tasks in various degrees of detail. This support works in real time so that students can use it directly while working with the online course. In addition, the online course can help students to better assess their own performance levels (Egetenmeier et al., 2018).

The second type of support at the micro-level are feedback emails sent to students taking part in the SSC's tests. These emails contain the individual test results of the students as well as the average results of all students who participated in the respective tests. By comparing their own results with the average of all participants, students get a first indication of how their performance compares to the group. In addition, the email contains a rating that communicates the expectations of the university. Moreover, the students receive specific information about which topics are not or only insufficiently mastered in order to repeat these topics in a targeted manner. Additional support includes links to prep course materials and to the mathematics online course that can help with the revision. The emails are sent to the students by the SSC once the correction of the prep course tests is complete. Fast feedback is important for achieving high effectiveness, allowing students to react quickly (Clow, 2012; Hattie & Timperley, 2007; Narciss, 2013) and increase study success. Due to the feedback, students shall be motivated to improve their mathematical skills independently and to internalize the mathematical basics in order to be able to better follow the lectures and to achieve better exam results. Analyzing the user data of the online course (cf. Egetenmeier et al., 2018) may give hints on the effectiveness of the feedback. In particular, it is of interest whether the frequency of participation in tutorials or of the use of the online course is altered by the feedback emails.

3.2 Meso-Level

The meso-level analytics supports two groups of stakeholders: faculty and course leaders and teachers. Both receive study course reports similar to the study course fact sheets of Pohlenz, Ratzlaff, and Seyfried (2012). These reports contain information on the composition of the first-semester group of the respective study course concerning educational biography (as in Fig. 3.7), the participation behavior in the prep course (as in Fig. 3.9), and their results and self-assessments in the SSC tests (as in Maier, Hommel, & Egetenmeier, 2018). The study course of interest is compared to the results for the entire university. A further description of the reports can be found in Maier et al. (2018).

The information contained in the reports is designed to raise the teachers' awareness of the heterogeneity of the student population in terms of their educational biographies, their mathematical prior knowledge, and their willingness to use support services. That way, teachers should be encouraged to adapt their lectures to the needs of the group, for example, through additional exercises or tutorials or through a basic introduction of specific topics that are not addressed in each type of school. In this way, the overall quality of the courses can be increased, so that the students can better follow the lecture.

Concerning faculty and course facilitators, the reports can support the curriculum and learning design. In particular, phenomena that span several semesters can be observed and taken into account in curricular adjustments. Examples are the introduction of additional tutorials, admission tests, or the attempt to motivate students to better use support services.

The SSC sends the reports to the person in charge at the beginning of the lecture period when the test correction of the prep course has been completed. This allows teachers to react to it already during the semester, which is essential for the LA project to be highly effective. At the beginning of the following semester, teachers receive a second report containing correlations of exam results with the participation in SSC support measures as outlined in Sect. 2.2.4 (Figs. 3.4, 3.5, and 3.6). This information can help in the long-term development of the study course. For privacy reasons, this information may only be shared with the teacher and not with the course facilitators.

Since two groups of stakeholders belong to the meso-level, the different reaction times of the interventions become clear (cf. Clow, 2012). While teachers can respond very quickly within the semester, but only reach the students in their course, faculty and course facilitators are more interested in long-term analyses that can affect course development and have an impact on a larger group of students.

3.3 Macro-Level

The macro-level LA support is an institution report that contains institution-wide analyses. On the one hand, it contains aggregated analyses for the entire university from the study course reports of the meso-level. On the other hand, further analyses such as the correlation of educational biographies and initial mathematical knowledge or examination results are included (cf. Nagengast et al., 2017). In addition, investigations of specific groups such as students who failed the exam are presented (see Sect. 2.2.4). Long-term analyses over several semesters should uncover trends that play an important role in future planning. This also includes the number of registrations for the prep courses or changes in the distribution of educational biographies of the freshmen. All this information can support decision-makers of the institution in strategic planning and further development of higher education. In this way, the SSC can contribute to quality management during the study entry phase (cf. Maier et al., 2018).

3.4 Mega-Level

LA support on the mega-level is expected to facilitate cross-institutional analytics. It should identify and validate patterns within and across institutions and help to inform educational policy-making (Ifenthaler, 2015). Concerning the mega-level, Aalen UAS presents the results of the evidence-oriented accompanying research in different committees, for example, the cooperation of schools and universities in Baden-Wuerttemberg (cf. Dürrschnabel & Wurth, 2015) or the University Federation SouthWest Germany (cf. Daberkow et al., 2015). In this way, the knowledge gained from the investigations can be communicated to other institutions and compared with their experiences. This could lead to cross-university measures that might also have an impact on educational policy. Thereby, the community of educational researchers also profits from the analyses.

4 Summary and Conclusion

High teaching quality, study success, and rising heterogeneity of students play an increasingly important role at UAS. Therefore, the SSC of Aalen UAS offers different measures for supporting students in the study entry phase. The positive impact of these support measures, e.g., on the results of the first mathematics exam, can be demonstrated by means of an evidence-oriented research based on an extensive database (Sect. 2). The results of these analyses can be helpful for stakeholders on different levels from students over teachers and faculty/university management to governance (Sect. 3). If each stakeholder uses the respective information, this can contribute to raising teaching quality and, thus, study success.

In order to achieve a high effectiveness, the SSC uses LA to reach all levels of decision-makers and stakeholders. Since many other LA-based projects or implementations only focus on one (or two) level, this provides the opportunity to reach the stakeholders with more impact as the results are accessible to each person included. In terms of Clow (2012), the loop of the LA cycle is closed. As stakeholders of the mega- and macro-level have a different view than the micro- and meso-level stakeholders, the focus of our research shifts from impact studies (micro-, meso-level) to long-term research (macro-, mega-level).

Although the LA framework of Aalen UAS is already very comprehensive, there are some limitations which can be improved in future. One obvious limitation of the feedback system in general is the lack of pedagogical recommendations (cf. Sect. 1.2). Hence, the implementation of a suitable advice system for each stakeholder could further improve the feedback system of the SSC.

The manual correction of the tests which serve as the basis for many analyses is another limitation because there is a certain time delay until the stakeholders receive the feedback and can react accordingly. As online assessment is getting more and more important, the transition from paper/pencil tests to online tests could help here to improve the speed of response and, therefore, the effectiveness. Furthermore, the availability of this user data may provide new insights into the learning process of students and lead to a further benefit for all stakeholders.

The LA framework of Aalen UAS is based on data and analyses of the accompanying research originally initiated for evaluating the effectiveness of the SSC's support measures. Therefore, the test concept and the type of data to be collected were chosen specifically in order to reach this aim. Since some aspects are not easily transferable (e.g., test concept, form of response) to other institutions, a "one-to-one" implementation of the model is not recommended. However, the research questions in general, the idea of evaluating support measures, analyzing learning behavior and study progress, as well as serving all levels of stakeholders with appropriate data are, of course, transferable. The basis for this is that concerns of data protection have been clarified. Depending on institutional conditions, some adjustments may be necessary. For large institutions, for example, the manual data entry reaches its limits. This could be overcome, for instance, by using online tests. Furthermore, the form of response and the presentation of the information may need adjustments.

Despite the limitations mentioned, the LA framework of Aalen UAS provides good approaches to a comprehensive model in the study entry phase. By implementing further improvements, this can contribute even more to increasing study success in the future.

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Chapter 4
Implementing Learning Analytics into Existing Higher Education Legacy Systems

Daniel Klasen and Dirk Ifenthaler

1 Introduction

The field of learning analytics (LA) is generating growing interest in data and computer science as well as educational science, hence, becoming an important aspect of modern digital learning environments (Ifenthaler & Widanapathirana, 2014). LA are often discussed and linked with regard to self-regulated learning where one general assumption is that each learning process demands a certain degree of self-regulation (Zimmerman, 2002). How effective a learner can regulate his or her learning depends on cognitive, motivational, volitional and metacognitive dispositions (Bannert, 2009). Accordingly, self-regulated learning can be seen as a cyclical process including three major phases: (1) starting with a forethought phase including task analysis, goal setting, planning and motivational aspects. (2) The actual learning occurs in the performance phase, i.e., focusing, applying task strategies, self-instruction and self-monitoring. (3) The last phase contains self-reflection, as learners evaluate their outcomes versus their prior set goals. To close the loop, results from the third phase will influence future learning activities (Zimmerman, 2002). Current findings show that self-regulated learning capabilities, especially revision, coherence, concentration and goal setting, are related to students' expected support of LA systems (Gašević, Dawson, & Siemens, 2015). For example, LA facilitate students through adaptive and personalised recommendations to better plan their learning towards specific goals (McLoughlin & Lee, 2010). Other findings show that many LA systems focus on visualisations and outline descriptive

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information, such as time spent online, the progress towards the completion of a course and comparisons with other students (Verbert, Manouselis, Drachsler, & Duval, 2012). Such LA features help in terms of monitoring. However, to plan upcoming learning activities or to adapt current strategies, further recommendations based on dispositions of students, previous learning behaviour, self-assessment results and learning outcomes are important (Schumacher & Ifenthaler, 2018). In sum, students may benefit from LA through personalised support and adaptive content recommendations throughout their learning journey.

One of the features with a high impact potential on this personalised support are prompts (Schumacher & Ifenthaler, 2018). Prompts are ad hoc messages which provide or request individualised information from the students. They can be used to offer hints to the current learning material, to trigger students' self-reflection on their learning process or to request student-specific information. At best, prompts are directly injected into the students' learning environment. Prompts are effective means for supporting self-regulated learning (Bannert, 2009). They are an essential instructional method for aiding certain aspects which are needed for self-regulated learning. Prompts support learners in activating their metacognitive strategies. These strategies make self-regulation, self-monitoring and evaluation possible (Ifenthaler, 2012; Veenman, 1993).

Davis (2003) investigated when (before, during or after the actual learning process) a prompt should be presented to the learner in order to achieve the best learning outcome. Accordingly, prompting depends on what the prompt is aiming at. If the aim is to promote the planning of the learning procedures, a presentation before the learning task is advisable. By contrast, prompting during the learning process is appropriate, when the learner is to be induced to monitor and evaluate learning procedures (Davis, 2003; Ifenthaler & Lehmann, 2012).

However, implementing prompts into existing legacy systems in learning environments with high data privacy concerns is quite a challenge. This research shows how a prompting application has been implemented into such an existing university environment by adding a plug-in to the local digital learning platform which injects user-centric prompts to specific objects within students' digital learning environment. In this paper, we describe the concept and implementation of the LeAP (Learning Analytics Profile) application including flexible prompting and present preliminary findings of the data we are able to generate.

2 Concept and Implementation

2.1 General Concept

The main idea of the LeAP application was to provide a system which can easily be embedded into the existing legacy environment of the university and is easy to maintain and to upgrade in future. Therefore, it had to fit into the world of legacy systems while simultaneously generate few dependencies to the other established applications.

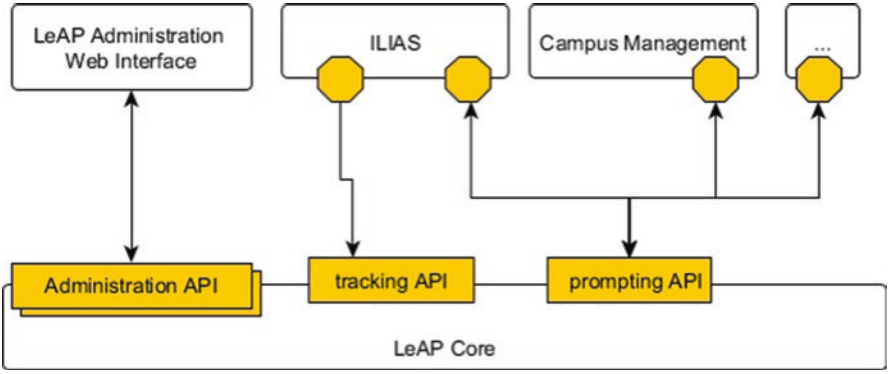

Fig. 4.1 Concept of the LeAP application

We therefore decided to split the solution into as many different modules as necessary. These modules communicate with each other via a RESTful API and can easily be improved or replaced without affecting the rest of the solution. LeAP can be divided into three types of components (see Fig. 4.1). The main part is the core module which holds the largest part of the business logic and deals with the connection to the database. It consists of several sub-modules which are quite independent of each other. Each of these modules provides a separate API to the other components. The second type of component are the plug-ins for the existing legacy applications. Currently, this is mainly the university's digital learning platform ILIAS (Integriertes Lern-, Informations- und Arbeitskooperations-System; www.ilias.de). As a further development, the integration into the campus management system and further applications like email or the university library are planned. The first plug-in was embedded into the web appearance of the digital learning platform. It gathers the system-specific user data and sends them to the LeAP core application. In addition, the plug-in checks the availability of prompts for the current user, injects the prompt into the web page and deals with the prompt's response. The third type of component are stand-alone web applications. At the current stage of the project, this only includes the administration web interface. It is a stand-alone web application, written with the Angular.js library which communicates with the core application via a separate administration API as shown in Fig. 4.1.

2.2 Data Privacy Issues

One of our main concerns was the handling of data privacy issues. As almost every LA feature collects and processes user data by default, it was inevitable to consider this topic, particularly in regard of the country's data privacy act and the requirements originated by the General Data Protection Regulation (GDPR) by the European Union. We decided to work within the running, productive environment of our university as soon as possible. Therefore, we were able to collect real data and were not biased by an experimental setting. But convincing the university's IT department to set up our solution within their running environment required additional security and privacy arrangements. Such issues have been documented in recent publications regarding ethical issues and privacy dilemmas in LA (Ifenthaler & Schumacher, 2016; Ifenthaler & Tracey, 2016; Slade & Prinsloo, 2013).

As shown in Fig. 4.2, we decided to use a pseudonymisation in two steps. Wherever we are in direct touch with the students' activities, we use a 32-bit hash value as an identifier. All tracking events and prompting requests use this hash value to communicate with the LeAP core application. The LeAP core API then takes this hash, enriches it with a secret phrase (a so-called pepper) and hashes it again. The doubled hash is then stored within the core's database. As a result, we can match new student-generated data to already existing data but are not able to directly trace back a specific student by a given date within the database.

Another benefit of the cooperation with the university's administration is that we do not need to collect demographic student data, as we can catch hold of them from the university's administration afterwards. We are able to receive this data pseudonymised in the same way, so it can be matched with the rest of our collected data. Upon completion of the current project phase, we will be able to combine the tracking data, the prompting feedbacks, the students' grades and demographic data for a full-featured analysis without need to have access to this personal data during the data collection phase.

2.3 LeAP Core

The LeAP core component is developed in Java and deployed as a Spring-Boot application. Spring-Boot applications are Java systems which use the spring web framework and are deployed with an integrated web application server. Therefore, they can be started as a separate process without the need of an extra web application server like Tomcat or Glassfish. In fact, a Tomcat, Undertow or Jetty web server is embedded directly into the executable java file when building the application (Spring Boot Project, 2018).

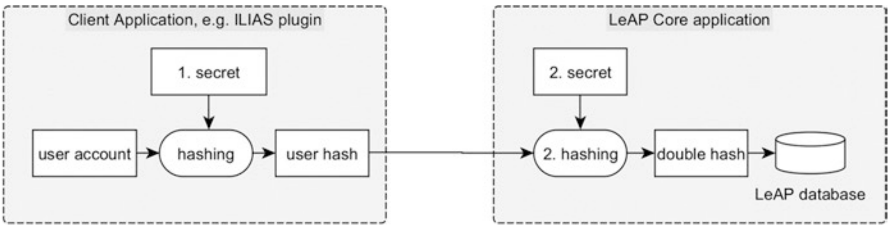

Fig. 4.2 Encryption of student's identity

The structure of the core component is built upon several disjoint modules as shown in Fig. 4.3. These modules offer a separate API to one of the other component types outside of the core. This independence of the modules ensures an easy maintenance and improvement of individual modules without interfering with each other. The application's core part offers a few functionalities which can be used by all modules. The core mainly consists of universally available data objects and database functionality. Beneath the data objects are students, courses, resources and events. In contrast, prompts are not part of the core and are organised within a separate module. Data stored in the application is categorised into two types.

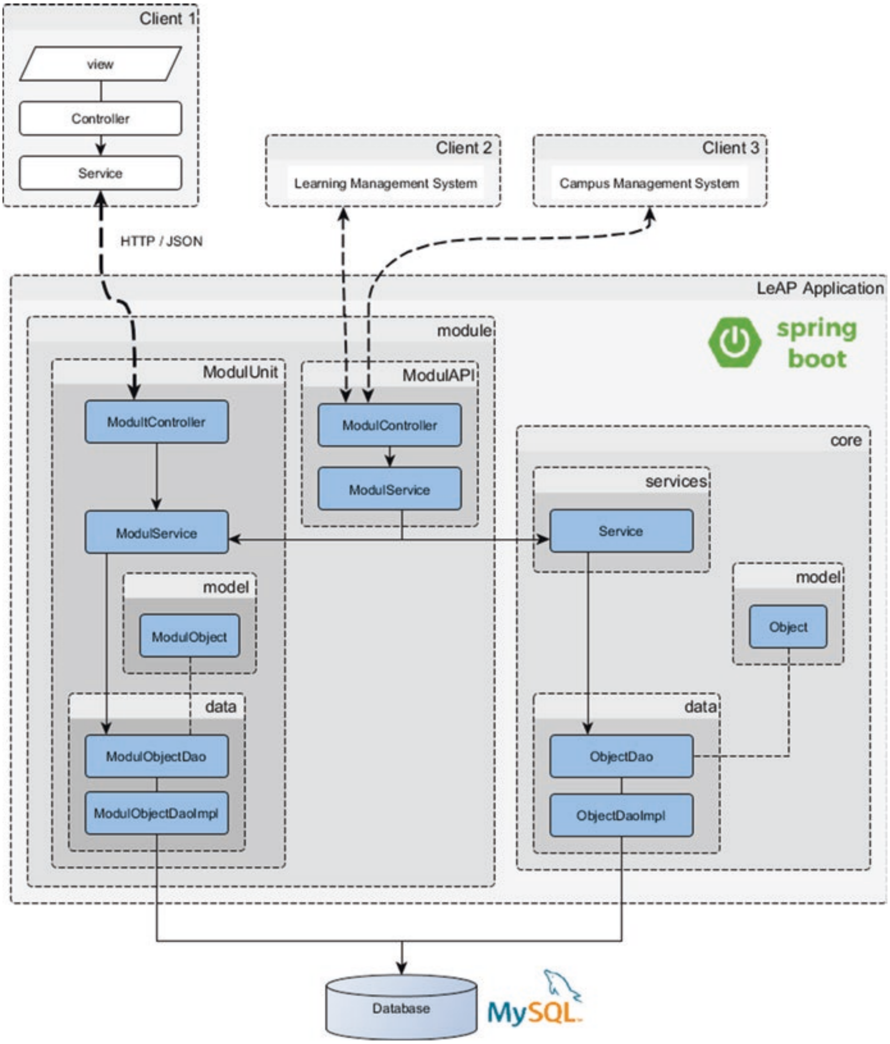

Fig. 4.3 Technical structure of the LeAP core architecture

The first type are resource data like courses and objects. These are stored with an obvious external relation to the object within the source system. For example, reading materials are stored with an external id, which is similar to the id given to the file within the e-learning platform. The second type of data are individual-related. Beneath these are the students themselves and events which can be assigned to them. These dates have no obvious relation to an external object. They are identified by an individual hash value which is built upon the student's university account and additional secret as described before. This data is not completely anonymous, but it ensures a certain amount of privacy through this pseudonymity. Thereby, new user-generated data can be connected to a specific hash; however, the user cannot directly be identified by this hash. Data like name, gender, or age are not stored within the LeAP core as they can be gathered from the university's administration later on.

For the projects pilot phase, we only use one instance of the core component which is responsible for the connection to the database and handles all data streams which occur in the current learning analytics environment. But the concept is oriented to duplicate this core component to spread data load and to approach a variety of security requirements. We operate one API at 24/7 which accepts the incoming tracking events and simultaneously operates an API for the lecturer's administration interface which can easily be taken down for steady improvements.

2.4 Plug-In for Digital Learning Platform

The student's first point of contact with the LeAP application is the learning management system. We developed a plug-in for our local learning management system ILIAS which coordinates the tracking and prompting within this system and allows students to choose their current tracking status. The plug-in is written as a UserInterfaceHook which adds a new function to the visible layout of ILIAS. The functionality can be enabled for a specific course, which allows the students to see a new tab 'LA-Profile' for setting their personal tracking status. These status are 'active', 'inactive' and 'anonymous'. While in status 'inactive', no data is tracked. In status 'active', the data is allocated to the described, individual, pseudonymous hash. Whereas in status 'anonymous', the data is tracked, but not allocated to a personalised id. As depicted in Fig. 4.4, additional JavaScript libraries for tracking and prompting are dynamically embedded during the rendering phase of the page. This new code is augmented with tracking and user information and handles the communication with the LeAP core application. Thus, the tracking and prompting features almost completely run within the user's web browser and do not interfere with the ILIAS system. As ILIAS is written in PHP, the plug-in is also written in PHP. The tracking and prompting libraries are asynchronous JavaScript.

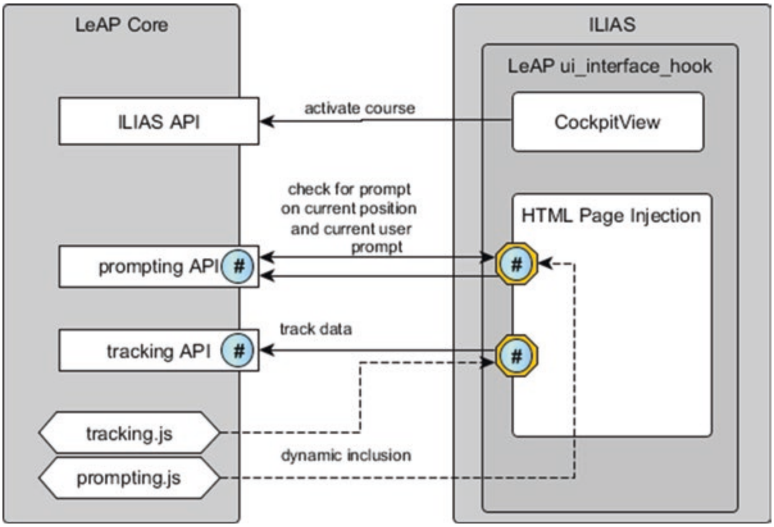

Fig. 4.4 LeAP plug-in figure for injection

2.5 Prompts

Besides the pseudonymous and anonymous tracking of the students' activities, prompting is currently the second main feature of the LeAP project. Tracking allows us to identify individuals, which should receive personalised prompts. For example, students who over- or underuse some of the learning features or materials. But prompts can also be given to a complete course. Prompts are always person and location related. We can put a prompt for every student at the start location of the course or position a prompt for an individual student to a specific learning material. The prompt is then fired when the student hits that location. But whereas the location is identified by an obvious identifier, persons are only visible in their hash value representation. No personal data like the name of the persons are available within the prompting functionality. Students can only be chosen by their course membership and activities.

When a prompt is fired, it is displayed as a small message window in an overlay above the active page as shown in Fig. 4.5. The underlying page is greyed out and cannot be used as long as the prompt is visible. The prompt can consist of a static information message, a question with a text input possibility, a question with a five-point Likert answer possibility, a checkbox or a combination of these. In addition, we can present a link to a research questionnaire which dynamically adds the student's personal hash value. Thereby, we are able to collect data for accompanying research without collecting the student's personal data or forcing them to reuse a given token. The various questionnaires are all brought together by the hash, which remains constant. Beside student and location, prompts can also be executed at a

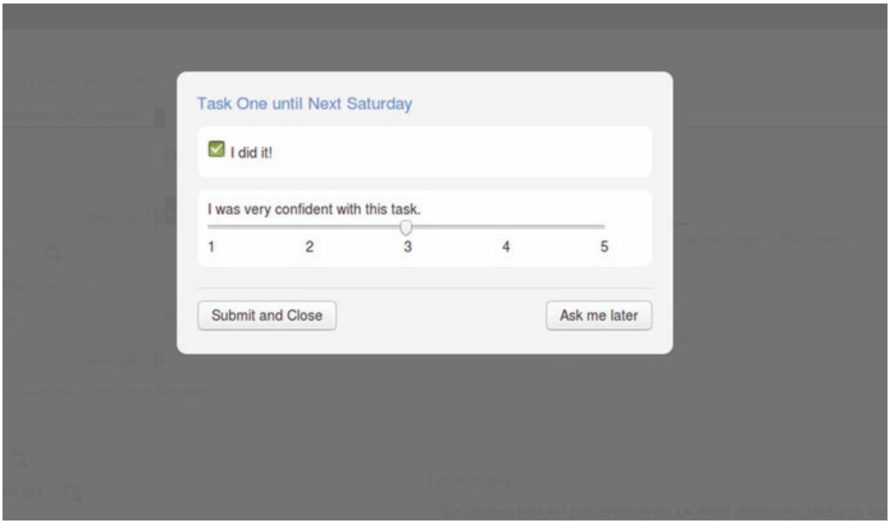

Fig. 4.5 Prompt example of a five-point Likert question

given time and for a given duration. Prompts can therefore be active for a few hours or several weeks. Multiple, different prompts can be active at the same time for several students.

3 Pilot Study

3.1 Research Focus

The pilot study focussed on the usability and practicability of the LeAP application. The research focus was to (1) validate the storage of tracking data, (2) performance of the prompting feature and (3) use of the privacy settings.

3.2 Tracking Data (RQ1)

Initial data was collected after the system was running reliably for 2 months (since the start of the fall semester 2017). It was activated in two courses with approximately $N = 400$ students. One course was in the field of economic and business education, the other in the field of computer sciences. We collected more than 120,000 events and tracked the usage of over 200 learning resources. The underlying technology stack works flawless. The collected data is reliable and satisfies the requirements for later analysis.

3.3 Prompts (RQ2)

During the fall semester 2017, we performed nine prompts in the productive learning environment. Each prompt lasted for 1 week. We prompted between 150 and 250 students and received response rates between 11% and 64%. The handling of the prompting tool is flawless. The pilot lecturers had no difficulties to create, manage and submit their prompts. The prompts have been widely accepted and we received no information about noticeable difficulties. Additional survey data is currently analysed which investigates the students' perception towards learning support of the prompts.

3.4 Data Privacy (RQ3)

The default tracking for students' data at the beginning of the semester is set to 'anonymous'. The students are free to change this to 'active' or 'inactive' at every point in time. We informed them several times about the functionality and options. Indeed, we informed them that it is an active research project and would be happy to have as much participants as possible. But we also guaranteed that we are not able to identify the individuals until the end of the semester and therefore it could not have an influence on their grading or future studies. After 3 weeks, we had $n_a = 65$ active students, $n_i = 4$ inactive students and $n_n = 348$ anonymous students.

4 Discussion

4.1 Data Privacy

As we are seeking to provide a full learner centric system in the future, our approach starts with the learners' decision to provide their learning progress data. The solution with using a MD5 hash value of the students' university accounts at the front, and a doubled hashed value in the core application ensures a satisfying amount of privacy for the projects pilot phase (Ifenthaler & Schumacher, 2016). We are able to compute an anonymous, complete, coherent dataset at the end of the semester, without the need to store critical, personal data during the semester.

But as a MD5 hash is not unique, it exists a minuscule possibility to dilute our dataset. In theory, two different university accounts could be hashed to the same value. The current system would not be able to separate them. Nonetheless, this probability is quite low. The hashing and merging of the different data sources is therefore a topic of current research in our project.

The students appreciate the option to include or exclude themselves from the data tracking but mostly ignore this possibility and stay in status 'anonym'. To what

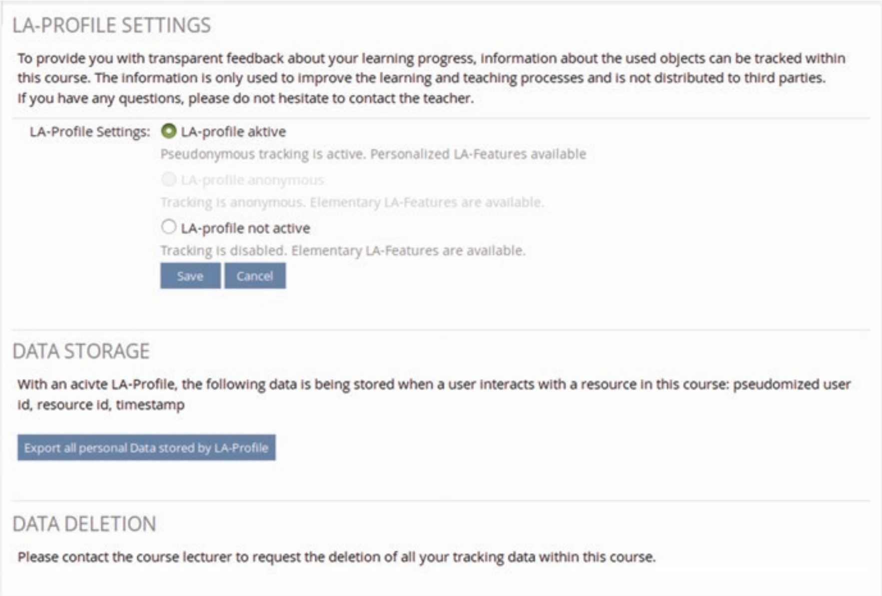

Fig. 4.6 Screenshot of the privacy feature of the LA dashboard

extent this is based on an active decision or passive laziness is a topic of further investigation and depended on their individual privacy calculus for disclosing personal data (Ifenthaler & Schumacher, 2016).

After a qualitative follow-up study with participants in the first semester and an in-depth conversation with experts in data protection and privacy regulation, we decided to change the privacy settings including two options (see Fig. 4.6): (1) LA profile active including anonymous tracking and personalised support and and (2) LA profile not active including no tracking but basic LA features, e.g., personal goal setting or reminders. We also updated the data privacy setting to be compliant with the GDPR which requires that students may export all stored data as well as may request to delete all stored data (see Fig. 4.6).

4.2 Impact of Prompts on the Learning Progress

As this part of the project started just at the beginning of the fall semester 2017, we are not yet able to provide convincing insights regarding the impact on the students' learning progresses. We are currently performing a larger research study focussing on the learning support, acceptance and learning outcomes of the students. Beside the prompts within the productive digital learning environment, we set up a dedicated copy of the university's learning platform and used this laboratory system to investigate the impact of different prompting types on the students learning progress under laboratory conditions with various experimental groups.

5 Conclusion

We implemented a tracking and prompting solution into the existing digital learning infrastructure of our university by injecting the respective functionality through separate JavaScript libraries into the legacy systems. By tracking the students via a pseudonymous hash, we are able to collect students' data throughout various systems without the necessity to collect further personal data (Ifenthaler & Schumacher, 2016). We are further able to merge this data with other university known data like demographic data and grades at the end of the semester into a complete, anonymous dataset for further investigation.

The solution is used to perform various educational research studies, focussing on effects of prompting for self-regulated learning (Bannert, 2009). We are further planning to extend the various LA features. The next step is the extension of the students' direct feedback. The students will get a more transparent feedback on the amount and type of data which was collected and how this data can be allocated to their current learning processes (see Fig. 4.7). Furthermore, we will steadily improve the application and plan to extend the area of research to more courses in the following semester. Another development includes a teacher application for insights into individual learning processes, opportunities to interact with students whenever needed (Kuhnel, Seiler, Honal, & Ifenthaler, 2018) and further developing learning materials and curricular planning (Ifenthaler, Gibson, & Dobozy, 2018).

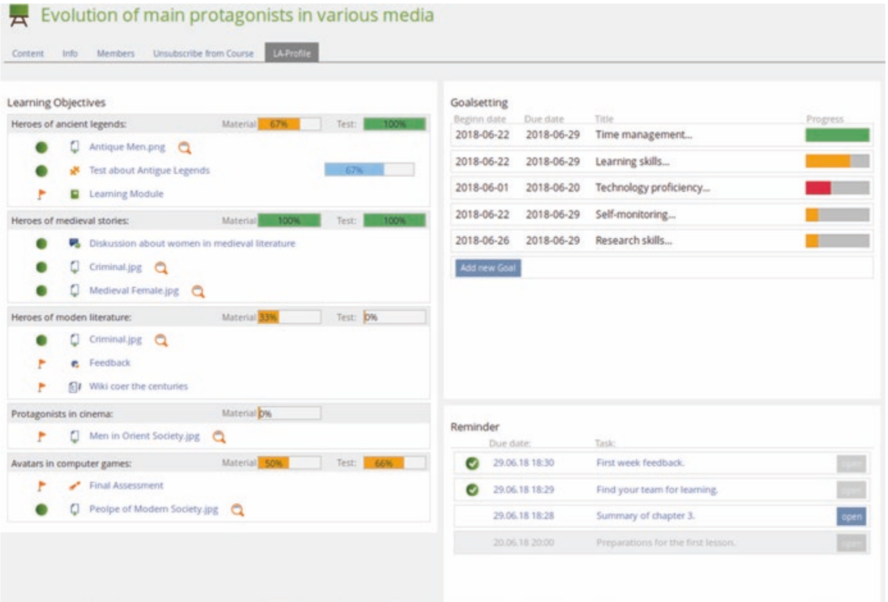

Fig. 4.7 Overview of the LA student dashboard as plug-in of the digital learning management system

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Chapter 5
When Students Get Stuck: Adaptive Remote Labs as a Way to Support Students in Practical Engineering Education

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1 Introduction

The field of computer science has to deal with a relatively high number (over 40%) of dropouts at German universities (Heublein, 2014). However, dropout in computer science is not only a problem at German universities but also in other European countries (Kori et al., 2015) or in the USA (Talton et al., 2006). The dropout rate of female students is often even higher than that of their male fellow students (Talton et al., 2006), which might be a result of being underrepresented in the discipline (Cox & Fisher, 2008). The reasons for dropout are complex. Most often the students have false expectations about the contents of study, which lead to motivational problems, or they are frustrated due to high performance requirements. At the same time, the increasing heterogeneity of students leads to dropouts, in particular due to problems with different prior knowledge but also because of sociodemographic factors, e.g., an increasing number of students who have to balance study, work, and/or parenting (Isleib & Heublein, 2017). Especially, prior knowledge and academic preparedness of students are correlated with retention in computer science programs (Horton & Craig, 2015; Kori et al., 2015; Talton et al., 2006). Also motivation and interest of the students play an important role. The higher the motivation and interest in the content, the lower the probability of dropout (Kori et al., 2015, 2016).

The situation at course level is similar. Within a meta-analysis in 161 introductory programming courses in 15 countries worldwide, Watson and Li (2014) revealed a dropout rate of approximately 32%. The percentage of students who

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did not pass the introductory programming course remained nearly constant between 1980 and 2013. There were no significant differences in dropout rates with regard to programming language taught. Furthermore, while the authors found significant differences between the dropout rate in the different countries (Portugal and Germany had the highest dropout rates with over 50%, whereas Canada and Taiwan, e.g., had noticeable lower rates of about 20%), because of small sample sizes, these results should not be overestimated or generalized. If reasons for dropout are already reflected on the course level, this could be a starting point for providing individual support to students who have a higher probability of dropping out. With the help of learning analytics, it becomes possible to detect students at risk automatically (Papamitsiou & Economides, 2014). Learning analytics is the collection, storage, analysis, and evaluation of learner data to optimize learning and learning environments (Ferguson, 2012). A growing number of universities all over the world already use the data generated by their students for the evaluation of teaching, the provision of adapted content, and as an early warning system. The latter, for example, filters out students at risk of dropping out on the basis of their activities in the learning management system, e.g., time spent in exercises or quizzes (Arnold & Pistilli, 2012). There are different options to support these students: lecturers probably offer additional material or repeat the basics for the course or individual students. The additional effort addresses the specific needs of the learners, for example, concerning the sequence, difficulty, or scope of content (Leutner, 2002; Melis et al., 2001; van Seters et al., 2012). The goal of implementing adaptivity is to facilitate individualized learning environments to support efficient and effective learning and avert high dropout rates. If it is possible to identify the needs of users on the basis of patterns of user behavior, it is also possible to implement a more fine-grained form of adaptivity without the usage of assessment tests and questionnaires. The challenge here is that knowledge about user behavior, which reveals students at risk might not be sufficient for helping these students. To give an example, on the basis of user behavior, it is not directly evident whether a user spends little time on an exercise in the learning management system and has a result below average in an accompanying quiz because (1) he is demotivated because the task is to difficult or (2) he had too little time because he had to work to finance his study or (3) he is frustrated due to low usability of the learning management system or (4) for any other reasons. Different reasons for an undesirable user behavior require a different reaction of the learning system or the lecturer. This is only possible if the underlying causes are known. While user behavior alone can provide evidence that there are problems in the learning process and that intervention might be necessary, the choice of what type of intervention is needed will usually not be based solely on user behavior. Therefore, in this study, we will start at an earlier point of the analytics and begin by examining which learner characteristics are relevant for dropout in a blended-learning course in computer science. In a second step, we examine whether user behavior is related to such factors and/or to dropout rates.

2 Dropout in Blended Learning

In computer science, as in other STEM subjects, studying in laboratories is especially important. In these laboratories theory and practice are combined, and students acquire practical skills for their professional career. Blended learning is a promising approach for a laboratory learning setting. Blended learning is the attempt to combine the time in the course on-campus, which is highly relevant for the learning performance (Schneider & Preckel, 2017; Schulmeister, 2017), with the advantages of online learning, such as greater local and temporal flexibility of the students. In comparison with courses that take place only online, the dropout rates in blended learning are lower, presumably due to the regular face-to-face time with the lecturer and other students (Park & Choi, 2009). Results from studies suggest that blended learning might also be superior to courses without any online learning, i.e., which only take place on-campus (Al-Qahtani & Higgins, 2013; Bernard, Borokhovski, Schmid, Tamim, & Abrami, 2014; López-Pérez, Pérez-López, & Rodríguez-Ariza, 2011). The remote control of a laboratory (via web interface) provides students with experiences and competencies they will need in a digitized workplace. In addition, there are the advantages already mentioned: Students can access the learning environment regardless of location and time and are not bound to limited laboratory hours. They can work in the laboratory as often and as long as necessary for their individual learning processes. However, despite the advantage of blended learning, to combine the best of e-learning and face-to-face-learning, the online phase is still a challenge because there is no direct contact between the lecturer and the students. Thus, the probability of problems (e.g., if code is not doing what it is supposed to do) leading to frustration and in the long run to dropout is much more likely to occur than in face-to-face time on campus with the possibility of direct feedback and help. In the scientific literature, different factors in the use of digital learning environments are examined with regard to the dropout rate. Park and Choi (2009) distinguish factors that affect the decision to drop out in those that occur prior to the course and those that are relevant during the course. Factors prior to the course are sociodemographic variables. Often, studies hereby focus on age and gender (Marks, Sibley, & Arbaugh, 2005). Factors which affect the possibility to drop out during the course can be distinguished in external factors resulting from influences from outside the course, e.g., family time constraints and job working hours. Internal factors arise from the student's engagement with the learning setting and the digital learning environment. Learners are not a homogenous mass. There are differences in cognitive and affective variables (Narciss, Proske, & Koerndle, 2007), affecting the perception and the effects of a learning environment, for example, whether the instructional design fits the needs of the learner or whether usability issues might result in a lack of motivation. In this study we focus on the internal factors because these are especially important for gaining insight into the learning processes and related factors which are relevant for the decision to dropout (see also the results from Park & Choi, 2009).

With regard to the internal factors, we can distinguish approaches that have a focus on motivational components of learning and approaches with a focus on cognitive processing.

2.1 Motivation and Dropout

Motivation is a basis for learning. Motivation determines whether and how learners (1) deal with the content and (2) use a digital learning environment. Some studies target learners' satisfaction, which in fact appears to have a relevant impact on the dropout rate (Fredericksen, Pickett, Shea, Pelz, & Swan, 2000; Park & Choi, 2009). The more satisfied learners are with the learning environment, the lower the likelihood of dropouts (Levy, 2007). However, satisfaction is a very broad concept that can be influenced by different underlying factors. This is also reflected in questionnaires used in some of the studies, which integrate items for ease of use, usefulness, intrinsic motivation, and social interaction (Levy, 2007). In this study we want to analyze different facets of motivation in order to adapt interventions more precisely to the learners needs. Therefore, we focus on the technology acceptance model which highlights the relevance of user evaluations of learning environments against the background of a cost-benefit model of motivation. Relevant questions for the user therefore are: Is the digital learning environment useful for me? Is the effort I have to invest justified in the light of the benefits? The Technology Acceptance Model (TAM) and the further developments, like TAM2 and UTAUT, have gained particular influence concerning studies on the behavioral intentions to use and the actual usage of software (Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Furthermore TAM is also used to analyze and explain the effectiveness of digital learning environments (Legris, Ingham, & Collerette, 2003; Liaw, 2008). Perceived usefulness and perceived ease of use are the most influential factors in the model. The more satisfied a learner is with the usefulness and ease of use of a digital learning environment, the higher the persistence of the learner and the lower the dropout rate (Joo, Lim, & Kim, 2011; Park & Choi, 2009). The self-efficacy of learners in dealing with the learning environment or requirements of the content seems to be a crucial intervening variable (Liaw, 2008; Schneider & Preckel, 2017; Wu, Tennyson, & Hsia, 2010). Additionally learners can also be highly motivated when dealing with a digital learning environment because they are interested in the content and/or they enjoy working on the tasks, i.e., they have intrinsic motivation. The benefits that intrinsically motivated learners derive from engaging with the remote lab are thusly less focused on outcomes, but more on intrinsic incentives of the activity as such. The assumption that learners with more intrinsic motivation drop out less frequently and have a higher learning performance is obvious (Giesbers, Rienties, Tempelaar, & Gijselaers, 2013; Law, Lee, & Yu, 2010).

Accordingly our first research question is as follows: Do persistent learner and dropouts show differences concerning motivational variables as perceived usefulness, ease of use, intrinsic motivation, and self-efficacy?

2.2 Cognitive Load and Dropout

Based on the assumption of a limited cognitive capacity in working memory, research on cognitive load theory (CLT) tries to identify instructional designs which make the usage of cognitive resources for dealing with information as efficient as possible (Plass, Moreno, & Brünken, 2010; Schnotz & Kürschner, 2007; Sweller, Ayres, & Kalyuga, 2011). CLT differentiates between different kinds of cognitive load (Kalyuga, 2011). Extraneous cognitive load (ECL) is caused through suboptimal design of an instruction. An inefficient design requires cognitive capacity that is not due to learning but due to other cognitive activities. During learning extraneous cognitive load should be as low as possible, ensuring that more cognitive capacity is available for the learning processes. Intrinsic cognitive load (ICL) on the other hand is caused by complexity of task and information, especially by the number of interrelated elements that have to be processed simultaneously for understanding the content (element interactivity). However, ICL depends also on the prior knowledge of the learner. More experienced learners have knowledge structures stored in long-term memory, which help them to process and organize novel information in working memory. Therefore, they are able to treat single elements of a task as a whole element (or schema) which in fact leads to decreased element interactivity (Chen, Kalyuga, & Sweller, 2017). Research consistently reveals that to take the domain-specific prior knowledge into account is of high relevance for efficient instructional design (e.g., Chen, Kalyuga, & Sweller, 2017; Kalyuga, 2007; Schneider & Preckel, 2017). Depending on prior knowledge, the learner needs more or less support to process the learning content and to avoid cognitive overload or boredom. Additionally, prior knowledge seems to have a compensation effect: learners with low prior knowledge highly depend on appropriate instructional design to reach an optimal learning performance, while learners with higher prior knowledge could also deal with poor instructional design, e.g., an instructional design which causes a high amount of extraneous cognitive load (Kalyuga, 2007).

In CLT some researchers assume a third type of cognitive load, namely, germane cognitive load, which is caused through schema acquisition; however, there is an ongoing discussion about the necessity to distinguish between intrinsic and germane cognitive load. A reconceptualization of germane cognitive load as germane processing, e.g., the amount of mental effort invested dealing with intrinsic cognitive load goes hand in hand (Kalyuga, 2011; Leppink, Paas, van Gog, van der Vleuten, & van Merriënboer, 2014; Sweller, Ayres, & Kalyuga, 2011). The mental effort learners invest in the cognitive processing of learning content is on the other hand a question of motivation (Bures, Abrami, & Amundsen, 2000). Although the influence of motivation on the amount of invested mental effort was considered in research on cognitive load early on (Paas, Tuovinen, van Merriënboer, & Darabi, 2005; Moreno, 2006), there is still a research gap (Leutner, 2014; Mayer, 2014; Park, Plass, & Brünken, 2014). Leppink et al. (2014) examine an interesting approach by operationalizing germane cognitive load (or rather germane processing) with items that apparently measure the perceived usefulness of the content for the learning process. This way they implicitly implement a factor which is highly relevant for motivation as is already mentioned in the context of TAM. However, in their study they found no significant correlation between germane cognitive load (or usefulness respectively) and the learning performance.

Whereas it seems plausible that the amount of extraneous cognitive load and germane processing is crucial for students dropping out or persisting, there are no empirical results yet. The potential effects of prior knowledge seem to be especially important. In computer science, there are students in the first semester that have been programming for years, attending hackathons, and using GitHub, while others are just beginning with their first “Hello World.” Since the remote lab is a complex learning environment in which students actively solve problems and thereby explore and construct knowledge, it is cognitively very demanding in particular for novice learners. Results of a study on a remote lab indicate that the learning performance of the students at least partially depend on their prior knowledge (Zug, Hawlitschek, & Krenz, 2017). Students with lower prior knowledge have lower grades in the exam. However, it is not clear if this effect also is transferrable on dropout rates.

So our second research question is: Do persistent learner and dropouts show differences in cognitive variables like extraneous, intrinsic, and germane cognitive load and their prior knowledge?

2.3 User Behavior and Dropout

Programming is an iterative process, in which the functionalities are implemented as features, step by step. It is common to write a part of a program, for example, a function or a class, with its basic components first and check if the execution of the program with the inclusion of the new code works. If the execution or compilation fails, the code needs to be revisited and amended. As soon as the program compiles with the new code, the complexity of the function or class can be extended, or new features can be implemented. Rinse and repeat.

An experienced programmer will add several lines of code before checking its correctness by trying to compile the code, while a novice might only add a few lines or commands before compilation, since it is easier to isolate the cause of an error with the latter strategy. It could be expected that an experienced programmer’s code revisions would grow faster and have fewer failing builds, the time spent between builds would tend to be longer, and the amount of added lines per revision would be higher, than it would be expected for an inexperienced programmer. Especially situations where the code compilation fails several times in succession, we consider to be of high relevance. This could be an indication for an inexperienced programmer, who fails to interpret the error messages in a way that would allow them to get the code working. The complex process of writing program code could thusly be reduced to the occurrence of such error streaks, in order to classify persons as experienced and inexperienced programmers on a macro level. On a micro level, a system that is aware of the error streak concept could provide assistance to students that are currently stuck.

Therefore, the third research question is: Do dropouts and persistent learners show differences concerning the probability of an error streak? Is the probability of an error streak related with prior knowledge?

In the following sections, we will examine how students who have successfully completed the entire course (i.e., got a participation certificate) differ from students who left the course at any point in time. On the basis of the findings, an adaptation to the needs of specific target groups can take place.

3 Study

3.1 Description of the Course

The subject of the study is a course at the Faculty of Computer Science of a German university. The investigated course started with 70 students in the first lecture, 22 of them dropped out prematurely. So, the dropout rate in this course was about 31%. This is slightly better than the general dropout in computer science, but there is still much room for improvement.

The course conveys the fundamentals of embedded systems in theory and practice. In addition to a lecture and weekly appointments with tutors, the students had to program real robots located in the laboratory via remote access in five exercises. These practical exercises are built on each other. Whereas in the first exercise the students only had to establish a connection to the robots, in the last exercise they had to program the robots to escape from a maze. The program code has to be developed in C++ for Atmel microcontrollers.

For the exercises we provided a digital learning environment with task description and literature on the one hand and a programming interface with livestream from the robots on the other hand. The students prepared their code, compiled it, and sent the executable to one of the robots. Based on outputs and by the video stream, the students evaluated the correctness. At the end of each exercise season (2–3 weeks), the program code and the results are checked by a tutor.

3.2 Methods and Instrumentation

The study was conducted in the winter term 2017/2018 (see Fig. 5.1). During the first lecture, the students filled out a quantitative questionnaire concerning their prior knowledge and sociodemographic variables. The prior knowledge test consisted of two parts. The first part was a multiple-choice test based on the content of the course. The test was supplemented by two code snippets in the programming language Java, whose functionality the students had to evaluate. In the second part, the students had to self-esteem their prior knowledge concerning different thematic fields of computer science as well as their general programming skills in comparison with their fellow students (Siegmund, Kästner, Liebig, Apel, & Hanenberg, 2014).

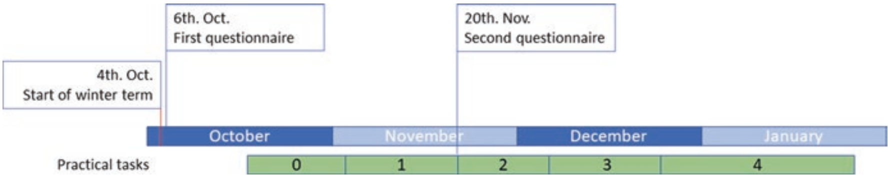

Fig. 5.1 Procedure of course and study

The second questionnaire was submitted after the second exercise. In this questionnaire the students had to rate their intrinsic motivation while working on the exercises in the remote laboratory (based on Isen & Reeve, 2005) and the ease of use of the learning environment (Legris, Ingham, & Collerette, 2003). The extraneous and intrinsic cognitive load as well as the germane cognitive load was examined with an instrument by Leppink et al. (2014). For the measurement of ECL and ICL, we used the original questionnaire. For the measurement of GCL, we used one item to measure perceived mental effort in understanding the content ("I invested a very high mental effort in enhancing my knowledge and understanding."; see Leppink et al., 2014, study 2). We applied the remaining items to operationalize the perceived usefulness of the learning environment. While usefulness in TAM studies is usually operationalized in terms of software efficiency measures (Legris, Ingham, & Collerette, 2003), concerning genuine learning environments and in the context of our thematic focus on dropout, this operationalization seems more appropriate to us. We used a Likert-type rating scale ranging from 1 (very low) to 5 (very high).

The remote system used in our project stores the whole programming code, whenever the user starts the compilation process, alongside the messages the compiler returned: error messages, warnings, and compiling reports. For the analysis presented in this article, we transformed these detailed information into a vector of consecutive build statuses, classifying each compilation attempt as failing or successful. As a next step, we calculated the probabilities of one status turning into the other or staying the same. These probabilities can be visualized as a simple network plot.

3.3 Sample

In the first questionnaire 58 students (f, 8; m, 49; missing, 1) with a relatively homogeneous age (M = 23.6; SD = 4.2) took part. The second questionnaire was accomplished by 37 students (f, 4; m, 28; missing, 5). The participants were students of the 3rd to 5th semester. The majority were undergraduate students from computer science (80.7%); additionally, there were 10.5% students from computer systems in engineering (B.A.) and some from other computer science-related bachelor programs.

4 Results

With analyses of variance (ANOVA), we examined the differences between students who dropped out and students who persisted. The results of the prior knowledge test revealed higher means for the persistent students ($M = 8.45$; SD = 3.89) in comparison with the dropouts ($M = 6.76$; SD = 3.65), but no significant differences between both groups ($F(1.55) = 2.60$, $p = 0.11$, $\eta^2 = 0.05$). The self-estimation of their prior knowledge on different thematic fields in the context of the course also showed no significant differences (see Table 5.1).

Concerning the self-estimation of the programming skills in comparison to the fellow students, the means were nearly the same in both groups. There was no significant difference ($F(1.54) = 0.00$, $p = 0.95$, $\eta^2 = 0.00$) between dropouts ($M = 2.95$; SD = 0.89) and persistent learners ($M = 2.94$; SD = 0.95).

We applied a principal component analysis (with oblimin rotation) to analyze the items we used for measuring ease of use. Two components were extracted, which could be interpreted as actual ease of use (e.g., "The remote lab is easy to use.") and technical reliability (e.g., "The remote laboratory has worked reliable."). The results of the group comparisons on the motivational variables showed higher means for the persistent students in intrinsic motivation and ease of use. However the ANOVA yielded no significant difference between the groups concerning motivational variables (Table 5.2).

Table 5.1 Prior knowledge group comparison

Variables	Dropout learners ($N = 22$)		Persistent learners ($N = 35$)				
"Please rate your prior knowledge concerning …"	M	SD	M	SD	F	p	η^2
Roboter applications	2.14	1.24	1.83	1.24	0.82	0.36	0.02
Embedded controller/boards	2.05	1.04	1.91	1.17	0.18	0.67	0.00
Embedded operating systems	1.45	0.96	1.37	0.64	0.15	0.69	0.00
Smartphone apps	2.00	1.19	2.31	1.07	1.05	0.30	0.02
Web front end	2.86	0.99	2.43	1.19	2.03	0.16	0.04

Table 5.2 Motivation group comparison

Variables	Dropout learners		Persistent learners				
	M	SD	M	SD	F	p	η^2
	$N = 21$		$N = 34$				
Self-efficacy (Cronbach's alpha, 0.86)	3.27	0.84	3.39	0.79	0.29	0.59	0.00
	$N = 9$		$N = 27$				
Intrinsic motivation (Cronbach's alpha, 0.90)	3.39	0.70	3.74	0.78	1.29	0.26	0.04
Ease of use (Cronbach's alpha, 0.89)	4.00	1.02	4.55	0.78	2.61	0.11	0.07
Technical reliability (Cronbach's alpha, 0.86)	2.62	1.18	2.67	1.03	0.01	0.91	0.00
Perceived usefulness (Cronbach's alpha, 0.84)	3.34	0.32	3.67	0.88	1.07	0.30	0.03

Table 5.3 Cognitive load group comparisons

Variables	Dropout learners ($N = 9$)		Persistent learners ($N = 26$)				
	M	SD	M	SD	F	p	η^2
Intrinsic cognitive load	3.60	0.82	3.05	0.82	2.73	0.10	0.08
Extraneous cognitive load**	3.87	0.81	2.54	1.05	10.75	0.00	0.25

$^{**}p < 0.01$

We applied a principal component analysis (with oblimin rotation) to analyze the items for measuring extraneous, intrinsic, and germane cognitive load. Against our expectations, the analysis only yielded two components—intrinsic cognitive load (Cronbach's alpha, 0.86) and extraneous cognitive load (Cronbach's alpha, 0.87). The item for measuring germane cognitive load actually loaded on the intrinsic cognitive load component.

The group comparison yielded higher means for the dropout learners for both load types (Table 5.3). However, the results of the ANOVA revealed a significant difference between the groups only concerning extraneous cognitive load.

We analyzed the differences between both groups concerning the probability of error streaks with ANOVA. Indeed the means for the dropout learners ($N = 14$, $M = 0.41$, SD = 0.14) were significantly higher $F(1.53) = 8.14$, $p = 0.00$, $\eta^2 = 0.14$) than for the persistent learners ($N = 40$, $M = 0.24$, SD = 0.17). With a regression analysis, we checked whether prior knowledge had a significant effect on the probability of error streaks. Indeed our finding indicate that students with lower prior knowledge had a higher probability of error streaks ($b = -0.29$, $t = -1.96$, $p = 0.05$, $R^2 = 0.06$).

5 Discussion

In our study we tried to identify learner characteristics which are relevant for dropout rates in computer science courses. We therefore focused on a course with a combination of face-to-face instruction and online study. Such a blended learning approach gives students the possibility to learn at their own pace and in their individual learning spaces, at their chosen time, while at the same time give them the opportunity of direct interaction with the teacher and fellow students in the lecture on-campus. This configuration offers manifold methods of additional support for dropout candidates.

To ensure a specific assistance, we analyzed whether we could identify differences between motivational as well as cognitive variables between students who drop out and students who persist in the course. We assume that finding such differences is the first step for making our remote lab adaptive. An adaptive learning environment should automatically detect whether a student is at risk of dropping out and give adequate support. To know why a student is about to dropout is a precondition to provide a suitable intervention. It is a difference if a student has motivational or cognitive problems because of a lack of usability or because her programming skills are way too low to deal with the challenges of an exercise or because of other problems.

Unlike in previous studies (e.g., Kori et al., 2015, 2016), we could not find significant differences on the motivational variables between students who dropped out and persisting students (our first research question). Neither the intrinsic motivation or the self-efficacy nor the usefulness of the content or the ease of use of the learning environment were different between both groups. Motivation is a complex theoretical construct, with a lot of influencing variables. Hence, we can only guess why we have results which not support previous research. The ratings of the ease of use of the remote lab were relatively high on average so we might conclude that given a sufficient usability, the effects of that variable are not as relevant as in a poorly working system. This should be a target of further research. Given the fact that attendance and learning in the course is not entirely self-determined but also driven by external goals (e.g., a need of a participation certificate), it might be useful to include items in the questionnaire, measuring not only intrinsic but also extrinsic motivation (see also Kori et al., 2016). However, since a limitation of our study is the small size of participants and especially of dropouts in our sample, the results have to be interpreted with care. This also holds true for the results on prior knowledge which were in contrast to earlier research as well (e.g., Horton & Craig, 2015; Talton et al., 2006). Again we could not find statistically significant differences between the groups, though the mean of the prior knowledge test was rather lower for the dropouts.

The cognitive variables on the other hand revealed an interesting pattern (our second research question). While we could not find a significant difference between both groups concerning intrinsic cognitive load, this was different for extraneous cognitive load. The dropout group rated the cognitive load which was irrelevant for learning significantly higher than the persistent group. That result goes hand in hand with earlier results from cognitive load theory concerning the high relevance of eliminating extraneous cognitive load (Sweller, Ayres, & Kalyuga, 2011). Our results indicate that extraneous cognitive load not only affect learning outcomes but also persistence in a course. Students who drop out had problems that mainly arise from the design of the instruction and not necessarily from the difficulty of the exercises itself. For them, it was not always clear, what they should do in an exercise and what the next steps should be. Apparently they got stuck in the instruction rather than in the programming of the code.

However, there were also students who had the latter problem: from our results, we consider the detection of error streaks as a promising approach for learning analytics in computer science (our third research question). There was a significant difference between students who dropout and students who persist in the probability of error streaks. The former had a significantly higher probability of error streaks in the process of programming. The less prior knowledge the students had (according to prior knowledge test) the higher was the probability of error streaks. Although it seems likely that the probability of error streaks and extraneous cognitive load might correlate, there is no statistic correlation ($r = 0.08$, $p = 0.64$). So in our study, students at risk had two different problems which we have to deal with differently.

5.1 Extraneous Cognitive Load: Practical Implications and Future Work

Concerning extraneous cognitive load, there are two approaches how to proceed. The first one is a learning analytic approach. Because we know that there are students that got stuck in the instruction, in the following semester we can explicitly search for a pattern of user behavior this learner might show. Since we know that these students have difficulties to understand the task and the further steps to go on, we could explicitly look for user behavior which might correlate with disorientation, uncertainty, and help-seeking behavior, i.e., extensive clicks or time in the task section or a high proportion of switching between task section and editor. The second approach is to improve the design of the instruction to avoid extraneous cognitive load. Empirical research on instructional design of remote labs, for example, suggests different forms of guidance, e.g., prompts, process constraints or scaffolds to help students to keep extraneous cognitive load as low as possible, and manage intrinsic cognitive load as well (de Jong & Lazonder, 2014). Learners with lower prior knowledge highly benefit from guidance, while for a learner with higher prior knowledge guidance often is redundant or even annoying, this should be a case for adaptivity as well (Kalyuga, 2007).

5.2 Error Streaks: Practical Implications and Future Work

Apart from the ad hoc and postmortem detection of error streaks, the aim of this endeavor is to administer assistance to students in situations where they are stuck and unable to help themselves, in order to reduce the time students spent on a certain problem and ultimately prevent students from dropping out of the course. The detection of error streaks would allow the lecturer and trainers to intervene in person or to make the system pull up appropriate instructions to guide the students out of their error valley. In person interventions could be triggered by the system, which would flag the user and notify the lecturer about the occurrence of an error streak. The trainers could then sit down with the student, analyze the problem, and help to solve misconceptions or understandings the student might have. Of course, the trainers could point the students to resources, which cover the problematic topic. An alternative in-person intervention could be to invite other students for a common debugging session. They would then proceed to solve a similar task using the method of pair programming. In such a process the experienced students would be enabled to make the knowledge behind their capabilities explicit, thusly helping the less experienced student to confront their knowledge deficits with appropriate strategies. In system interventions could administer, whenever an error streak occurs in a manner that has been observed and solved several times before and certain resources proved to be key in their solution.

One method of implementing adaptive support is directly related to the error messages. Compilers or interpreters of programming languages encode the error in "cryptic" expressions. The correct interpretation of these messages in some cases requires years of experience. Students without the necessary background knowledge might apply trial and error programming strategies instead of evaluating the compiler outputs systematically. In a future implementation of our framework, we intend to support the students at this step on different levels. There exist some databases providing examples and additional information for specific error messages. Hence, the students are able to earn experiences in a realistic but augmented environment, where the error class is explained by isolated examples, possible solutions are sketched out, and links to further resources are provided (Czaplicki, 2015).

In order to improve the detection of error streaks in further research, we will define and detect more differentiated statuses that allow employing more sophisticated and individually tailored assistance (see also Berges et al., 2016). Those statuses could include the duration of an error streak, the amount of repeated errors, and the meaning of specific errors. Another important part is the counter part of an error streak: success streaks. Whenever the code compiles without errors, several times in succession, we can assume that the user is not satisfied with the way the program is acting. Syntax errors might be absent, but logical and semantic errors are still present. Especially when programming embedded systems, which interact with their surroundings, the process of finding the configuration and values for sensors and actors that are needed to accomplish the given task can be a time and energy consuming part of the whole process. Automatically detecting such situations would expand the scope of application for these methods. While the current state, presented in this paper, allows to help students with little experience that struggle with the basics of programming, the extension of detecting logic and semantic errors would enable the lecturers to offer helpful assistance to more experienced students and advanced students projects, which focus the specific set of skills useful in the context of programming embedded systems (Table 5.4).

Table 5.4 Practical statuses, detection strategies, and error classes

Practical steps and statuses	Representations in logs	Measurements	Corresponding error class
Code compiles without errors	Built success message	Count of successful builds	–
Code compiles with errors	Error messages; describing the error	Count of failed builds	Syntax errors
Code that compiled without errors before, now fails	Error message following a built success message	Probability of a code revision that worked before turning into non-compiling code	Syntax errors
Code that failed before, now compiles	Built success message following an error message	Probability of a code revision that didn't work before turning into compiling code	–
Code compiles; features are functional	Indication: built without errors	–	–
Code compiles; features are not functional	Indication: successive builds without errors	Size and time differences between code versions	Logic and/or semantic errors

This study is a first step to an adaptive remote lab tailored to the needs of the learner. We could show that the perception of extraneous cognitive load as well as the probability of error streaks is relevant for dropout rate. On the basis of our finding, we can now automatically detect learner that got stuck (in either way) and apply interventions suited for the different needs of these learners. We assume a combination of both, explorative analysis of variables which affect the decision to drop out as well as detection of related patterns of user behavior as a promising way for defining and implementing rules for adaptivity in a digital learning environment.

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Part II
Issues and Challenges for Implementing Learning Analytics

Chapter 6
Learning Analytics Challenges to Overcome in Higher Education Institutions

Philipp Leitner, Markus Ebner, and Martin Ebner

1 Introduction

Over the past decade, learning analytics (LA) have received more and more attention as a rapidly growing and promising research field in the area of technology-enhanced learning (TEL) (Ferguson, 2012; Khalil & Ebner, 2015). Since it was first mentioned in the Horizon Report of 2012 (Johnson et al., 2012), different tools have been used and initiatives carried out concerning different aspects of LA. Thereby, LA is now finally reaching the point at which it will affect research and practice, as well as policy- and decision-making (Gašević, Dawson, & Siemens, 2015).

Currently, many different definitions for the term learning analytics are accepted. Long and Siemens (2011) defined it as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs.” Duval (2012) summarized LA by saying “learning analytics is about collecting traces that learners leave behind and using those traces to improve learning.” Despite the different approaches, all definitions of LA indicate that it should provide actionable insights (Siemens et al., 2011).

Therefore, the purpose should remain in focus when implementing LA initiatives. Obviously, the potential actions strongly depend on the utilization of data and the information contained. However, what kind of data representation is necessary to implement LA in an institution, and what ethical and moral aspects need to be considered? Currently, the members of the European Union are particularly strongly affected by the enforcement of the EU General Data Protection Regulation (GDPR) (Leitner, Broos, & Ebner, 2018). The issues of data ownership and privacy are becoming increasingly significant (Drachsler & Greller, 2016). Therefore, the

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location and accessibility of the data need to be kept in mind (Leitner et al., 2018). For example, where is the data stored? On an internal or external server hosted by a service provider? Additionally, many LA projects do not move past the prototype phase because of issues related to transferability and scalability (Leitner, Khalil, & Ebner, 2017). These aspects should already be considered at the beginning of the development.

The goal of this study was to provide a practical tool that can be used to identify risks and challenges that arise when implementing LA initiatives and how to approach these. This gives implementers the opportunity to deal with these problems at an early stage and, thereby, not lose time or invest effort needlessly later on when the realization of the initiative becomes critical. In this study, we identified and categorized seven criteria for implementing successful LA initiatives. Although we are aware that these areas are co-dependent, we addressed them individually throughout this study.

In the remainder of this chapter, we showcase relevant and related work, placing an emphasis on similar research questions, and extract relevant problems that generally emerge during the implementation of LA and identify possible solutions. In Sect. 3, an overview is provided of the seven areas that are most significant when implementing LA projects. The reason behind choosing these areas is described in greater detail. In Sects. 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, and 3.7, we describe what we consider to be part of these areas and what we explicitly exclude and which challenges exist and which approaches to solve appear promising in more detail. Finally, we conclude with a discussion and remarks about future work.

2 Related Work

In this chapter, the results of a survey of previous work regarding possible challenges and solutions when implementing LA initiatives are presented. We read the literature to find work on similar topics and determine how the authors met these challenges and what kind of solutions and/or framework they used/proposed. The literature review of Leitner et al. (2017) showed that, in the last few years, various publications have been published in which parts of the challenges summarized in our seven main categories are described. In her paper, Ferguson (2012) documented the concerns about ethics and privacy which began to surface once tools used to analyze student data became more powerful and readily available. She additionally addressed four challenges, one of which was the development of a set of ethical guidelines. Prior to this, Campbell (2007) had already defined a framework for locating potential areas of misunderstanding in LA, which he based on definitions, values, principles, and loyalties. Later, to clearly differentiate between ethics and privacy, Drachsler and Greller (2016) defined ethics as “the philosophy of moral that involves systematizing, defending, and recommending concepts of right and wrong conduct. In that sense, ethics is rather different to privacy. In fact, privacy is a living concept made out of personal boundary negotiations with the surrounding ethical environment." Ferguson, Hoel, Scheffel, and Drachsler (2016) summarized the challenges presented by the special issue of ethics and privacy in LA in 21 points, as shown in Table 6.1.

The first six challenges are related to helping learners achieve success during their studies. Therefore, the data should or—even better—must be complete, accurate, and up-to-date. It is the learner's responsibility to ensure this. On the other hand, the institutions also have a responsibility to ensure a state-of-the-art, valid, and reliable evaluation process, which is carried out in an understandable way. Challenge 7, originally derived from the field of the medical sciences (Murray, 1990), however, relates to the issue that informed consent is also needed today with regard to LA. Students should be involved as collaborators and, therefore, give their informed consent to data access. The obtained analysis from the data is then used to support learning and improve the learner's chances of success. Challenges 8–10 are concerned with the rights and interests of students and teachers, as well as the responsibility held by educational institutions to safeguard and protected these. Providing access to data and allowing the possibility to make corrections and/or file a complaint also play important roles (Rodríguez-Triana, Martínez-Monés, & Villagrá-Sobrino, 2016). The next two challenges are concerned with providing equal access to education for everyone (Challenge 11) and a fair and equally applied legal system for all citizens (Challenge 12). Challenges 13–19 are related to data protection and place a focus on the legal responsibility for data security.

Table 6.1 Learning analytics challenges and dimensions (Ferguson et al., 2016)

1.	Use data to benefit learners
2.	Provide accurate and timely data
3.	Ensure accuracy and validity of analyzed results
4.	Offer opportunities to correct data and analysis
5.	Ensure results are comprehensible to end users
6.	Present data/results in a way that supports learning
7.	Gain informed consent
8.	Safeguard individuals' interests and rights
9.	Provide additional safeguards for vulnerable individuals
10.	Publicize mechanisms for complaint and correction of errors
11.	Share insights and findings across digital divides
12.	Comply with the law
13.	Ensure that data collection, usage, and involvement of third parties are transparent
14.	Integrate data from different sources with care
15.	Manage and care for data responsibly
16.	Consider how, and to whom, data will be accessible
17.	Ensure data are held securely
18.	Limit time for which data are held before destruction and for which consent is valid
19.	Clarify ownership of data
20.	Anonymize and de-identify individuals
21.	Provide additional safeguards for sensitive data

The harvested data are the property of another person, and the institution must assure data protection and security. The last two challenges are concerned with the privacy of data and how data should be used and treated (cf. Ferguson et al., 2016).

To meet these challenges, the scientific community already takes a variety of approaches with regard to data protection and ethics in connection with LA (Ferguson et al., 2016): for example, a code of conduct was developed that can be used as a taxonomy of ethical, legal, and logistical issues for LA (Sclater, 2016). Rodríguez-Triana et al. (2016) expanded the recommendations of Sclater's (2016) code and added consent, transparency, access, accountability, data protection, validity, and avoidance of adverse effects. A framework for privacy and data protection has been proposed by Steiner, Kickmeier-Rust, and Albert (2016). Cormack (2016) has published a paper which deals with European data protection practices and in particular with the transparent communication of data usage. The codes of conduct and frameworks developed so far have been supplemented by Berg, Mol, Kismihók, and Sclater (2016) with tools and approaches that enable us to put them into practice. Khalil and Ebner (2016) focused on the de-identification and anonymization of data for analysis within LA. An examination of the study conducted by Hoel and Chen (2016) shows that the discussion on data exchange and Big Data in education is still at an early stage. Prinsloo and Slade (2016) addressed the rights and problems of students as well as the supervising institutions, arguing that the primary responsibility for LA system providers is to promote individual autonomy and provide each individual learner with enough information to make informed decisions (cf. Ferguson et al., 2016). To help institutions enter the area of LA, Drachsler and Greller (2016) developed a checklist (the DELICATE checklist), which helps users identify and examine possible problems and obstacles that could hinder the introduction of LA in the education sector in advance. The term DELICATE stands for the eight points that need to be considered if one wants to use LA (see Drachsler & Greller, 2016).

In the context of the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project, a team of research and institutional leaders in LA is currently developing a policy framework for formative assessment and personalized learning. They have used the Rapid Outcome Mapping Approach (ROMA) and validated their outputs through case studies. Their focus has been placed on the development of a policy agenda for higher educational institutions by taking advantage of direct engagement with the different stakeholders (Macfadyen, Dawson, Pardo, & Gasevic, 2014). Tsai and Gasevic (2017) identified several challenges related to strategic planning and policy:

- Challenge 1—Shortage of leadership: The leadership lacks the capabilities to guarantee the implementation of LA in the environment of the institution. Therefore, different stakeholders and their interests must be taken into account to ensure their commitment to the topic. Otherwise, these stakeholders may become stoppers.
- Challenge 2—Shortage of equal engagement: There are gaps between the various stakeholders within institutions with regard to understanding LA. Teams who work in technical areas showed the highest level of understanding, while

other teams did not know much about LA. This can be seen as a barrier for the institutional acceptance of LA.

- Challenge 3—Shortage of pedagogy-based approaches: When designing LA tools, it is also important to include pedagogical approaches in the LA process. Institutions tend to focus more on technical aspects rather than pedagogical aspects.
- Challenge 4—Shortage of sufficient training: As highlighted in challenge 2, there is a lack of understanding of how LA can be beneficial to all stakeholders. A good staff training program, which helps them improve their skill sets on this topic, is key to success.
- Challenge 5—Shortage of studies empirically validating the impact: A budget must be allocated to support LA. Therefore, senior staff members need a basis for the decision-making to do so. However, the evaluation of the success of LA seems to be a challenging task.
- Challenge 6—Shortage of learning analytics-specific policies: Institutions have regulations regarding data and ethics. However, few institutions have codes of practice for LA. This lack of clear guidance regarding LA practice needs to be addressed.

Furthermore, Tsai and Gasevic (2017) reviewed eight policies (Jisc, LACE, LEA's Box, NUS, NTU, OU, CSU, USyd) concerning their suitability based on the six abovementioned challenges. Although the policies partially lack pedagogical approaches, guidance for the development of data literacy, and evaluations of the effectiveness, they serve as valuable references for institutions interested in establishing LA in their field of work. Particularly institutions that are interested in developing their own practice guidelines for LA (Tsai & Gasevic, 2017) can benefit from the findings.

In our research, we found that several publications have focused on different aspects of this topic. Overall, it can be said that the creation of clear guidelines based on a code of practice is needed when planning to introduce LA in an institution. Our knowledge and thoughts are summarized in seven main categories and presented in the next section.

3 Seven Main Categories for LA Implementations

Bearing in mind the related work, the issues identified during previous research, as well as our own experiences with implementing LA projects and initiatives in higher education (De Laet et al., 2018; Leitner et al., 2018; Leitner & Ebner, 2017), we developed a framework for LA implementations. Based on the results of the literature review and a workshop with LA specialists, stakeholders, and researchers, different issues were identified. These core issues were discussed, were verified, and could be categorized into seven main areas (Fig. 6.1).

In the following subsections, we explain the seven categories in detail, pointing out the challenges they present and providing possible solutions.

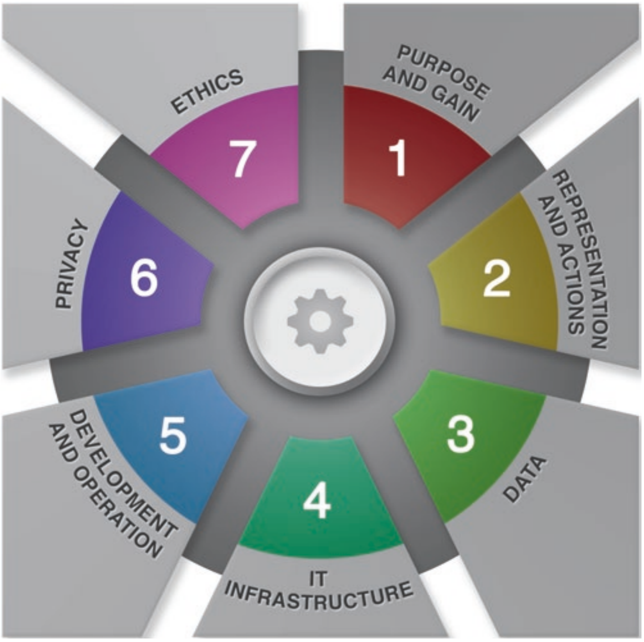

Fig. 6.1 Framework with seven main categories for LA initiatives

3.1 Purpose and Gain

The expectations related to improving learning and teaching when talking about LA in higher education are extremely high. However, at an institutional level, the line between LA and academic analytics is blurred. Therefore, it is advisable to distinguish between the different stakeholders with regard to the various goals and perspectives of stakeholders such as learners, educators, researchers, and administrators.

The goal of *the learners* is to improve their performance. LA supports this by providing adaptive feedback, recommendations, and individual responses on their learning performance (Romero & Ventura, 2013).

The educators are interested in understanding the students' learning processes; understanding social, cognitive, and behavioral aspects; reflecting on their teaching methods and performance; as well as optimizing their instructions to achieve a better learning outcome (Leitner et al., 2017). They want to be able to assess the students' activities more effectively and draw conclusions to find out where they need to take more action to improve the students' learning performance.

Researchers use the data to develop theoretical models for new and improved teaching and learning methods. This includes pursuing the goal to predict future learning paths and support the needs of learners more appropriately. Educational technologists and researchers in the field of pedagogy review existing didactical models and develop new didactical ones by carrying out field studies in classrooms.

For this reason, they conduct research continuously and adapt LA techniques based on the data collected to meet the new expectations of the younger generation.

Administrators are interested in implementing their agendas in a more efficient environment. Their aim is to offer students a more pleasant and efficient learning environment. Additional goals are to reduce the failure rates and numbers of dropouts, increase performance, and, thus, optimize and improve the curricula. The government is responsible for the enforcement of data privacy and data protection issues.

Challenges may occur when dealing with the different stakeholders. If stakeholders are confronted with hard facts without being asked for their thoughts and opinion first, they may rebel. Additionally, despite the generally positive intentions of those introducing LA into institutions, stakeholders often have their own thoughts about LA. Students and teachers might be afraid that the results of the analytics, if made public, would put them in bad positions. Or even worse, the representatives of the different stakeholders have their own in-game and expect to use the results to expose their counterparts. Therefore, it is necessary to make the goals of the LA initiative transparent, clarifying exactly what is going to happen with the information and explicitly what is not.

When the purpose of the LA initiative is very clear from the beginning, this does not seem to be a problem. However, if it is not, the situation might become complicated when attempting to explain the LA initiative to the stakeholders. Fuzziness not only puts you in a weak negotiating position but can also become a major problem when the stakeholders try to bring you over onto their side. Therefore, implementers need to specify and adhere to the ultimate objective of the LA initiative.

3.2 Representation and Actions

The purpose of LA is to use the data collected to optimize the students' learning processes and improve teaching. The aim is to make learning itself more predictable and visible. Actions derived from this can serve as a basis for developing a catalogue of measures to support risk groups and provide them with better assistance during their study. Based on this, recommendations are made to support learners and encourage them to reflect on their behaviors. The information is provided within a suitable environment and clearly visualized as being included in the student's personalized learning process. The personalization of the working environment and the associated advantages are placed in the foreground. This should have the effect of motivating the learner in terms of improving their attitude. The feedback received is intended to stimulate reflection and lead to a shift in goals and the associated improvement in learning success.

Choosing the right environment for the learner's feedback and the correct visualization technique can present a large challenge for all parties involved. Due to the quantity of data harvested and the focus placed on quantitative metrics, teachers sometimes consider LA to be antithetical to an educational sense of teaching. Dashboards with performance metrics are becoming increasingly popular in these contexts (Clow, 2013). The interpretation of this data can sometimes seem incredibly difficult if it has not been properly prepared before it is presented to the student. Therefore, it can be better not to provide the student with all information related to the learning outcome. A mentor can discuss the results with the student. However, university staff who are acting as mentors need specialized training so they can interpret the data and pedagogical and psychological skills to discuss his/her results with the student and provide deeper insights about the data.

3.3 Data

Universities and schools are constantly analyzing data from their students for a variety of reasons. LA can, therefore, be seen as an innovative continuation of this principle, applied to make use of the advantages of modern technology and the various data sources available today. The data can be examined and analyzed for their impact in the learning context to improve the quality of learning and teaching, as well as enhance the chances of the students' success. Of course, universities require the individual's permission to collect and evaluate sensitive data for the purpose of LA. Students must be made aware of the purpose of collecting and the process of analyzing the data. Consent is mandatory for the use of these data, which then can be used as a basis for strategic decisions by the various stakeholders. Teachers are able to monitor and analyze a student's behavior and actions while they are interacting with the learning management system. Thus, teachers are provided with insights into the student's learning culture, for example, whether the student has submitted all of their assignments or how actively they engage in their studies. Derived models can be used to provide better student support so that they can reach their goals more efficiently.

Students leave various data traces while using the university infrastructure. The data collected will be used together with statistical models and methods for the purpose of LA when a benefit for student learning is expected. Students may want to know why they have been categorized as potential risk candidates in specific courses. Therefore, the data and models used must be communicated and explained to them by trained staff in a comprehensible way to provide them with guidance. Access to that data must be secured, and only a few staff members are allowed to have access permissions to students' data. The institutions must enact policies that address data protection and access. Students must be informed of who has access to the data.

The data used will not only have impact on the individual student but also influence the practice of teaching at the university. Therefore, the data have to be re-evaluated over time and adjusted to meet the new demands. Furthermore, to ensure the best support and quality of the data, students need to keep their data up-to-date. Giving them the (proactive) opportunity to check and update their data supports them and the university during this process. Additionally, all of these points must comply with the GDPR and local data protection acts.

A policy needs to be created for LA that aligns with the organization's core principles. Transparent communication about where the data are stored, what is being done to ensure data security and privacy, and how the data are evaluated and used (and by whom) is essential. Responsible handling of the students' data by all stakeholders, especially university staff members, is important. Further training and skill-building for responsible tutors/mentors in interpretation of the students' data and action-taking in this context are required. Interventions should be recommended to the student, which are based on the collected data, and must be delivered in a transparent and comprehensible way (e.g., which methods and models have been used) to ensure broad students acceptance and engagement. Students need to clearly understand how the data are interpreted and manipulated and which techniques are used to ensure optimal handling and verifiable recommendations.

3.4 IT Infrastructure

IT infrastructure refers to a set of information technology (IT) components such as hardware, software, network resources, and services that are the foundation for the operation and management of an enterprise IT environment (Laan, 2011). This infrastructure allows organizations in higher education to deliver IT services to its students, teachers, and administrative staff. This IT infrastructure is usually internal and deployed with in-house facilities, but it is possible to commission an external provider. However, IT infrastructure is the basis for any LA measurements and, therefore, has to be considered carefully.

Why is it important to think about the IT infrastructure? To understand its relevance, it is necessary to know where the data is located. Therefore, we can distinguish between two different scenarios. First, the data are stored and processed in a university-owned service center. Thereby, the responsibilities and liabilities are located at the university itself, and national and organizational rules must be obeyed. This scenario has the advantage that access to the data and the data ownership are located at the university, which makes it easier to work with the data. However, it also presents some disadvantages, such as the fact that initiatives with special technology requirements need to comply with the standardized rules held by the internal service provider. Also, the cost-benefit ratio should be kept in mind because hosting and support services privately might be more expensive than outsourcing.

The second scenario concerns working with external service providers. In this scenario, individual solutions can be applied, as many providers are available that might meet the specific needs. In contrast to the internal service center of a university, external service providers can concentrate their efforts on their smaller and highly specialized digital product. Furthermore, the costs that arise can easily be estimated and should be much lower than providing a private, individual solution. The negative aspects of working with an external service provider are related to issues of access and data ownership as well as meeting the necessary security standards when working with sensitive data, such as student performance data.

Regardless of whether one works with an internal or external service provider, it takes time to establish the appropriate basis. Therefore, efforts should be made from the beginning to search for possible solutions to set up the necessary IT infrastructure and contact and establish connections with relevant people (Leitner et al., 2018). This will save time and resources when the implementation of an LA initiative becomes critical.

3.5 Development and Operation

This category combines the process of developing and operating LA initiatives. It includes a wide range of different developments, from designing a simple questionnaire to developing an enterprise software solution. Additionally, the activities cover research on and the development, prototyping, modification, reuse, reengineering, monitoring, and maintenance of LA initiatives or projects.

Once the first prototype has been produced, implemented in a real-life context, and evaluated, the discussion can proceed to the next step. How can the prototype be realized? How can it move from the prototype phase to the production phase? These are quite critical questions because new tasks and challenges will appear. For example, the scalability of the implementation has to be taken into account. The number of learners may differ arbitrarily, and this can lead to a complete new concept for the existing IT infrastructure. Furthermore, processes which were first created manually must be redefined so that they can be performed at least semiautomatically or completely automatically.

Even if student data is stored, this is typically done via different information systems. Normally, several information systems are responsible for performing different tasks and, therefore, storing the data—in different formats, on different servers, and with different data owners. The efforts that are required to receive and manage all data can be stressful and tedious. Additionally, converting raw data into a useful format can be another big challenge. This is a highly complicated process, which needs thorough planning and a consistent final implementation. Additionally, the implementation should include working in different layers and should probably be implemented in a modular manner. In doing so, any changes in the circumstances of the different, associated information systems can easily be adapted.

From the first stages of any learning measurement, we suggest that the scope should be specified in detail. Will the LA be established merely for testing and to obtain initial impressions, or will it be implemented at a university-wide level? Scalability is maybe one of the most frequently underestimated problems in today's IT industry. Furthermore, we strongly emphasize planning the LA implementation beforehand, so that the costs can be estimated as exactly as possible. A distinction must be made as to whether processes have to be carried out manually, semiautomatically, or fully automatically.

3.6 Privacy

The term privacy is defined as an intrinsic part of a person's identity and integrity and constitutes one of the basic human rights in developed countries, as it should be an established element of the legal systems (Drachsler & Greller, 2016). All LA implementations have to ensure the privacy of the involved parties. Learners must trust the final systems, and, therefore, keeping information private is of the utmost importance. Additionally, depending on the country where the higher education institution is situated, different regulations in addition to the General Data Protection Regulation (GDPR), which is applicable in Europe, are enforced. Organizations have to deal with different tasks while finding a suitable legal framework that covers the GDPR. They could take another tack and start to minimize the data harvested and/or take actions to anonymize or pseudo-anonymize their data.

Nevertheless, even when keeping privacy in mind when handling LA initiatives from the beginning, the situation can become highly complex. For example, by merging different data sources, new and surprising results can be visualized, and, therefore, new insights which were never intended can be provided. Due to the fact that universities are huge institutions, there is a high risk that unauthorized people receive access to these data interpretations.

Another large problem that is closely related to privacy is the fact that a person/learner is reduced to their stored data. Society is made up of individuals, so every situation has to be considered in a differentiated way. For example, an activity profile can be created, but we will never know exactly how those activities actually took place and to which extent. The reduction of people to categories and profiles can be particularly dangerous, because a learning individual could be reduced to a merely few parameters. Since society seems to like to fall back on so-called facts, the derivation of causal connections on the basis of learning algorithms always needs to be critically questioned. This also means that gaps in data need to be analyzed and handled.

Finally, the general lifetime of personal data is a topic that requires further discussion. The data may be interesting at a time when the activities and learning outcomes are relevant, but the data may no longer be relevant in the future. Arguments for keeping data could be presented for the purposes of training algorithms and machine learning. Improvements could also be made by providing a larger data resource. However, these steps should only be carried out with absolute anonymization of the data. Khalil and Ebner have shown how this should be done (Khalil & Ebner, 2016).

First, privacy is a fundamental right of every person and must be respected. This means that any LA implementation must take this into account from the very beginning. However, this is often difficult or perhaps not clarified at all, because complex situations can arise as a result of data mergers. Therefore, we suggest working with the highest possible level of transparency, because this encourages confidence: the learners know what happens to their data and what statements can be made. At the same time, unauthorized people cannot be allowed to access the data, and the personnel need to be well-trained in terms of data interpretation but also know how to deal with questions about privacy. If doubts with regard to privacy arise, the LA measure must always be omitted.

Finally, we would like to point out once again that the mere use of data—i.e., "facts"—will not be sufficient to adequately represent such a complex situation as a learning process. LA is only an auxiliary tool that can be used to gain a better understanding of this process.

3.7 Ethics

Ethics is defined as a moral code of norms and conventions that involves systematizing, defending, and recommending concepts of right and wrong conduct. It exists external to a person in society (Drachsler & Greller, 2016). In the context of LA, various ethical and practical concerns arise as the potential exists to harvest personalized data and intervene at an individual level (Prinsloo & Slade, 2015). Therefore, privacy poses as a major challenge for the implementation of LA initiatives.

Additionally, working with sensitive data presents a particular challenge. Sensitive data includes information on medical conditions, financial information, religious beliefs, or sexual orientation, but also about student performance. If made public, such information could result in harm to that particular person. Therefore, it is necessary to ensure restrictions on who has access to the information and for which purpose(s) it is used.

Some questions arise when looking at data from an ethical point of view. First, which data of a person are permitted to be harvested, used, and processed, regardless of whether they are a student or an educator? Second, which information can be communicated to someone, and what may be the resulting consequences? These are increasing concerns in the context of ethics, because LA enables the improvement of accuracy of the predictions for different learning profiles by combining different data sources. The LA implementers must find a suitable way to meet high ethical standards and ensure a beneficial outcome for all stakeholders.

Another important point is the option to opt in and opt out for participants from harvesting, storing, and processing the individual data of a single person. However, how should institutions relying on LA deal with students who take the right to opt out? When implementing LA in an institution, it is advisable to involve all stakeholders at an early state in the process of creating rules and the legal framework for the use of data. Transparency is key, as well as understanding the different needs of the interesting groups involved in the process. All intentions, goals, and benefits for harvesting and using the data have to be explained in a clear and comprehensible way to all stakeholders. The consent for using the data begins with the log-in into the system, which tracks data from their users. During this process, the consent of all parties involved must be communicated. In this context, the areas in which the data will be used must be clearly communicated. During discussions, the possibilities of interpretation of the provided information need to be described to prevent misunderstandings and incorrect decisions. As a precautionary measure, the institutions can introduce codes of conduct and procedures that provide initial support on this subject.

At the Learning Analytics and Knowledge Conference 2018 (LAK18) in Sydney, a draft code of ethics v1.0 was presented (Lang, Macfadyen, Slade, Prinsloo, & Sclater, 2018). This document may be considered as a foundation for ethical matters when implementing LA initiatives. Additionally, a legal counsel could offer their advice when the interpretation of a topic or situation seems unclear. The European Learning Analytics Exchange (LACE) project offers workshops on ethics and privacy in LA (EP4LA). The LACE project also plays a key role in advancing the issues on the ethical dilemmas of using LA.

4 Conclusion

Within higher education institutes, researchers are still full of enthusiasm and excitement about LA and its potential. Furthermore, LA is now at the point at which affects research, practice, and policy- and decision-making equally (Gašević et al., 2015).

However, to facilitate successful LA initiatives, a few things have to be kept in mind. In this chapter, we presented seven main criteria, which can be used for initial orientation when implementing LA. The order of appearance was intentionally chosen, although the order of application depends on the implementer.

We hope that the classification of the seven main criteria, the presented challenges, and the approaches that can be taken to overcome them will be helpful to implementers of LA initiatives. We are aware that the presented examples cover only a small range of the challenges an implementer might encounter, but we hope the results of this study can help researchers and educators understand the bigger picture and become aware of other potential issues.

In future research, we plan to investigate the seven categories in more detail to identify different examples and validate our framework to foster future LA measurements.

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Chapter 7
The LAPS Project: Using Machine Learning Techniques for Early Student Support

Mathias Hinkelmann and Tobias Jordine

1 Introduction

Early support of students can be a successful instrument to improve the academic achievements. Universities are challenged to identify students who may take advantage of early support from the university's student and learning support center. This chapter will introduce the LAPS project ("Learning Analytics für Prüfungsleistungen und Studienerfolg"/"Learning analytics for exams and study success"), developed and used at the Hochschule der Medien (HdM), Stuttgart, Germany, which is set up to cover these challenges. The particular approach of LAPS project is that completed study progressions are analyzed via machine learning techniques. These results are compared to the grades reached by the students in their study program so far. Since the progression of an enrolled student will statistically not differ from students, who either completed or failed in their study program, the comparison can be used to make an individual statement about students' risk of failure or possibility of success. Based on the findings of the risk calculation, students can be advised more focused. In addition, the findings support both, under and top performing students. Also, the results of the statistical analysis by the LAPS software can be used as a factual basis for discussions aiming at improvements of the study programs. This chapter is structured as follows: The Sect. 2 introduces current approaches and projects in the learning analytics research area. Section 3 provides insights into several aspects of the presented project: the used data basis is shown, technical implementation details are provided, and findings of the feasibility study are presented. Further, the privacy and ethical considerations that were identified are explained. The section concludes how LAPS can be used for academic quality

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assurance. The software and the LAPS process are reviewed in Sect. 4. Finally, Sect. 5 concludes this chapter by providing information about possible improvements concerning the LAPS project.

2 Existing Work

Based on Ferguson (2012), the research area of learning analytics has its roots in business intelligence, web analytics, educational data mining, and recommender systems and is defined as follows:

> Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs. ("1st International Conference on Learning Analytics and Knowledge 2011," 2010)

Besides technological aspects like data collection and big data analysis, learning analytics must be seen as holistic as technology, socialization, and pedagogy are involved (Siemens, 2010). Figure 7.1 shows the process of a traditional learning analytics approach.

As the LAPS project is aiming at the German academic system, related German approaches are presented below.

- *Study progression analysis approaches*
  In the case of study progression analysis, the focus is on comparing the progression of individual students with the study plan and the progress of the entire group of students in a study program. This approach, which is pursued at many universities, is represented by the "tempo 30" project of the Ravensburg-Weingarten University or "StuVa" at the University of Freiburg (Hermann & Ottmann, 2006). A special approach to study progression analysis is module-based monitoring (Jaeger & Sanders, 2009). In this particular approach, budget-oriented views on university management and approaches to ensuring the quality of teaching are considered.
- *Predictor models*
  With this approach, a presumed predictor for academic success is analyzed in detail. At the Kiel University of Applied Sciences, for example, two study programs were

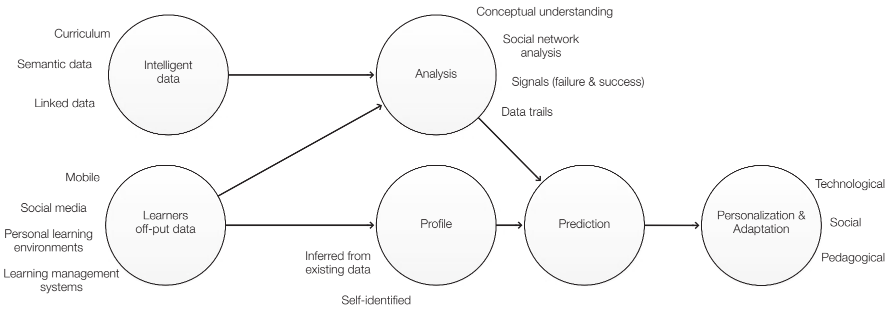

Fig. 7.1 The learning analytics process (Siemens, 2010)

used to examine the success of studies in the first semester as a predictor for overall success and to show that early indicators are indeed present. These indicators can be used to control advisory services (Christensen & Meier, 2014). Other studies (e.g., Trapmann, Hell, Weigand, & Schuler, 2007) have investigated the extent to which school grades can be used as predictors. But recent developments in the field of increasingly heterogeneous access to higher education show that simple predictors are no longer sufficient. Instead, multidimensional predictors must be used.

3 The Laps Project

3.1 Data Basis

Efficient administration of universities requires the use of Campus-Management-Systems (CMS) which allows to track and support the entire Student-Life-Cycle starting from his/her application till his/her de-registration. One of the key elements of such a CMS is the management of exams. Because of the required legal certainty, all CMS record all exam-related student data. This means that a high data quality in terms of students' master data as well as collected exam data is available. Additionally, retention periods given by legal provisions lead to a large data basis.

The development of this data basis adds value for the organization of study and exam regulations. For doing so, personal data like type and grade of the university entrance qualification, date of enrollment, date of de-registration, as well as detailed information about students' exams can be used and analyzed. Due to the similarity of the tasks and requirements for a CMS, it can be assumed that the considerations for the indexing of data within the CMS are not limited to specific systems (e.g., the products of HIS eG[1]) but are directly transferable to other CMS. Table 7.1 shows typical data available in Campus-Management-Systems.

Table 7.1 Typical data available in campus-management-systems

Student-related data	Exam-related data
• Gender • Birthday • Grade of the university entrance qualification • Type of the university entrance qualification • Date of the university entrance qualification • Course of studies • Date of enrollment • Date of de-registration • Study success	Data on academic performance • Name of the academic achievement • Number of ECTSs awarded • Assignment to a study stage • Mandatory/optional/additional academic achievement Data on the trail • Date of exam • Assignment to a semester • Exam result • Attempt counter • Identification of withdrawals from exams

[1] https://www.his.de/.

3.2 The LAPS Approach

An approach that uses the data described in the above is developed at the Stuttgart Media University since 2014. Analyses that were made in advance of the development of LAPS have shown that:

1. A combination of the type of higher education entrance qualification, the grade of the higher education entrance qualification, and the time interval for admission to a course of study.
2. The gender of the students has a measurable influence on the probability of dropout. Analysis performed at HdM in advance of the LAPS project has shown that male students have a higher risk to fail. This finding is independent from the percentage of male and female students in a study program.

Overall, preliminary studies have shown that simple, experience-based predictors are not sufficient to identify critical study situations (Trapmann et al., 2007) and that a systematic and multidimensional analysis of the data (students' master data and data on the examination events) is required. This requires an automated, algorithmic evaluation. The LAPS software therefore uses machine learning methods. During machine learning, patterns are not set manually but are "learned" automatically from existing training data.

The transfer of this approach to the analysis of study situations is possible due to the existence of completed study progressions. Data of de-registered students are used to determine specific study situations. This approach is explained in the following, starting from the general principle of an automated learning process illustrated in Fig. 7.2.

In the training phase, a model is trained which is used to calculate forecasts and classifications. As training data, the LAPS software uses the enrollment data, study progress data, and study success data of all students who have already completed

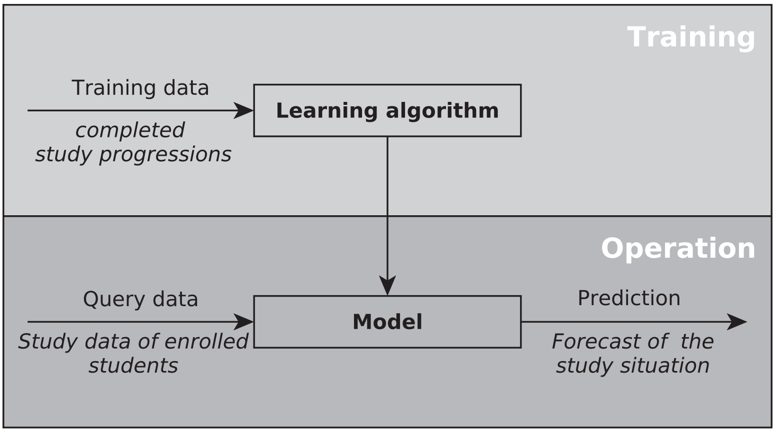

Fig. 7.2 The principle of machine learning

their bachelor studies. Each of these students is described by a data record, which in turn consists of a list of characteristic feature/value pairs: For example, "gender = female and type of university entrance qualification = Abitur" are two feature/value pairs of the enrollment data and "not successful exams after the first semester = 1 and ECTS after the first semester = 20" are two feature/value pairs of the study progression data. The machine learning method used in LAPS is the Apriori algorithm (Agrawal, Imieliński, & Swami, 1993). The model calculated by this algorithm is a set of association rules. Each association rule describes a frequently occurring combination of characteristic feature/value pairs in the form of an implication: A → B. In general, both premise A and conclusion B can represent any subjunctive link between characteristic feature/value pairs. A possible rule would be, e.g., "(number of exams graded with fail after 2nd semester = 3 and number of ECTS after 2nd semester < 20) → studies successful = no."

A rule is only recognized as relevant by the learning algorithm and included in the model if its support and its confidence are greater than a minimum value that can be set by the user. The support describes the composite probability P (A, B), i.e., the relative frequency with which the premise and conclusion occur together in a training data set. On the other hand, confidence describes the conditional probability P (B|A), i.e., the relative frequency for which the conclusion is also true in training data in which the premise is true. Support is therefore a measure of whether the pattern consisting of A and B occurs frequently enough in the training data to be considered statistically relevant. The confidence specifies the certainty with which rule A → B applies.

All association rules whose support and confidence are greater than the minimum values form the trained model. After training, the trained model is used as follows to predict a critical course of study: For a student to be analyzed, all currently available characteristic value pairs are entered in the system as a query. For this specific query, the subset M_S of the association rule set contained in the model is determined, for which the premise A is fulfilled with the entered student data. Since the conclusion of all the rules contained in the model is constantly "study successful = no," the confidence of each rule in M_S indicates the probability with which the respective rule predicts an unsuccessful completion. The median is calculated from the confidence values of all rules applicable to the student (quantity of M_S). This median represents a preliminary risk probability for the student. After the preliminary risk probabilities have been calculated for all students, they are adjusted for the purpose of better differentiation by assigning the final risk score of 100% to the student with the highest risk and 0% to the student with the lowest preliminary risk score. The final risk values of all other students are derived from their preliminary risk values by linear scaling.

By using the Apriori algorithm, a large number of possible risk dimensions with different characteristics can be defined for the analyses in LAPS. In this definition, it is not required to consider the relevance of the analysis dimension or characteristics. This task is performed during the training phase, in which the relevance of combinations of these characteristics is determined. The following list shows the currently used risk dimensions used by the LAPS software:

Dimensions of personal data:

- Age at beginning of study
- Gender

Dimensions of educational biography:

- Type of the university entrance qualification
- Date of the university entrance qualification
- Time interval between acquisition of the university entrance qualification and start of studies

Study course analysis dimensions by semester:

- Total of achieved ECTS points
- Achieved average grade
- Number of failed exams
- Number of successful exams
- Number of deferred exams
- Frequency of nonappearances in enrolled exams

The course of study dimensions grouped by semesters is additionally assigned different characteristics. The risk dimension sum of the achieved ECTS credits is analyzed after the first semester of studies with the following characteristics:

- <10 ECTS credits
- <20 ECTS credits
- <30 ECTS credits
- More than 30 ECTS credits

This results in more than 200 possible individual risk characteristics, which are linked in the training phase on the basis of completed courses of study and lead to the analysis model, which comprises several thousand combinations of risk dimensions. In the current version of LAPS, the risk dimensions and characteristics can be configured. It is the responsibility of user of the system to define a threshold for the predicted risk value above which the affected students are automatically classified as critical. In LAPS, student and examination data is updated every semester via a file upload interface incrementally. After the import, a training phase takes place automatically, which is followed by the analysis of the currently enrolled students. The described recognition of critical study progressions by predicting the risk of termination does not represent the only application of the model trained in LAPS. The learned rules are also able to identify typical patterns of under- and overstraining or frequent postponements of examinations.

Besides the functionality to identify risks, LAPS is also capable to identify study progressions with a high potential. This information can be used to support top performing students, e.g., with a fellowship or additional classes. To identify these students, achieved ECTS credits per semester are calculated and compared with set point of ECTS credits. If the achieved ECTS and the current average grade are significantly better than the mean of the cohort, respectively, the set point of ECTS credits, the student is identified as a top performer.

3.3 Feasibility Study and Use in Consultations with Students

At an earlier stage of the project, students' risk data were analyzed and used in consultation situations by staff members of the student support center and course leaders. In contrast to the current version of LAPS, students were directly contacted by the users of the system when a risky study progression was identified. This version of the tool only supported the identification of risks and was not able to detect positive study progressions.

Having this setup, students were invited for a consultation discussion. The results of the risk analysis served as an evidence-based foundation of this talk and helped students to understand their situation. This was especially useful when students had a different impression on their study progression. It was found out that by using the LAPS software, students can be advised at an earlier stage of their studies and can be one addition to reduce students' dropouts as additional support like trainings or adjustments of the study progression can be offered.

Users' feedback of this early version of LAPS was positive. It was liked that in contrast to traditional grade overviews, the LAPS profiles are much more detailed and potential risks are immediately visible. This allows to develop individual counteractions. But the feasibility study also showed that the handling with students' personal data was not ideal, since lecturers (i.e., persons who do the grading as well) can access and view students' risk details without their permission. This is why it was required to define premises for the privacy and ethics for the project, which will be explained in detail in the following section.

3.4 Privacy and Ethics

The LAPS software serves to create an evidence-based discussion basis with students at an early stage of their studies. This evidence-based approach contrasts with legitimate data privacy aspects. For the LAPS project, privacy and ethical premises are a foundation of the whole project. These premises are voluntariness, self-determination and self-responsibility, respecting individuality, confidentiality, as well as anonymity and are taken into account in several ways, which are explained in the following. Figure 7.3 provides an overview of the LAPS data access process.

When students de-register for any reason, their personal data is no longer visible for any user of the system. In the case of enrolled students, students must opt-in to be considered by the system. Only with their explicit agreement it is possible to view their personal data and risk analysis. Students always have the chance to change their decision whether they take part or not. New students can take part at the LAPS project during enrollment, whereas current students are informed via e-mail. Transparency is very important as students get informed how their data is used. For example, in advance of the opt-in, a privacy information sheet that explains the use of data is presented to each student. Additionally, the project is presented at the general student meeting each semester as well as an information booth where students can ask project members about LAPS once a semester.

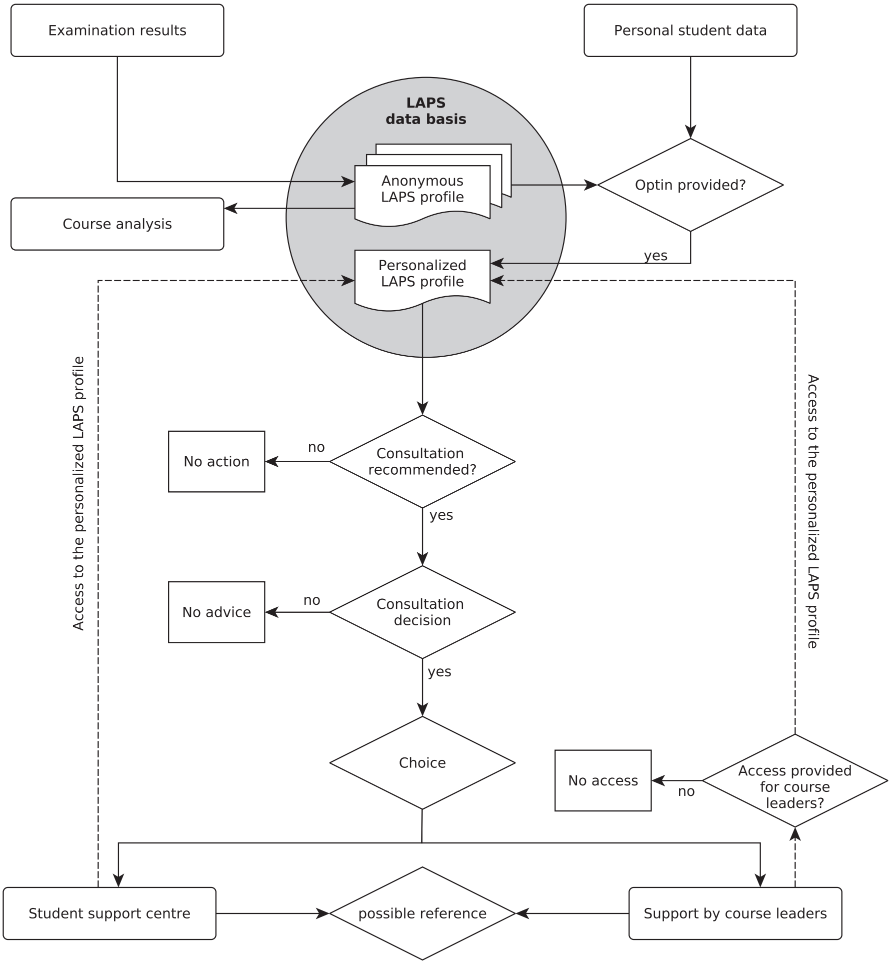

Fig. 7.3 The LAPS process

Access to the data is strictly limited by the limitation of the user group. In the case of the HdM, course leaders have access to the personal student data of their respective course after they have taken part at a LAPS consultation introduction workshop. This workshop is aiming to help course leaders to understand the data and analysis results calculated by the system and how they can use this information for a successful consultation. Besides course leaders, staff members of the student support center have access to the results of the students who agreed to take part at the LAPS project.

When a risky or an exceptional good study progression is identified, students are informed via an automatically generated e-mail. After receiving the e-mail, the decision is up to the students to ignore it or to choose an individual consultation discussion with either members of the student support center or their according course leaders. As part of the ethical and privacy decisions of LAPS, students will not directly get the results of the analysis. This is intended to prevent self-fulfilling prophecy: Without having the knowledge how to interpret the analysis and identifying specific needs and students' personal life situation, the results could be misunderstood as the algorithm is only able to do calculations based on data stored in the Campus-Management-System.

The project is already compatible with the EU-DSGVO (General Data Protection Regulation, 2018). This ensures that the project complies with the currently valid data privacy laws.

3.5 Functionalities of the Tool to Support Students

The relevance of the data on the enrolled students increases with the import of the examination results from the previous semester. At the HdM, the system is updated in the seventh week of the lecture period of the following semester onward due to administrative constraints. After the update of student data, a list of critical study progressions of participating students can be reviewed. The displayed data is initially anonymized in the list view (all students) as well as in the individual view (individual student). The de-anonymization of individual cases must be done consciously by clicking a button and is only possible when the student takes part at the project. This should limit bias effects with regard to the identity of the individual student. This detailed view provides the advisor compact information about the student (see Table 7.2).

Table 7.2 Detailed student information in LAPS

General	• Course of studies • Enrollment date and type of the university entrance qualification • Start semester • State of studies
Student	• Birthday • Age at enrollment • Gender • Name (after explicit de-anonymization) • Banner ID • E-mail address • Type of the university entrance qualification • Grade of the university entrance qualification • Date of the university entrance qualification
Examination data	• Number of examinations • Successful examinations • Failed examinations • Excused cancellations • Total ECTS • Current average grade • Average grade base studies • Average grade main studies • Risk score

76.0% (13.3%) 861 / 1133 / 6485	Semester with examinations **>=1**	Type of university entrance qualification **College**	Not successful in first semester **>1**	Successful study? **No**

76.0%: (Confidence): Failure probability
13.3%: (Support): Frequency of a case of this constellation (filter criteria & risk criterion)
861: Number of students to whom the filter criteria and the risk criterion apply
1133: Number of students to whom only the filter criteria apply
6485: Number of students considered

Fig. 7.4 Identified risk and its representation in LAPS

This information is supplemented by a report and presentation of the actual status of the examination results and the course of studies at various levels:

- The semester table lists the acquired ECTS, the ECTS total, the average grade (weighted according to ECTS), and the number and status (passed, failed, approved cancelled) of the examinations taken per semester.
- An overview of the registered examination performances of the previous semesters is provided.
- The performance chart lists detailed information on all examination (e.g., ident number, description, status, ECTS, grade). By clicking on the ident number of an examination, a detailed view is presented, and the grades for all available semesters can be seen. In this way, the student's performance can be compared to the overall cohort.

The individual view is completed by the risk details: a graphical representation of the distribution of risks (with which frequency risk criteria of a certain probability of failure apply to the student) as well as a representation of the risk criteria applicable to the student. Figure 7.4 provides an example of an automatically identified risk.

3.6 Using LAPS for Quality Assurance

Besides the functionality to support students based on the LAPS profile, the software supports quality assurance of study programs. The following functionalities are designed to provide information about specific programs, lectures, and student cohorts. The analysis results presented are based on the anonymous LAPS profiles, which mean that personal data is not visible.

- *Programs*
  In this view, study program information can be obtained. The following data is available for each program: number of enrolled students, number of dropouts, number of successful study progressions, average risk possibility, minimum/average/maximum student age, gender distribution, average grade of the university entrance qualification, and retreats from examinations.

- *Cohorts*
  For the development of study programs, it is important to get information on the consequences of the changes on module level, e.g., to the examination regulations and the curriculum. The cohort's view allows to compare the distribution of students obtained ECTS credits per semester and to identify possible structural problems when students do not achieve the required ECTS.
- *Lectures*
  This view allows an in-detail analysis for each semester of lectures and provides access to distribution of grades, number of successful examinations, average grade, number of retreats, and number of registrations.

4 Discussion

Although the LAPS project is developed at HdM, it is open to be used at any other university. This achieved by being released as an open-source software and the data import is not bound to a specific CMS. The only requirement is that the CMS data needs to be exported into a LAPS-readable CSV format. For doing so, it is required to write export scripts that allow to export the data. Additionally, it could be possible to adjust the definitions mentioned in the above as the study progression differs from each university.

Nevertheless, some lacks and points of discussion were identified for the project, which are described in the following:

- *Using students' gender as part of the risk calculation.*
  As a part of the risk analysis, the LAPS software uses students' gender information. It is not intended to make differences or judgements between the genders. In fact, the risk analyzation results can identify potential problems of gender groups.
- *Validity of the used data model.*
  When the LAPS software is used for consulting students, advisors need to be clear about the underlying data that are used to calculate the possibility of a positive/negative study progression. As the algorithm considers sociodemographic and examination data, all derived risk probabilities are based on these facts. During a consultation situation, it is required to know that the algorithm may identify a student progression as risky which is due to a small number of ECTS credits obtained during the first semesters. This could have multiple reasons, e.g., illness of the student. To cover this issue, the LAPS software is inextricably bound to the LAPS consultation process which includes a mandatory consultation introduction workshop.
  Illnesses that result in a long-lasting absence from university, such as illnesses that are part of the general risk of life, such as influenza, etc., usually result in vacation semesters and are considered accordingly in the LAPS risk assessment. The underlying data for such events is recorded by the CMS. Other data, e.g.,

other health issues and possible labor of students, is not recorded due to the strict privacy laws in Germany. These students' information can be taken into consideration during the consultation, which is part of the LAPS project.

- *Low response rate for course leaders taking part in the LAPS consultation introduction workshop.*
  As described in the above, course leaders need to take part in mandatory workshops that provide an introduction to consultation of students using LAPS data. All course leaders of the bachelor programs were invited, but only a few of them responded. The main problem was that the workshop was planned during semester holidays and many of the invited course leaders were not available for two consecutive days. This could be improved by splitting up the workshop into smaller lessons (e.g., 3 × 3 h) during semester.
- *Student response rate could have been better for the first run.*
  For the first run of LAPS, all students were invited via e-mail. For the targeted student group (all students in the fourth semester or below, $N = 1500$), 98 students (6.53%) participated. It is planned to increase the number of participating students by integrating the opt-in registration into the enrollment process. Nevertheless, only a single student of the students who filled the opt-in form did not want to participate.
- *Data analysis is CPU intensive and requires time.*
  As the analysis is complex data mining process, the calculation should be integrated into a batch job executed when the application is not used interactively, e.g., during nighttime.

5 Future Work

For the further development of the LAPS project, it is planned to analyze data on how students accept the system. It has to be tracked how many of the students who choose the opt-in are receiving a system-generated e-mail. Last but not least, it has to be tracked how many of them are taking advantage of the conversation offer with either staff members of the student support center or their according course leaders. A consultation guideline is currently developed to give support on how to use the system in such situations.

Technically, an automated ETL process (extraction, transformation, load), which is a standard process model for data warehouse and big data computing, could improve the upload of new student and examination data. By adding a functionality to track student progression within a lecture (e.g., by integrating the results of interim tests), students would be able to get information about their progression in a specific lecture. In addition to automatically identified risks, a manual student tagging functionality could extend the LAPS software: student progressions are anonymously presented to course leaders, and based on their experience, they could decide if the student needs additional support.

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[2] http://s-beat.de.

Chapter 8
Monitoring the Use of Learning Strategies in a Web-Based Pre-course in Mathematics

A Comparison of Quantitative and Qualitative Data Sources

Katja Derr, Reinhold Hübl, and Mohammed Zaki Ahmed

1 Introduction

One of the challenges tertiary institutions have to face is the growing diversity in first year students' educational backgrounds and knowledge levels. Not all undergraduates seem to be adequately prepared for the demands of their course; in technical degree programs many students have knowledge gaps in secondary school mathematics and some even struggle to apply basic (Armstrong & Croft, 1999) or "extremely basic" (Ballard & Johnson, 2004) rules. Such deficits are a considerable threat to academic achievement in STEM subjects (science, technology, engineering, and mathematics) (Croft, Harrison, & Robinson, 2009; Knospe, 2011).

Technical faculties have met this problem by providing preparatory and bridging courses in mathematics, offered face-to-face (Abel & Weber, 2014), online (Krumke, Roegner, Schüler, Seiler, & Stens, 2012) or in blended versions (Biehler, Fischer, & Wassong, 2012). High participation rates suggest that these are welcomed by students (Bargel, 2015). Web-based learning environments have been found particularly useful when addressing heterogeneous groups of learners and students who not (yet) live near the campus. They also allow to collect learner data at a very early point in time, in the "liminal phase" between secondary and tertiary education (Clark & Lovric, 2009).

Such data are considered relevant from different perspectives. First, mathematics test results can be used to predict tertiary achievement in engineering and, based on these observations, develop "early warning systems" for "at-risk" students (Greller & Drachsler, 2012). Second, analyzing learning behavior during the pre-course

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may help identifying effective and less effective uses of learning strategies. Such observations could result in suggestions for individual learners and thus support their transition to tertiary education. Third, analyses of pre-course outcomes inform practitioners of "what works" and thus contribute to the growing body of literature on "transition pedagogy" (Kift, Nelson, & Clarke, 2010).

The evaluation of preparatory courses, however, can be conceptually and methodologically challenging. Being extracurricular activities, pre-courses are not mandatory and students are free to participate or withdraw at any time. Such threats to internal consistency may be increased in web-based environments which, compared to traditional face-to-face courses, are characterized by poorer learner commitment (Ashby, Sadera, & Mcnary, 2011; Smith & Ferguson, 2005; Street, 2010) and lower answer rates (Cook, Heath, & Thompson, 2000; Fan & Yan, 2010; Tourangeau, Conrad, & Couper, 2013). Finally, organizational and technical barriers may prohibit relating pre-course learner data to subsequent student performance.

This study measured learner behavior in a web-based pre-course in mathematics and related these outcomes to achievement in five engineering courses at Baden-Wuerttemberg Cooperative State University Mannheim (subsequently abbreviated DHBW for Duale Hochschule Baden-Württemberg). Funded by the joint research project *optes* (www.optes.de), the team at DHBW Mannheim successively developed, revised, and re-evaluated the course program consisting of diagnostic self-tests, interactive learning modules, and additional support structures.

Using the theory of self-regulated learning as a theoretical framework, the interplay between students' preconditions when entering the course, their learning behavior, and the learning environment was accounted for in quantitative and qualitative analyses. By exploring which variables positively influenced pre-course learning gains or academic achievement, this study aimed at

- Identification of variables that distinguish between successful and less successful pre-course participation of "at-risk" students.
- Clarifying if and how data collected from web-based pre-courses can contribute to the emerging field of learning analytics (Greller & Drachsler, 2012; Scholes, 2016).
- Making suggestions for the support of "at-risk" students in the transition phase between secondary and tertiary education.

2 Literature Review

It is generally agreed upon that secondary and tertiary achievement are strongly correlated with each other (Hattie, 2009) and that this relation is of particular relevance in engineering (Ackerman, Kanfer, & Beier, 2013). Thus cognitive predictors like secondary school GPA (Hell, Linsner, & Kurz, 2008; Söderlind & Geschwind, 2017), school grades in mathematics (Faulkner, Hannigan, & Gill, 2010; Liston & O'Donoghue, 2009), as well as placement tests in mathematics (Carr, Bowe, & Ní

Fhloinn, 2013; Ehrenberg, 2010; Zhang, Anderson, Ohland, & Thorndyke, 2004) have been found significantly related to measures of academic achievement, like tertiary grade point average (GPA) or retention in STEM subjects.

To isolate the impact of remedial courses from the effect of these cognitive predictors and to quantify their effects has been found difficult. For the UK, Lagerlöf and Seltzer (2009) as well as Di Pietro (2012) found only weak or no effects of participation in a remedial mathematics course on "at-risk" students' achievement in economics. Similar observations were made at US-American universities by Ballard and Johnson (2004), Moss and Yeaton (2006), and Bettinger and Long (2009).

Greefrath, Koepf, and Neugebauer (2016) found that participation in A-level mathematics classes and results in a placement test were the strongest predictors of first year mathematics performance in computer science and electrical engineering at two German universities. Participation in a blended pre-course positively affected placement test scores, but not necessarily first year exam grades. The authors suggested that the influence of the pre-course was not strong enough to overpower the dominant role of prior knowledge. Similar observations were made in studies on face-to-face courses by Polaczek and Henn (2008) as well as Abel and Weber (2014).

These studies, however, did not evaluate students' learning activities during the course. Closing knowledge gaps in a relatively short period of time demands a lot of effort and is also likely to be influenced by the course's design. Vuik, Daalderop, Daudt, and van Kints (2012), for example, performed a quantitative evaluation of a web-based course for aerospace engineering and computer science students. In their study pre-course participants outperformed nonparticipants in their first mathematics exam, particularly when they had been classified "active participants."

When interpreting such results it needs to be considered that the ability to benefit from preparatory courses is dependent on prior domain knowledge, as well. High-performing students are more likely to make effective use of learning strategies, to plan and structure the learning process, and to self-evaluate the outcomes of this process (Pintrich, Smith, Garcia, & McKeachie, 1991; Weinstein, Zimmermann, & Palmer, 1988). The concept of self-regulated learning provides a theoretical framework that accounts for the complexity of the learning process and interactions between learner characteristics (e.g., prior knowledge, age, or gender), environmental factors (e.g., design of the course), and the mediating effects of learner behavior (e.g., use of learning strategies) (Azevedo, 2005).

Evaluations of students' use of metacognitive strategies have shown, for example, that time management and organizational strategies are good predictors of academic achievement (Barnard, Lan, To, Osland Paton, & Lai, 2009; Barnard-Brak, Lan, & Paton, 2010; Broadbent & Poon, 2015; Carson, 2011; Credé & Phillips, 2011; Entwistle & McCune, 2004). Inexperienced students and students with poor domain knowledge seem less able to structure and plan the learning process and are more likely to procrastinate (Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011; Plant, Ericsson, Hill, & Asberg, 2005). The learning environment may positively affect this group's learning behavior by providing external guidance and structure (Artino & Stephens, 2009; Azevedo & Cromley, 2004).

Task strategies like rehearsal or self-monitoring have been found less consistent predictors of achievement; while Morris, Finnegan, and Wu (2005), Samson (2015) and Tempelaar, Rienties, and Giesbers (2015) found that taking self-tests positively affected learning outcomes, two meta-studies reported contradicting results (Broadbent & Poon, 2015) or no effects (Credé & Phillips, 2011).

The effort students put into their learning may also be dependent on motivational aspects like task interest or task value: attitude towards the subject has repeatedly been found to correlate with performance (Richardson, Abraham, & Bond, 2012; Robbins et al., 2004). As mathematics is not the prior study interest of engineering students, negative attitudes could be an obstacle for successful pre-course participation (Meyer & Eley, 1999).

The motivation to learn may also be influenced by social interaction with peers and lecturers. Help seeking refers to a learner's ability to activate social resources (Karabenick, 2004; Newman, 2002). As suggested by Zimmerman and Moylan (2009), it indicates a high level of self-regulation if learners seek out help from others to improve their learning. Not all students, however, are able to benefit from help-seeking or from peer-learning activities, making it difficult to quantify the effects of social environment on achievement (Barnard et al., 2009; Broadbent, 2017).

Finally, students' ability to self-reflect and evaluate the learning process is an essential characteristic of successful learning processes (Zimmerman, Moylan, Hudesman, White, & Flugman, 2011). Learning environments may induce or suppress self-reflection; an extremely high workload, for example, is likely to evoke surface approaches to learning and a stronger focus on grades and scores (Dweck, 1986).

3 Method

A multi-method case study was conducted, using quiz and survey results, log files, interviews, and administrative data. Based on Yin's case study framework, the research design was a holistic single case, one university's implementation of a web-based pre-course in mathematics for engineering students (Yin, 2009). The first part of the study used mainly quantitative methods to gain data from whole student cohorts. In-depths insights were captured through a set of guided interviews at the end of the study.

3.1 Pre-course Design

Prospective students were able to access the web-based pre-course in June; the first semester started in October. Students could find the course on the university's homepage but were also informed via mailing lists, encouraging them to register and take the diagnostic pre-test. This two hour self-test covered ten mathematical fields, from Arithmetic to Vectors, each addressed by four to six items (see curriculum as suggested by SEFI mathematics working group, 2013, as well as cosh, 2014). After submitting the test, participants received a diagnostic feedback, suggesting learning contents if test scores per mathematical field fell below a predefined threshold. All learning modules were open for self-study, combining texts, graphs, animations and videos, examples, and exercises. At the end of each module, students could take a subject-related final test, consisting of 10–15 randomized items. Students who wanted additional support in their learning could enroll in either a weeklong face-to-face course or a one-month e-tutoring course.

The complete interactive learning material, animations, tests, and surveys were developed by the team at DHBW Mannheim. The technical environment used for this project was the open-source learning management system (LMS) Moodle 3.1. Some considerable changes to the LMS's design were made in order to improve usability. The feedback based on students' results in the diagnostic pre-test was significantly improved by a plug-in developed by Dreier (2014) for his student research project in computer science.

At the beginning of the semester, all first year engineering students participated in another diagnostic test, or post-test, taken at the university's computer labs. The post-test covered the same ten mathematical fields and was of similar difficulty (for a more detailed description of course and tool development process, see Derr, Hübl, & Ahmed, 2015). The difference between post-test and pre-test result, the gain score, then indicated the learning outcome per student. Fig. 8.1 shows an overview of the different pre-course elements and data sets.

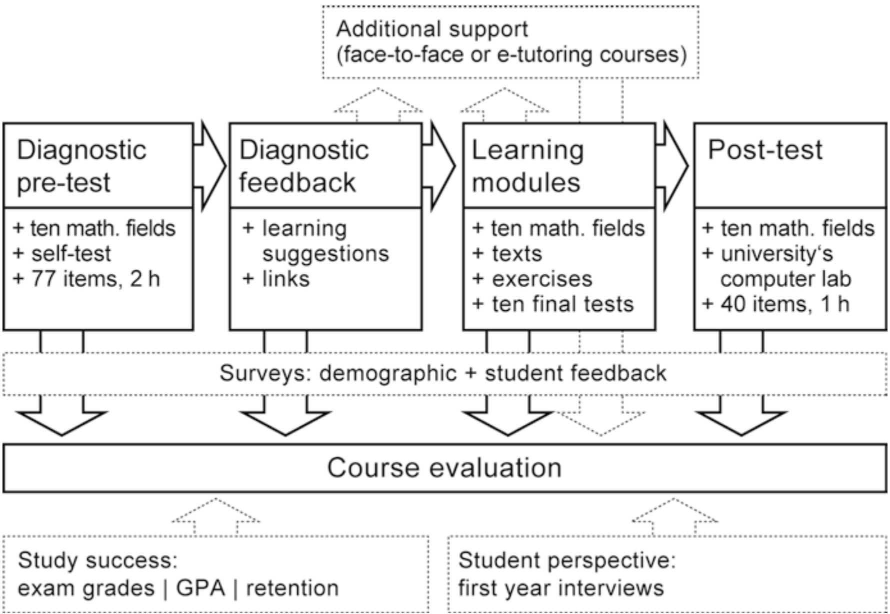

Fig. 8.1 Overview of the design of the pre-course and the data collected for course evaluation

3.2 Data Collection

In this report, data and results obtained from the years 2014 to 2016 are summarized, but some earlier evaluations will be referred to, as well. Relations between students' prior knowledge, first year performance, and graduation, for example, were analyzed using anonymized administrative data from three complete cohorts who graduated between 2014 and 2016. Participants were students from five degree programs (computer science, electrical engineering, industrial engineering, mechatronics, mechanical engineering). Each year between 70 and 80 per cent of all first year students registered on the web-based platform and participated in the diagnostic pre-test (see Table 8.1). These students were ascribed to the group of pre-course participants (regardless of their learning activities on the platform).

Nearly all first year students participated in the post-test. The first year examination Mathematics I was taken 6 months later.

The student perspective was based on interviews with nine purposefully selected first year students who had participated in the pre-course and had been considered to be "at risk" based on their pre-test results.

3.3 Data Analysis

3.3.1 Quantitative Data

Test results and questionnaire data were inputted into SPSS V 23. Descriptive analyses and single linear regressions were used to analyze and control for interactions between predictive variables. A p-value of less than 0.05 was considered statistically significant; p-values of less than 0.01 or 0.001 were reported if applicable.

Table 8.1 Summary of collected data

Interest	Dataset	2014	2015	2016
Pre-course participants				
Prior knowledge in mathematics	Diagnostic pre-test	603	551	596
Demographic and attitude towards mathematics	Survey	593	535	582
Use of learning strategies	Survey	200	117	122
Learning activities	Survey and log files	603	551	596
Pre-course learning gains	Post-test minus pre-test	603	551	596
Pre-course evaluation	Survey	205	117	122
Nonparticipants				
Prior knowledge in mathematics	Post-test	105	156	171
First year students		708	707	767
First year mathematics achievement	Exam grades (Mathematics I)	674	660	747
Student experience	Interview			9
Final year students[a]				
Study success	Grade point average	589	650	554

[a]Cohort of 2011 graduated in 2014; cohort of 2012 graduated in 2015; cohort of 2013 graduated in 2016

3.3.2 Qualitative Data

The interest of the final interview study was to learn about “at-risk” students’ experiences in the pre-course and during their first months at university and relate these observations to findings made in the quantitative evaluations. It was expected that the qualitative results would clarify and enrich those outcomes. At the same time, the interviews were to show if further themes that had not yet been addressed would emerge.

The single interviews, ranging from 25 to 35 min, were conducted using a semi-structured interview technique that allowed responding to the situation at hand. A list of open-ended questions was used to guide the interview but varied in order, wording or focus (Robson, 2011). All interviews were digitally recorded, transcribed verbatim by one of the authors, checked for accuracy, and loaded into MAXQDA V12. Each transcript was coded by examining the raw data and identifying statements referring to the study interest. The analysis was performed at two levels, within each case and across cases (Stake, 1994).

3.4 Ethical Considerations

The university’s data privacy official gave ethical approval. Pre-course participants were informed of the purpose of the study and agreed that their data were collected, anonymized, and evaluated. Students aged under 18 provided parental consent. Tests and questionnaires were completed voluntarily and anonymously. The interviews with first year students were prepared by giving short information about background and goal of the study in selected first year mathematics lectures. An e-mail invitation with an attached information sheet was then sent to all potential participants. Students willing to participate were asked to respond to the researcher by email. Students attended the face-to-face interviews voluntarily and were informed that all data were treated confidentially. The pseudonyms used were Anne, Ben, Chris, Daniel, Eric, Frederic, Julia, Marc, and Nora. All data were kept securely and anonymized.

3.5 Limitations

Pre-course participation in this project was free for all entering engineering students, causing a bias that needs to be accounted for in all interpretations.

Regarding the evaluation of tracking data, it needs to be considered that only learning activities in the university’s LMS could be monitored, but students may also use external links, social networks, learning tools, or apps (Pardo & Kloos, 2011; Tempelaar et al., 2015).

Missing information may also have weakened the representativeness of the scales used in this study. While response rates in the e-tutored courses were acceptable to good (between 64% in 2014 and 38% in 2016), they were relatively poor in the self-study group (27% in 2014 and only 16% in 2016). Distributions in the group of respondents (prior knowledge, first year performance) were not significantly different from the general student body, but it can be assumed that students who participated in the evaluation survey had different mindsets and feelings towards the pre-course than those who did not (Nulty, 2008; Tourangeau et al., 2013) (Table 8.1).

4 Results

4.1 Prior Knowledge in Mathematics and Study Success in Engineering

Using data collected from three previous cohorts (entering 2011–2013), the first year examination Mathematics I was identified as a significant predictor of study success at the end of the engineering degree program. In a linear regression, this exam alone explained up to 43% of the variance in cumulated grade point average (GPA) at the end of the course and thus was considered a good early indicator of study success.

Based on these observations, students' prior knowledge in mathematics was found the strongest determinant of Mathematics I. In a multiple regression, results in the diagnostic pre-test outperformed all other person-related variables (including gender, age, gap between school and university, German federal state, type of secondary school, mathematics grades at secondary school, and secondary GPA). In 2014, for example, a student with a pre-test mean score of 40 was predicted Mathematics I grades 0.6 higher than a similar student with a pre-test mean score of 20 (see Table 8.3).

Secondary school grade point average (GPA) was the second best predictor of first year mathematics performance (plus 0.4 grades in Mathematics I for each increase of 1.0 in GPA in 2014). By comparison, the influence of demographic and other school-related variables was weaker and much more inconsistent (for a more detailed quantitative report, see Derr, Hübl, & Ahmed, 2018).

4.2 Effects of Pre-course Participation on First Year Performance

After having established the relevance of prior knowledge in mathematics for study success in engineering, it was investigated if participation in the pre-course would show a moderating effect on this relation. Each year between 70 and 80 per cent of first year students participated in both tests. The average pre-test score (in %) in this group varied between 49.1 (2015) and 51.1 (2016); the average post-test score ranged from 53.9 (2015) to 56.6 (2015). By comparison, students who had *not* participated in the pre-test achieved a post-test mean score between 42.7 (2015) and 47.3 (2014). Between-group difference was significant ($p < 0.01$), but in both groups a large variance in test results could be observed (see Fig. 8.2; Table 8.2).

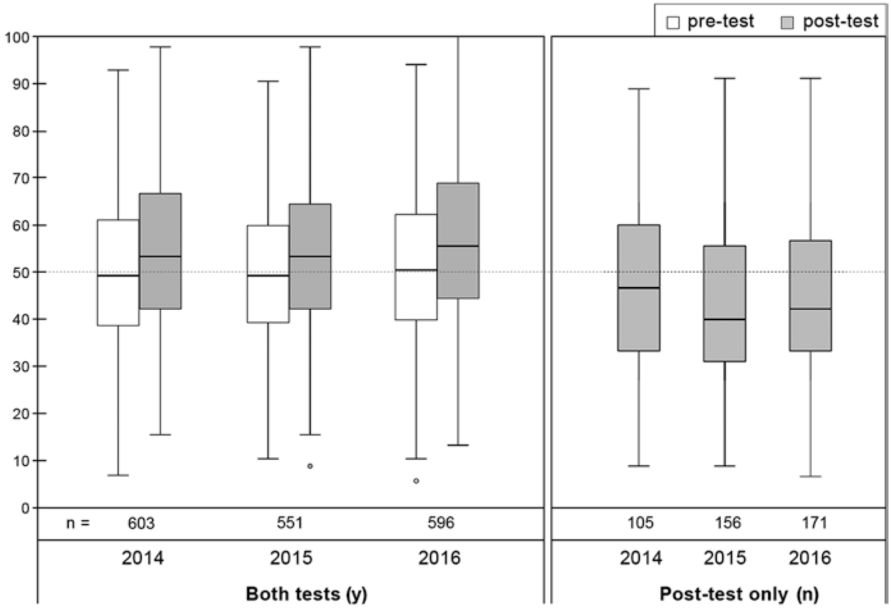

Fig. 8.2 Pre-post-test scores (2014–2016) pre-course participants (=participation both tests) versus nonparticipants (participation post-test only)

Table 8.2 Pre-post-test scores (2014–2016) pre-course participants (*y*) and nonparticipants (*n*)

	Both tests (*y*)						Post-test only (*n*)		
	2014		2015		2016				
	Pre-test	Post-test	Pre-test	Post-test	Pre-test	Post-test	2014	2015	2016
n	603	603	551	551	596	596	105	156	171
Mean	49.7	55.2	49.1	53.9	51.1	56.6	47.3	42.7	43.7
Median	49.4	53.3	49.4	53.3	50.6	55.6	46.7	40	42.2
Variance	255.4	304.9	215.4	266.5	262	304.4	330.4	288.8	288

The average gain score (post-test minus pre-test) across cohorts was 5.3 (median = 5.7), with a maximum value of 61.8 and a minimum of −40.1. Students with poor pre-test results (mean score <50), thus considered the "at-risk" group, had an average gain score of 8.1 (median = 7.3; max. = 61.8; min. = −25.3).

Added to the multiple regression predicting first year mathematics performance, the gain score significantly contributed to the model. Compared to the dominant role of prior knowledge, this effect was not very strong; a noticeable change in Mathematics I was only predicted for students with very high learning gains. For example, in 2014 a student with a gain score of 20 was predicted an increase in Mathematics I grades by 0.28 ($B = 0.014$), compared to a similar student with a gain score of zero.

The quantitative analyses also indicated that pre-course participants on average were able to improve their starting position at university. Students who had *not* participated in the pre-test or the pre-course program showed significantly poorer first

Table 8.3 Regression analysis Mathematics I (2014–2016)

	2014			2015			2016		
	B	*SE B*	β	*B*	*SE B*	β	*B*	*SE B*	β
1. Gender[a]	0.17	0.12	0.06	0.03	0.12	0.01	0.16	0.11	0.06
2. Age (years)	0.05	0.04	0.09	−0.04	0.05	−0.07	−0.04	0.04	−0.07
3. Gap school/university (years)	−0.07	0.06	−0.08	0.12	0.06	0.16	0.17	0.05	0.25
4. Federal State[b]									
Rhineland-Palatinate	0.05	0.11	0.02	0.10	0.12	0.05	0.04	0.11	0.02
Hesse	−0.05	0.11	−0.02	−0.05	0.12	−0.02	−0.13	0.12	−0.05
NRW	−0.07	0.14	−0.02	0.10	0.15	0.03	−0.23	0.14	−0.08
Bavaria	0.37	0.15	0.11*	0.16	0.14	0.06	−0.14	0.16	−0.04
5. Type of school: Gymnasium[c]	0.13	0.16	0.06	0.45	0.16	0.21**	0.40	0.16	0.18*
6. Secondary school mathematics grades	−0.06	0.14	−0.02	0.39	0.16	0.18*	0.09	0.16	0.04
7. Secondary school GPA	0.38	0.10	0.20**	0.36	0.11	0.20**	0.62	0.10	0.36**
8. Pre-test score (%)	0.03	0.00	0.49**	0.02	0.00	0.24**	0.02	0.00	0.26**
9. Gain score (%)	0.01	0.00	0.18**	0.01	0.00	0.13*	0.01	0.00	0.03*
R^2/R^2 adj.	0.35 / 0.33			0.27 / 0.25			0.31 / 0.29		
F for change in R^2	17.47**			10.21**			13.64**		

Mathematics I exam grades measured on a scale from 1 to 5
B unstandardized beta coefficient, *SE B* standard error, β standardized beta coefficient; *$p < 0.01$; **$p < 0.001$
[a]Baseline, male
[b]Baseline, Baden-Wuerttemberg
[c]Baseline, vocational school

Table 8.4 Mathematics I grades (2014–2016) pre-course participants (*y*) and nonparticipants (*n*)

	2014		2015		2016	
	y	*n*	*y*	*n*	*y*	*n*
n	578	96	519	141	583	164
Mean	2.8	3.3	2.7	3.3	2.7	3.2
Median	2.8	3.3	2.7	3.4	2.7	3.2
Variance	0.97	1.24	0.90	0.96	1.01	1.08

ANOVA: 2014: $F(1, 672) = 28.3$, $p < 0.001$; 2015: $F(1, 658) = 39.7$, $p < 0.001$; 2016: $F(1, 745) = 29.1$, $p < 0.001$

year mathematics performance and more failures. The difference between participants and nonparticipants accounted for distances between 0.5 and 0.6 grades in Mathematics I (on a scale from 1 to 5), and ANOVA suggested significant between-group differences for all three cohorts (see Table 8.4).

The student perspective, as well, suggested a favorable interpretation of pre-course participation; all interviewees claimed that they had benefitted from the course. While these outcomes are only a spotlight, the many positive comments indicate that additional mathematics support was strongly needed and welcomed by students entering tertiary education.

> “And if I hadn’t taken part in this pre-course I would have thought: ‘Why was he able to just leave out the brackets there?’ Because that part isn’t explained any more … And that’s why […] to follow the lecture it really does help.” [Frederic].

> “Yes, it was pretty helpful, that you could find out, yeah, okay, that is where you’re lacking a bit of knowledge, because otherwise I would have walked right into the first lecture and would have been struck dead. And with this course it wasn’t so bad.” [Ben].

It also emerged that students were quite aware of the relevance of mathematics for their course and that their first year experience had increased this awareness.

> Julia: “Many pre-course contents were useful later and I thought ‘oh, thank goodness I repeated that’.”Interviewer: “Can you name an example?”Julia: “There was this lecture in maths where I noticed that … Wait, it was prime … some ization.”Interviewer: “Prime factorization?” Julia: “Exactly. Because then I thought, goodness, where could you possibly need that? And then it was needed in this proof and I was quite happy that I had done that.” [Julia].

> “The basics in maths, those aren’t highly complicated calculations. You have to be able to solve them quickly and not ponder for three hours.” [Nora].

4.3 Drivers of Successful Pre-course Participation

In order to identify variables that helped distinguish between successful and less successful pre-course participation, analyses of variance on gain score were performed for different sets of independent variables. All investigations were carried out with a special focus on the group of “at-risk” students, thus controlled for prior domain knowledge (=results in the diagnostic pre-test). Variables that showed a significant influence on the gain score were also added to the multiple regressions predicting first year achievement in mathematics.

4.3.1 Attitude Towards Mathematics

Two subscales from the Trends in International Mathematics and Science Study (TIMSS) were used to investigate the relevance of students’ attitudes towards the subject for pre-course learning outcomes (Kadijevich, 2006, p. 41f; Mullis, Martin, Foy, & Arora, 2012, p. 333f). It had been hypothesized that high scores on items like “I am interested in mathematics” (from the subscale “Liking mathematics”) or “I learn things quickly in mathematics” (from the subscale “Self-confidence in learning mathematics”) would positively affect pre-course learning gains.

The scales correlated with each other, thus replicating previously reported relations between mathematics liking and self-confidence (Parsons, Croft, & Harrison, 2009).

It should be noted, however, that the results were skewed and that only a minority of students expressed outright negative feelings towards the subject. Very positive attitudes were mainly observed for students with very good results in the diagnostic pre-test. Both attitude scales were unrelated to pre-course learning gains.

In the interviews, all participants stated that they had liked mathematics at school and that they had been good at it. This was remarkable as, based on their pre-test results, all interviewees were in the "at-risk" group.

4.3.2 Time Management and Organizational Strategies

Seven items from the subsets "Cognitive and metacognitive Strategies" and "Resource management strategies" of the LIST inventory were related to pre-course learning gains (Schiefele & Wild, 1994). LIST is a German adaptation of the Motivated Strategies for Learning Questionnaire MSLQ (Pintrich et al., 1991). The answer patterns in this analysis were quite irregular; students who "strongly agreed" to items like "I always followed a certain learning schedule" also had high or very high pre-test scores, whereas the rest of the data showed non-linear distributions. The time management and organizational scales thus only allowed to distinguish between students with a very proficient use of learning strategies and the rest of the sample. All seven items were unrelated to the gain score and thus failed to differentiate between more and less successful pre-course participants.

In the interviews students found it difficult to describe how they had planned and structured the learning process. It became apparent that those who had participated in the e-tutored course [Anna, Ben, Marc, Nora] had acted upon the schedule provided by this course, while those who studied alone did not follow a certain plan. One exception was Frederic, who had worked through the complete pre-course alone and had managed to complete one learning module per week. In the interview he admitted that he might have benefitted from a course on "learning to learn" and on the issue of time management but was also sceptical if he would find the time for "yet another course":

> "And something like that could be useful, maybe a small lecture for time management. But I don't know if anyone would stick to it, if anybody would really do it […]. It's probably difficult to carry out, you just think: 'Yeah, sure' but then … you forget about it." [Frederic].

4.3.3 Time on Task

Different sources to measure quantitative aspects of learning were available, like students' answers to the evaluation questionnaire (number of learning modules, weeks, hours per week) and the LMS's log files. Self-reported study time per week, for example, was moderately correlated with outcomes; students who spent more hours learning on average had poorer pre-test results and also higher learning gains. Similarly, the number of learning modules a student had accessed was positively related to the gain score. However, ANOVA or single regression with these variables did not account for significant differences. The interviewees' accounts of their time on task varied strongly, from "about a day, taken all together" [Chris] to about 10 h per week over a period of 10 weeks [Frederic].

4.3.4 Task Strategies

Task strategies like reading or rehearsal were measured by tracking the number of learning module pages students had accessed and by the number of (randomized) self-tests submitted at the end of each learning module.

A high number of learning module page views could be ascribed to a higher gain score, but this relation was very weak and not significant. By comparison, the number of test attempts could be related to a significant increase in gain score. Transformed to a four-step ordinal variable, with "no test attempts," "1–4 attempts," "5–8 attempts," and "9 and more attempts," this variable significantly differentiated between higher and lower achievement in the pre-course ($p < 0.05$).

Summarizing pre-course participation from 2014 to 2016, students with no test attempts on average had the poorest learning gains (gain score = 3.8), and students with 9 and more attempts had an average gain score of 10.4 (Table 8.5). The effect of this variable was even stronger when the sample was reduced to the "at-risk" group (see Table 8.6).

4.3.5 Additional Face-to-Face or e-Tutoring Support

Two additional support programs were provided: a weeklong face-to-face course and a one-month e-tutoring program. On average, 15% of pre-course participants enrolled in the face-to-face course, 15% in the e-tutoring course, and 70% studied alone.

Students who participated in an additional program had below-average pre-test results. The gain score was significantly affected by the type of course a student had chosen to attend. In 2014, for example, face-to-face course participants had an average gain score of 3.5 (n = 91), whereas students who completed the e-tutoring course had an average gain score of 6.7 (n = 85). The highest learning gains were

Table 8.5 Pre-course gain score of all pre-course participants (2014–2016) by number of test attempts

	Total (pre-course participants)	Number of test attempts			
		None	1–4	5–8	9 and more
n	1750	973	490	132	155
Mean	5.3	3.8	6.0	7.5	10.4
Median	5.6	3.8	6.4	8.1	9.2
Variance	162.3	154.1	142.1	221.0	185.0

ANOVA: $F(3, 1746) = 2.8$, $p < 0.05$

Table 8.6 Pre-course gain score of "at-risk" group (2014–2016) by number of test attempts

	Total (pre-course participants)	Number of test attempts			
		None	1–4	5–8	9 and more
n	906	490	274	64	78
Mean	8.0	6.4	8.2	13.1	13.8
Median	7.3	6.3	7.5	11.3	11.0
Variance	160.1	155.7	131.1	174.2	214.8

ANOVA: $F(3, 902) = 11.9$, $p < 0.001$

achieved by students who had participated in both course types, e-tutoring and face-to-face, with an average gain score of 9.1 (n = 28). While learning gains of students in the e-tutoring course were highest, the differences between the different groups were not significant (ANOVA: $df1 = 3$; $df2 = 599$; $F = 1.578$; $p = 0.194$).

Descriptive analyses suggested that in the face-to-face course students had even poorer pre-test results and more often had attended vocational schools. Although these differences were not significant there was a tendency that the e-tutoring course was more often chosen by higher-performing students. In any case, e-tutoring participants showed much more online learning activities and submitted significantly more test attempts.

It is suggested that the more structured design of the e-tutoring course positively affected students' activity level and was much more efficient than the shorter and less binding face-to-face course that had not demanded the submission of course work.

> "…because, you only got a certificate after submitting all exercise sheets. And I thought that was quite all right because you were somehow forced to do some problems. Because, in hindsight I guess they do help, even if you're not always in the mood to do them." [Ben].

> "I did two courses, one e-tutoring course and one in-class. And I was surprised, because I liked the online course better and I gained much more from it. …In retrospect I would say that the online course helped me more than the face-to-face course. Despite that, I'm happy that I did both." [Anna].

4.3.6 Social Interaction, Help Seeking, and Peer Learning

It had been hypothesized that the number of online interactions as an indicator of help seeking would be positively correlated with pre-course learning gains (Macfadyen & Dawson, 2010). The number of forum posts in the e-tutoring course, however, was unrelated to learning gains. The e-tutoring groups were highly heterogeneous regarding communication preferences, and the case numbers were too small for statistical interpretation. Analysis of single cases, as well, did not suggest that a high (or low) number of forum posts was related to achievement.

In the interviews it emerged that students had found it more helpful to learn alone during study preparation. However, social resources and help seeking emerged as highly relevant for the first weeks and months at university. Studying in groups was described as important to understand mathematics problems at tertiary level.

> "Studying in groups is what helps me the most, solving all kinds of problems, and talking it through with somebody, discuss it." [Anna].

> "Well, mostly I prefer studying on my own. But especially in maths I find it makes sense to study in groups. There will always be one person knowing something the others don't. And then the next person gets an idea the others would NEVER have. Yes, I really do think it helps." [Julia].

It also became apparent that not all students had positive attitudes towards learning in groups. Frederic, for example, only chose to participate in a study group after he had failed his first Mathematics I attempt. Ben and Marc found it difficult to benefit from group learning.

> "Well, in general [I prefer studying] alone, because I can concentrate better, because especially when I study in a group, I have often experienced that you easily let yourself be distracted, stray away and then in the end you have been sitting there for four hours and have hardly learnt anything." [Ben].

4.3.7 Self-Evaluation and Self-Reflection

The significant impact of the variable "test attempts" suggested that taking self-tests at different points in time positively affected achievement. The evaluation also revealed that opportunities to practice were highly welcomed by learners. The pre-post-test design in particular helped students to relate their prior knowledge to their individual learning gains. In the interviews it was investigated how interviewees interpreted their test results. Feedback in the form of grades or scores may evoke competitive behavior (Black, Harrison, Lee, Marshall, & Wiliam, 2003) and thus distract students from reflection. The qualitative analyses indeed revealed that some students considered their pre-test result a "negative surprise" [Marc], resulting in feelings of insecurity and a strong motivation to achieve better post-test scores [Frederic].

> "And in the pre-test I think I wasn't THAT good, I only had 40% or so. And then I just, until it really got started, up to then I just did all of the exercises. There was always a test after every exercise and then I just went through everything, and always solved all of the problems. And then there was this post-test again, here at the university and then I even managed to get 75%." [Frederic].

5 Summary and Discussion

5.1 Identification of Variables that Distinguish Between Successful and Less Successful Pre-course Participation of "At-Risk" Students

In order to evaluate the effects of pre-course participation on engineering study success, some underlying presumptions had to be confirmed. First, the relevance of prior knowledge in mathematics for academic achievement in engineering was established by relating preconditions (educational background, demographic, prior domain knowledge) to tertiary performance. In these analyses, results in a diagnostic pre-test in mathematics emerged as the most dominant predictor of the first year exam Mathematics I. In previous analyses of complete cohorts, Mathematics I had been identified as the best predictor of final year GPA in all five courses.

This study thus contributed to the existing body of literature that placement tests are good predictors of academic achievement in engineering (Abel & Weber, 2014; Carr et al., 2013; Ehrenberg, 2010; Faulkner et al., 2010; Greefrath et al., 2016; Zhang et al., 2004) and that below-average pre-test scores can be considered a risk factor.

To some extent this risk could be reduced by pre-course participation. Pre-course participants showed better Mathematics I results than nonparticipants, and the gain score (difference between post-test and pre-test) significantly contributed to a multiple regression predicting this exam. At the same time, there was a large variance in the data, suggesting that not all students were able to benefit from the course.

From the set of potentially influential factors only one variable emerged that significantly differentiated between successful and less successful pre-course participation of the "at-risk" group: Students who repeatedly engaged in self-assessments showed significantly higher learning gains than those who did not. Added to the multiple regression, this variable could also be related to a small but significant increase in Mathematics I performance.

Affective and metacognitive variables showed only weak or no correlation with learning gains of "at-risk" students. Students' attitude towards the subject, for example, seemed to be rather a covariate of prior domain knowledge (Richardson et al., 2012; Robbins et al., 2004) than a factor influencing learning gains. Two scales addressing the use of time management and organizational strategies were also unrelated to learning gains, an outcome that was inconsistent with the literature (Broadbent & Poon, 2015; Entwistle & McCune, 2004; Richardson et al., 2012; Weinstein et al., 1988). Descriptive analyses revealed interactions with prior domain knowledge; mainly students with a high pre-test result were likely to make use of such strategies, whereas for the majority of the sample the data were inconsistent and lacked linearity. Martin (2012), as well, found that mainly high-performing students would make use of organizational strategies in an e-learning environment. Based on similar observations, Eley and Meyer (2004) hypothesized that students' sometimes contradicting answers to learning strategy items were representative of the complex and irregular development from an ineffective to a proficient learner.

It is argued that for students with broad knowledge gaps, the "at-risk" group, effort-related variables might be more relevant than for other learners (Plant et al., 2005). In our study test attempts showed the strongest impact on this group's achievement. As task strategies like rehearsal and repetition are of particular relevance for the acquisition of basic skills such an outcome may not be surprising: rehearsal helped students to apply mathematical rules more confidently and thus enabled them to follow their first year lectures (Armstrong & Croft, 1999; Ballard & Johnson, 2004; Meyer, 2000).

At the same time, taking self-tests is a means to monitor and evaluate the learning process (Winne, 2004; Zimmerman & Moylan, 2009). Repeatedly engaging in self-tests thus may also be interpreted as an indicator of a higher level of self-reflection.

The qualitative analyses allowed the cautious interpretation that students who participated in study groups in their first year at university were more likely to reflect their learning and to successfully manage the transition to tertiary education. It is thus argued that social interaction and peer learning are indeed highly relevant to evoke self-reflection in "at-risk" students, even though such a connection could not be made based on the quantitative analyses.

5.2 Contribution of Data Collected from Web-Based Pre-courses to the Field of Learning Analytics

It was demonstrated that educational technology is an appropriate way to address learners with heterogeneous knowledge levels by providing them with tools to calibrate and self-monitor their learning (Winne, 2004). Formative self-assessment was found a fundamental driver of the web-based learning process in mathematics. Students highly appreciated opportunities to practice and to monitor their learning (Schumacher & Ifenthaler, 2018; Spector, Ifenthaler, Sampson, & Yang, 2016). The data collected from the pre-post-test design delivered consistent information and allowed to relate prior knowledge and learning gains to measures of academic achievement, thus establishing external validity.

Considering the contribution of pre-course learner data to the field of learning analytics, the most consistent results were obtained from cognitive variables, namely test scores (diagnostic pre- and post-test). The number of test attempts was significantly correlated with pre-course learning gains and thus outperformed other tracking data like time online, number of page views, or clicks. It is suggested that this variable is a good indicator of effort and engagement in web-based learning environments, which is in agreement with previous research on e-learning (Ledermüller & Fallmann, 2017; Morris et al., 2005; Samson, 2015; Tempelaar et al., 2015; Zacharis, 2015).

The web-based surveys used to collect information on affective and metacognitive variables showed less consistent results and particularly failed to explain learning outcomes of the "at-risk" group. It may be hypothesized that the sometimes skewed answer patterns were influenced by social desirability. It also has been suggested that in web-based environments surveys are answered less conscientiously (Cook et al., 2000; Fan & Yan, 2010; Nulty, 2008; Tourangeau et al., 2013) and that high-performing students find it easier to answer metacognitive items, resulting in interactions between cognitive and metacognitive predictors (Case, 2004; Thiessen & Blasius, 2008). Concerns thus might be raised regarding the general idea of "measuring" the use of learning strategies with the help of Likert-scaled items in e-learning environments; probably more sophisticated ways to evaluate e-learning are needed to adequately describe the complex construct of self-regulated learning (Hadwin, Winne, & Nesbit, 2005; Winne & Jamieson-Noel, 2002).

Although some of the data collected from the pre-course were significantly related to first year performance, this study also showed the limitations of predictive models. The multiple regressions accounted for 35% of the variance in Mathematics I at most. Thus many students succeeded in spite of a poor pre-test result, and there also remained a number of students who performed reasonably well in the pre-test and yet failed their course (Robinson & Croft, 2003). The literature suggests that indeed many more factors are involved when it comes to study success (Ackerman et al., 2013; Heublein, Richter, Schmelzer, & Sommer, 2012).

Making individual suggestions based on pre-course data thus does not seem advisable and even may have counterproductive effects. Students with a positive prediction might be provided with a false sense of security (Clark & Lovric, 2009), whereas students with poor prior knowledge might try to avoid the "stigmatization" of being "at risk" (Case, 2004).

It is suggested that quantitative pre-course evaluations have "blind spots" as they fail to inform if students' learning activities remained on the surface or resulted in deeper understanding or self-reflection. It is argued that the current state of technology does not allow to adequately address students who struggle with the learning process and that human tutoring is needed to identify misconceptions. A claim is therefore made to not overemphasize the role of predictive modeling for the individual student.

At the same time, the outcomes of such course evaluations are considered highly relevant for practitioners in this area. Students, as well, should be informed of the outcomes of these analyses and the relevance of basic skills on subsequent achievement at an early point in time.

5.3 Suggestions for the Support of "At-Risk" Students in the Transition Phase Between Secondary and Tertiary Education

Based on the observations made in this project, we draw the following suggestions for the design of preparatory courses in mathematics:

1. Raise entering students' awareness (in this case for the role of basic knowledge in mathematics) by providing information about the curriculum and tools for self-diagnosis. The results of pre-course evaluations should be made accessible for students; reviewing and discussing data from previous cohorts, for example, can be highly informative and evoke reflection (see example at www.optes.de).
2. Provide an environment to practice and self-monitor learning, fostering the use of task strategies like repetition, rehearsal, and reactivation of existing knowledge.
3. Provide external guidance like weekly schedules, submission dates, and immediate feedback by e-tutors.
4. Introduce students to the use of a set of learning strategies. These should include planning and structuring, self-reflection and analysis and interpretation of test results, but also social aspects like help seeking and how to benefit from group work.

Further research should reveal how e-portfolios can be implemented in mathematics courses and help induce self-reflection (Burks, 2010; McDonald, 2012). Some hands-on experiments have already been carried out in the *optes* project, suggesting that it is quite demanding to meaningfully connect cognitive and metacognitive learning in an engineering context. It will also have to be explored more deeply how to address not only different levels of domain knowledge but different needs regarding scaffolding and guidance in e-learning environments (Hannafin & Hannafin, 2010).

Finally, our results also draw attention to the issue of increasing heterogeneity in first year students' entry qualifications (Ecclestone, Biesta, & Hughes, 2010; Luk, 2005). Short-term remedial programs like the pre-course described in this study may help to reactivate school knowledge and thus ease the transition to university, but they are certainly not sufficient instruments when it comes to broad and fundamental gaps in knowledge. For many students a prolonged study preparation would be needed, providing the domain and meta-knowledge that is required to successfully study engineering.

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Chapter 9
Issues and Challenges for Implementing Writing Analytics at Higher Education

Duygu Bektik

1 Introduction

Most learning analytics applications provide quantitative information about learners, e.g. based on how many times they have logged in to learning platforms, viewed a forum post, and replied to it. However, learning analytics can move beyond reporting these quantitative logs and provide information on the quality of the contributions students made. One interest for learning analytics is in its potential for the analysis of discourse data. This is called 'writing analytics' which involves measurement and analysis of written texts, for understanding writing processes in their educational contexts (Buckingham Shum et al., 2016).

Effective written communication is an essential skill which promotes educational success for undergraduates. One of the key requirements of good academic writing in undergraduate higher education courses is that students must develop a critical mind and learn how to construct sound arguments in their discipline. Thus, when assessing student essays, educators look for students' ability to present and pursue well-reasoned and strong arguments. Yet, critical thinking and argumentation are not 'a student's mother tongue'. Undergraduate students struggle with argumentation: they are either unaware that they are expected to develop an argument in their essays, have difficulty in arguing, or have difficulty in constructing argumentative pieces. Thus, students require effective, timely, frequent formative feedback from their tutors to gain this skill. However, assessing written texts is a labour-intensive process. Marking and giving detailed feedback and commenting on several drafts of essays can be time-consuming, which is why writing analytics applications can aid this process.

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Learning analytics with a focus on the use of discourse to support learning and teaching is being developed at the intersection of fields such as automated assessment, learning dynamics, deliberation platforms, and computational linguistics. There exist today some powerful natural language processing systems which automatically detect writers' argumentative moves in scholarly/academic texts that can be adopted as part of writing analytics applications. When assessing their students' essays, educators could benefit from the available automated textual analysis which can detect students' argumentative discourse. The studies given in this chapter use a particular language analysis tool, the Xerox Incremental Parser (XIP) as an exemplar of this type of automated technology.

This chapter reviews student writing at higher education, automated analysis of written text, and issues and challenges faces in implementing writing analytics application, together with knowledge from empirical research as well as the theoretical considerations.

2 Background

2.1 Writing at Higher Education

Learning in higher education involves new ways of understanding, interpreting, and organising knowledge. Academic writing in higher education enables professional advancement for university students as it nurtures thinking and reflection. However, students' writing background dates back to school writing, which differs from academic writing in higher education.

Student academic writing is more than punctuation and grammar. When assessing student writing, academic tutors look for students' ability to present and pursue well-reasoned and strong arguments through scholarly argumentation (Sandoval & Millwood, 2005). Writing a university assignment is a thought-provoking activity that requires particular skills of critical thinking and argumentation which are not 'a student's mother tongue' (Lea & Street, 1998). Students, especially those in their first year at university, are unused to this form of writing, and most of them see themselves as novices (Lea & Street, 1998).

Undergraduates are expected to adopt higher-order writing skills such as argument writing and criticality, which are not taught or necessarily practised in secondary school. Thus, novice student writers join higher education with partial or incorrect conceptions about argumentation (Andrews, 2010), they are not familiar with what they are expected to produce, and they have difficulty in constructing argumentative pieces. Undergraduate students struggle with argumentation: they are either unaware that they are expected to develop an argument in their essays or have difficulty in arguing (Lillis & Turner, 2001; Norton, 1998), often because they have learned different concepts of argument at secondary school (Hounsell, 1984).

Additionally, argumentation is often not adequately explained by their academic tutors, who often struggle to provide effective feedback which would prompt good examples of argumentation (Coffin et al., 2002; Teufel & Kan, 2009), which is why adopting an effective writing analytics approach could potentially support to overcome these problems, yet its implementation brings up new dimension of issues and challenges.

2.2 Automated Analysis of Argumentation

'The best way to improve one's [academic] writing skills is to write, receive feedback from an instructor, revise based on the feedback, and then repeat the whole process as often as possible' (Simsek, Buckingham Shum, Sándor, De Liddo, & Ferguson, 2013). This cycle requires tutors to read and provide feedback on student essays, which can create an enormous workload (Simsek et al., 2013). Assessing written texts is a labour-intensive process for academic tutors. Marking and giving detailed feedback and commenting on essays can be time-consuming. This problem led researchers to study ways of developing applications that can automatically analyse and evaluate essays for assessment purposes.

Educators expect their students to learn to write in an academically sound way, specifically to learn to make knowledge-level moves and claims in their essays by recognising and deploying scholarly rhetoric. Argumentation is articulated by meta-discourse. Meta-discourse refers to the features of text that provide linguistic cues which engage the readers and explicitly convey the authors' intended meaning, expressing their viewpoint, argument, and claim and signalling their stance (Hyland, 2005). Therefore, when assessing their students' writing, educators will, among other features (e.g. spelling and grammar), be looking for scholarly meta-discourse as an indicator of argumentation.

Natural language processing (NLP) is the automatic processing of natural human language, such as English, rather than a specialised artificial computer language. 'NLP is the application of computational methods for the purpose of analysing language-related characteristics of electronic files of text or speech' (Shermis & Burstein, 2013, p. 56). Today, some natural language processing systems which automatically detect authors' rhetorical moves in scholarly/academic texts exist.

The archaic definition of rhetoric is the art and study of the use of language with persuasive effect in any given field (Dawson, 1998), or the art of trickery, a way of masquerading and obscuring information (Maynard, 1998). A more contemporary definition of rhetoric refers to the skill to analyse, evaluate, and employ writing strategies in order to respond to the audience and being aware of one's own ideological stance and the audience's stance (Cook, 2002). Rhetorical 'move' refers to a discoursal unit that performs the communicative purposes of a text (Swales, 1990).

One approach to automatic identification of rhetorical moves is 'Xerox Incremental Parser' (XIP) (Aït-Mokhtar, Chanod, & Roux, 2002), which assigns rhetorical move labels to rhetorically salient sentences only. The study described in this chapter adopts the XIP as an exemplar of this type of automated technology. The framework is implemented as the rhetorical module of the XIP, which detects and labels rhetorically salient sentences in scholarly writing based on the identification of meta-discourse conveying the author's rhetorical strategy. The unit of analysis

XIP uses is at sentence level, and each sentence can have multiple labels. The labels XIP has are shown in the following table with description and examples:

Label	Description	Example
Summary	Summarising the goals or results of the article	The goal of this study…
Emphasis	Emphasising the importance of ideas	… is crucial for understanding
Background	Describing background knowledge necessary for understanding the article's contribution	Recent studies indicate…
Contrast	Describing tensions, contrasts between ideas, models, or research directions	In contrast with previous hypothesis…
Novelty	Conveying that an idea is new	New insights provide direct evidence…
Tendency	Describing emerging research directions	Growing recognition of the importance…
Open questions	Describing problems that have not been solved	Little is known…

When assessing students' essays, educators could benefit from the available automated textual analysis which can detect meta-discourse. This way, academic tutors could overcome not only limited time they have for providing feedback but also the issue of providing effective practical examples of what argumentation should look like with readily available automatic machine output. However, the ethical and privacy concerns of whether these technologies can be used to analyse student writing reliably have been an ongoing debate since several decades (Attali, 2013).

2.3 *Ethical Concerns Associated with Writing Analytics*

Writing analytics and automated marking and feedback of student essays seem to be useful to overcome the problems tutors experience. Writing analytics can support the process of improving students' writing skills, as its results can start to produce meaningful dialogues between students and teachers (Ras, Whitelock, & Kalz, 2015). Yet, there has been an ongoing tension between the writing teachers, researchers, academic tutors, and essay markers on the one side and the developers of such automated technologies on the other regarding the use of automated essay evaluation. 'There is an inherent suspicion that technology can corrupt the essence of a fundamentally human activity' (Elliot & Williamson, 2013). Since many tutors see automated technology as a threat, this tension has often appeared in academic literature.

On the one hand, there is significant support for automated essay scoring (AES) as 'automated essay scoring and evaluation becomes more widely accepted as an educational supplement for both assessment and classroom instruction' (preface in Shermis & Burstein, 2003). There are several studies showing that AES systems work well, with studies reporting high agreement rates between AES systems and human markers (Bridgeman, Trapani, & Attali, 2012; Burstein & Chodorow, 2010; Landauer, Laham, & Foltz, 2003).

On the other hand, there has been and still is significant opposition to AES, particularly to the idea, originated by Page, that 'it might replace human scoring' (Ericsson & Haswell, 2006; Herrington & Moran, 2012). Harsh criticism comes particularly from the community of writing researchers. The tension is originated by the awareness of the limitations and dangers of such automated text analysis systems and what such systems cannot do. Critiques in Ericsson and Haswell's (2006) collection provide the following reasons for this tension. Writing teachers and researchers are worried because they question:

- Whether such systems can be gamed or fooled and whether students can break these systems
- Whether machine analysis programmes can fully understand the meaning of texts
- How students would react when they find out their work has been evaluated automatically
- How closely such software matches the careful evaluation of writing teachers
- Where automated text analysis leads the teaching profession and would tutors have greater or less control over courses

It is important that participants trust a machine that is analysing human writing, and therefore it is important to hear what queries or even doubts they have about how such a tool works, as well as how similar its output is to their judgement of quality, and how it can be improved, in the process of implementing writing analytics. This approach has been adopted to reveal any potential issues and challenges for implementing writing analytics at higher education, which is explained next.

3 Study

The qualitative data is collected in two parts: one-to-one interviews and a focus group, in order to understand and explore the opinions of educators on the matter of how they define the attributes of good student writing and to what degree the automated text analysis can capture the presence of these attributes.

3.1 One-to-One Interviews

Firstly, individual interviews were conducted with the Open University educators. Seven one-to-one interviews were conducted in total; each took around 90 min, and each interview consisted three sections:

1. Section one was a general, introductory part of the interview, in which tutors briefly set out their views on assessment and what they felt to be good student writing. This section investigated how these educators defined the quality of writing and its most valuable characteristics in this context.

2. Section two was the essay-marking exercise. In this section, all tutors were given a same student essay and their usual marking rubric to mark the essay. They were specifically asked to highlight the sentences that they thought had a positive effect on awarding a good mark, not just in terms of writing style but anything (e.g. spelling, grammar, content accuracy, references, etc.) that they considered should influence the quality and the essay mark.
3. Section three was a follow-up question-and-answer session on the highlighting exercise, to discuss specific assessment decisions by the participants and to learn why they had highlighted particular sentences.

3.2 Focus Group

Following these one-to-one interviews, a focus group with different educators and senior researchers in the area of academic writing were carried out. The aim was to observe and comprehend the ideas and the interaction between experts about implementing writing analytics at higher education, to discuss any ethical concerns they might have, and to discuss possible ways of resolving these concerns. One focus group discussion was held with six participants (different to the one-to-one interviews) at the Open University, UK. The study was advertised in the Faculty of Education and Languages (FELS) since many academics in this faculty have a particular interest in the area of student academic writing and have experience in teaching and marking student essays. The participant selection was not confined to these people, however, and an advertisement was also sent out to all those who carry out research in student writing and who matched the criteria of experience in teaching and marking.

The focus group discussion was started with a presentation on how the XIP tool works, what research has been carried out so far, and its results. All focus group participants were present for the presentation as well as for the focus group study itself. A question-and-answer session followed the presentation. The focus group was in three sections. Before the first section began, participants wrote down their initial thoughts and/or misgivings about the possibility of using a writing analytics approach in their educational practices. Participants were then given two pages of student writing, and, without any guidance, they were asked to highlight the sentences that they thought illustrated good-quality writing, with respect to good critical, argumentative, or analytical statements only. Then, the XIP analysis of the same writing was shown (note that the machine was not trained with this instrument). After receiving their reactions to the XIP results, participants were then asked to discuss the sentence category (i.e. summary, background, contrast) that XIP might have assigned to each salient sentence and whether they agreed with XIP's choice.

In the second section, after participants were informed about the potential of XIP, they were asked whether they would consider using XIP to analyse their own students' writing if the XIP tool were to be made publicly available to analyse any form of student writing. They wrote down three important features that would convince them to use the tool. After participants had shared their ideas, they discussed what would be the most important factor in their decisions.

In the final section, participants discussed what might need improvement and what sorts of change they would make to improve the approach. At the close of the session, participants were asked to write down their final thoughts and/or doubts about implementing writing analytics.

3.3 Results

3.3.1 One-to-One Interviews

The essay-marking exercise of the interviews required tutors to highlight the key sentences that they thought would have a positive effect on the final essay mark. They were each given the same student essay. Tutors were asked to perform regular marking activity with reference to the same rubric they use and to talk through their decisions, which were audio recorded. The essay was five pages long, excluding the bibliography, and contained around 3000 words. There were 88 sentences in total.

Taking the tools and the tutors' highlights, and the similarity and overlap between (a) tutor pairings, and (b) the tool and each tutor, were then measured using Jaccard similarity index. The Jaccard analysis results showed a highly significant similarity between the highlights of the tool and the first tutor ($p \leq 0.01$) and no significant similarity between the marks of tool and those of the other six tutors ($p \geq 0.46$). The Jaccard analysis was also performed between tutors to find out whether they agreed with each other and if their marking was similar. According to Jaccard analysis results, there are no significant similarities between any of the tutor pairings. According to the Jaccard analysis results, the highlighting carried out by each tutor was significantly different to that of the others. The assumption had been that tutors would share the same understanding about what makes good-quality student writing, so their highlights would be similar, and the overlap between the XIP and the tutors could be measured reliably. However, this proved not to be the case. There could be various explanations for this result. Considering that all these participants had more than 5-year experience of marking essays using the same marking scheme, one explanation could be that human marking is not reliable. Human marking is not always reliable, which supports the assertion that using automated technologies and writing analytics to support educators' essay assessment processes could be a good idea, yet it is a challenge to implement writing analytics taking tutor marking as a benchmark if it is not reliable.

It is important to underline though in normal circumstances to standardise the Open University marking would be balanced with the second marker's decision; and with the third marker's in case of a possible disagreement during the coordination meetings. Therefore, based on this small sample size, it is not credible to generalise the result that every tutor marks completely differently and unreliably. Yet, it is significant to note that human marking and assessment may vary depending on several factors, whereas automated analysis always provides the same result every time. This supports the argument that there is a benefit to using an automated technology, which could support educators' marking.

Following the essay-marking exercise, tutors talked about some problems with marking that they experience. One of the problems they raised was about the 'subjectivity of human marking'. Tutors also mentioned they only have a limited time to mark an essay; hence they spend too much time marking papers and feel pressured with hours of grading. Additionally, markers mentioned that they struggle with giving feedback and commenting and annotating students' essays, which are even more time-consuming to make sure they gave a clearer explanation about why they have given a specific feedback to their students. When tutors raised the problems they experience with assessment, they were asked whether they would consider using a computational language technology that might potentially help them to overcome such problems. They stated the worry that they might be replaced by technology and felt uncomfortable discussing how technology might be helpful to overcome their problems.

3.3.2 Focus Group

The focus group session was both audio and video recorded, and a full verbatim transcription (Poland, 1995) approach was followed. This approach involves noting down both the non-verbal actions like gestures, mimics, gazes, and nods and verbal actions signifying hesitations, ignorance, laughs, sarcasm, confusion, and excitement, like confusion in the tone of the voice, murmurs, hums, okays, etc. Adding observational data like facial expressions made it possible to observe how people's ideas had changed and were also influenced by others.

After transcription, qualitative thematic analysis of the qualitative focus group data was carried out. The responses yielded data for content analysis that permitted theme creation based on the frequency (number of appearances) and intensity (emotion) of the responses of the six participants. Analysis was undertaken both of the verbal data and the observational data of facial expressions. From the qualitative analysis of the focus group data, following overarching themes emerged, which are given in the next sections.

Theme 1: Belief

When academic tutors and writing researchers came to the focus group, they were initially not inclined to use an automated technology to analyse student writing and did not expect to gain any benefit from it. The participants came to the focus group session with preconceptions about automated technologies. Their belief was that such technologies were developed for commercial return and that they can never be as good as human markers; the aim of using automatic technologies is to automate the marking, not to support assessment processes. This shows in what ways writing analytics systems can be biased. However, a comparison of their initial and final thoughts demonstrated a change in the participants' opinion regarding what they believe an automated text analysis is capable of. Their initial thoughts were concerned with trusting a machine; their final thoughts focused on motivating its use.

Changes in their opinion occurred at different points. For instance, after the presentation session on what the tool does, learning about what had been already found in prior research in the earlier quantitative studies (Simsek et al., 2015) changed the participants' opinions positively towards the overall research. As they understood more, they became more interested. Similarly, after completing the highlighting activity, when participants examined the tool's analysis and compared them with their own highlights, they were impressed. This shows that they did not expect the analysis of the tool to resemble their own decisions. When the participants found out the tool's highlights were congruent with their highlights, their attitude was very positive which was a shift from their initial opinion.

This study revealed that when writing teachers and researchers are introduced to how automated technologies work, they are able to gain a better understanding of such writing analytics tools' capabilities and limitations. When they are made part of the process, in other words when it is made transparent to them, their opinion shifts and their bias can be broken.

Theme 2: Power and Politics

The participants were happier to discuss the weaker points of the tool than they were identifying its strengths, which implies that they did not want its quality to equal theirs. The theme power and politics emerged since the participants wanted to feel superior to automated technologies and 'harness' and control them to obtain benefit.

Emerging from the focus group discussions, the underlying issues of power and politics were due to the participants' fear of:

- What might happen to the future of the teaching profession and them losing their jobs as a result of that
- Being judged by their students who could potentially compare human and machine results

This finding triangulates with the literature (Attali & Burstein, 2006; Elliot & Williamson, 2013; Ericsson & Haswell, 2006; Shermis & Burstein, 2013) indicating the suspicion and tension of writing teachers and researchers towards the use of automated text analysis. It also triangulates and tallies with the one-to-one interviews, where tutors felt uncomfortable discussing how technology might help to overcome the problems they experience with assessment and stated the worry that they might be replaced by technology.

The study showed the key element which made participants open to accepting the idea of using such technology, that is, the 'power and politics'. They wanted to feel that they are in control of things and superior over the technology. They wanted to be the 'power' behind such technologies that should be driven and 'harnessed' by them. Eventually, they wanted to decide how and to what extent they would like to use the automated support. Educators, tutors, and markers wanted to be assured that they retain the power themselves in any decision.

Theme 3: Problems

The participants talked about some problems that markers and their students experience which automated support could potentially solve. These were identified as:

- The subjectivity of human assessment and marking.
- The limited time that markers have to assess an essay.
- The possibility that markers do not necessarily notice that their students are actually making an analytical point, since most of the markers are not linguists.
- Markers need to improve the quality of their feedback and make sure they give a clear explanation of why they have given a specific feedback to students.
- Markers need to generate discussion with students who are required to reflect on, critique, and edit their work.

Some of the problems identified tally well with the one-to-one interviews and are congruent with the literature. The problems of subjectivity in human marking, time limitations, and the need to provide better feedback and examples to ensure students understand their reasoning became evident in the one-to-one interviews with tutors. Earlier research (Lea & Street, 1998) indicating that academic tutors experience difficulty with providing effective examples and feedback is also supported by the focus group findings.

These problems, such as the labour-intensive, time-consuming essay assessment problem, could potentially be solved through automated support. Considering it took around 15 min for the focus group participants to highlight 13 sentences, it could be time efficient to use the automated support as the XIP analysis, for example, took less than a minute for the same piece. Additionally, automated support potentially could help to overcome the subjectivity of human marking. Participants were honest about how subjective their marking can be and that there was a mismatch between the way they interpret and mark things. This is a very critical point showing the possible inconsistencies between human markers. In line with earlier findings, human markers can disagree with each other and therefore they do not necessarily come to the same conclusion as their peers; which is a reliability concern. The automated output on the other hand is always the same, stays the same, and is not subjective. The writing analytics tool could therefore potentially be useful to help educators overcome this problem by using it for instance as a self-reflection tool.

4 Conclusion

This chapter evaluates the issues and challenges in the deployment of writing analytics to support assessment in higher education. It provides a systematic investigation of implementing an example writing analytics at higher education and discusses the issues and challenges revealed during this attempt. The studies conducted with academic tutors and writing researchers showed that implementing writing analytics applications can be useful to support feedback process, yet its limitations and risks should be acknowledged. Although these risks and limitations of using an automated text analysis were mentioned several times through during the discussions, the final thoughts of the participants were positive towards using writing analytics, and there was general agreement about the idea that writing analytics could support both educators and students.

It is true that current AES systems do not mimic human markers' ability to measure conceptual reasoning; thus AES measures a narrower range of skills than human markers (Deane, 2013), though they could measure a lot that human markers ignore. If human markers are inconsistent and unreliable, then the machine cannot be trained effectively (Bridgeman, 2013). Therefore, the aim of mimicking human markers is a difficult task to achieve. However, in order to deploy an AES system by considering such limitations, this deployment must be sensitive to AES' own limitations as well. It does not understand the essay, and therefore it is limited to measuring a subset of the written context; therefore, AES should currently be considered as a 'complement to human scoring' (Attali, 2013, p. 194). A 'division of labour' approach (Attali, 2013, p. 194) between human markers and machines can be used to overcome such issues. This study prompts consideration of how human markers and machines can work well together and mutually complement each other for their own sake and for their students. Advancing automated support for assessment is key when the strengths of both sides can be brought together: the speed and reliability of the machines and the vast capabilities and the knowledge of the human markers.

In summary, this study has proposed that, at the current time, automated text analysis should not be the sole method of evaluating student writing. Instead, it should be used in combination with human evaluation. It should be recognised that machines do not currently fully understand the language itself, the accuracy of the written material, the content, and the beauty and subtlety of sophisticated argumentation that would be credited by human markers because it flows beautifully (Whitelock & Bektik, 2018). Machines have limited capacity to understand language and literacy; this capacity is mostly dependent on the rules that its developers have written to train them. On the other hand, human language has endless possibilities of creating and forming new sentences each time. Therefore, machines and human markers should complement each other, with the aim of providing better feedback to students.

When adopting writing analytics, the relationship between humans and machines should be mutually inclusive rather than exclusive considering all stakeholders. This requires resolving the ongoing tensions between the researchers of writing and developers of automated essay evaluation tools, which, as this study has emphasised, can be achieved through the importance of the 'decisive power' that academic tutors and markers require to overcome their tension and worry about the use of automated text analysis and writing analytics.

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Chapter 10
Digital Applications as Smart Solutions for Learning and Teaching at Higher Education Institutions

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1 Introduction

Due to the digital change and the rapid technological development, higher education institutions have to cope with upcoming demands. Currently, blended learning concepts or virtual collaboration via mobile devices had already entered everyday university practice. With respect to the future, there will be more challenges and in this context also new opportunities for the academic education. A midterm trend is seen in a growing interest of making learning processes more measureable and finding innovative learning space (Adams Becker et al., 2017). The usage of mobile devices and all-time Internet access lead to the fact that our social and professional lives more and more take place in the virtual world. Due to these circumstances, large data amounts about individuals and groups are stored and available in quantitative as well as qualitative form. Learning analytics represent a dynamic approach to evaluate students' learning almost in real time (Ifenthaler, 2015). By analyzing and visualizing the individual data, learning deficits can be illustrated, feedback can be given, and interventions can be implemented. Currently, learning analytics are already used for making learning more personalized and adaptive. Receiving timely feedback is a great benefit, because it may lead to better and appropriate design of

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curricula (Ifenthaler, 2017b; Lockyer, Heathcote, & Dawson, 2013). At the same time, such approaches usually end up in a discussion about privacy and ethical standards (Ifenthaler & Schumacher, 2016; MacCarthy, 2014). Clear guidelines, minimization of data collection, and transparent procedure can support the implementation of new learning methods in a positive way (Ifenthaler & Drachsler, 2018). Higher education institutions regarded as training and developing facility for young academics also need to consider the labor market situation. With respect to the world of work, rising trends toward new technologies, virtual collaboration, and intercultural cooperation need to be considered. Due to this development, more and more employers require a certain digital skill set when hiring new employees. The so-called twenty-first-century skills (Griffin & Care, 2015) refer to the idea of developing viable workers for a modern knowledge society. By summarizing all aforementioned aspects, this chapter will provide a short historical review of smart solution in higher education. First, two approaches—mobile learning and learning analytics—will be considered in detail (Sect. 2). Next, an ongoing research project of Baden-Wuerttemberg Cooperative State University Mannheim and the University of Mannheim, which explores the short-term and long-term effects, risks, and benefits of the usage of mobile learning analytics in the students' daily life, will be described (Sect. 3). Building on an appropriate implementation of new learning methods, Sect. 4 summarizes the benefits as well as the challenges for three target groups—students, lecturers, and higher education institutions. Moreover, two approaches for a successful implantation of smart solutions into the classroom are presented (Sect. 5). Last, a conclusion will be drawn, and an outlook will be given (Sect. 6).

2 Smart Solutions in Higher Education

Digital media and learning found their ways into the higher education systems. Concepts like serious games, learning analytics, and gamification do no longer sound as unfamiliar as only a few years ago. Nevertheless, differences of actual usage of digital media and smart solutions can be identified in various countries. But what does smart actually mean? When using the concept smart to describe a person, we mean that someone is intelligent, can deal with difficult situation very quickly, and is flexible in his or her way of thinking (Cambridge Dictionary, , n.d.). On the opposite, a not so smart individual will find it difficult to react intuitively to upcoming situations and will not reflect about his or her behavior. So literally, the meaning is connected with the idea of innovation, certain flexibility, and a 360-degree perspective. The framework of smart solutions for higher education institutions assumes that a learning environment is innovative as well as offers alternatives to learn, collaborate, and motivate (Spector, 2014). Therefore, the following sections provide a closer look on smart learning environments.

2.1 Definition and Characteristics of Smart (Learning) Environments

In this section, the terminology of smart environments will be introduced and characterized. As this paper displays the situation for higher education institutions, we use smart environments and smart learning environments interchangeable.

According to the literature, the development of smart learning environments is rooted in the 1980s. During this time, intelligent tutoring systems (ITSs) and adaptive learning models were developed (Graf, Kinshuk, & Ives, 2010). These early attempts of a combination of virtual and pedagogical approaches are by far not comparable to the current state of various innovative learning and teaching methods. Particularly, wireless communication and the invention of mobile devices made a significant contribute to the present state (Sharples, 2013). Similar to the change of media and technology, humans have aligned to the digital shift. The new generation of digital natives has grown or rather grows up by using mobile devices naturally (Parment, 2013). Moreover, they place great demands on smart solutions as well as on the educational system. Hwang (2014) sees the students' preferences especially in personalized and adaptive learning. With respect to practical applications, this means that learning should not only be independent from location and time but also adaptable to an individual's personal prerequisites like individual dispositions, learning conditions, and personal life. Shaped by the digital change, the increased requirements, and the omnipresence of new media in daily lives, "context-aware ubiquitous learning environment (u-learning)" solutions have evolved. These approaches are able to detect real-world factors (e.g., learner's status quo, cultural influence) and offering support (e.g., learning material, feedback) (Hwang, 2014; Sampson & Zervas, 2013). Furthermore, the learners in a u-learning scenario are guided under consideration of their individual context. Digital media and new ways of communication have no special role when talking about adaptive learning but provide a base for the formation of smart learning environments (SLE). Koper (2014) mentioned four general features of smart learning environments:

- A physical learning environment, which is enhanced by one or more digital devices.
- The digital devices that have to be aware of the learners' status quo (context, culture, location).
- The digital devices that provide features like the possibility of assessment, virtual collaboration, feedback, or feed forward to the learners.
- Monitoring of the learner's process and presentation of relevant information to different stakeholders.

Various benefits for the learner emerge from the creation of SLE. Likewise, to a "context-aware ubiquitous learning environment," different real-world and virtual factors are considered. Furthermore, both approaches are able to provide personalized feedback and interaction through multiple channels and push informal as well as formal learning (Hwang, 2014). SLEs enable adaption of content, tasks, as well as interfaces to the learners. Hence, smart learning causes a redefinition of the classroom through the combination of educational prerequisites (e.g., pedagogic approaches) and innovative methods (e.g., virtual collaboration, learning analytics, cloud learning, etc.) (Aguilar, Valdiviezo, Cordero, & Sánchez, 2015). Overall, SLE offers a learner-centered approach which collects and displays various information and leads to a better as well as faster learning by using digital devices (Graf et al., 2010).

2.2 *Mobile Learning and Learning Analytics*

This section will extend the idea of learner-centered approaches. According to the literature, self-regulated and adaptive learnings are well-received concepts when it comes to academic success (Postareff, Mattsson, Lindblom-Ylänne, & Hailikari, 2016; Vrieling, Stijnen, & Bastiaens, 2017). Mobile learning and learning analytics fit to the basic concepts of personalized learning which are currently being implemented in the context of higher education. In the following sections, both terms will be defined, and typical attributes will be presented.

2.2.1 Mobile Learning Definition and Features

Mobile learning or m-learning is related to learning and teaching. Mobile learning is linked to an appropriate usage of digital media and the possibility of learning independently from time and location (Traxler, 2009). Due to its focus on flexibility (i.e., time and location), the concept is clearly differentiated from e-learning (Gourova, Asenova, & Dulev, 2015). While the borders between private and professional life get further blurred, learning develops into a ubiquitous process which inter alia takes place independent from time, location, persons, institutions, and cultures. Mobile devices provide ideal conditions for such altered life conditions. In the context of higher education, they meet the requirements of the new generation of students. According to a meta-analysis investigating the trends of mobile learning between 2010 and 2015, the results figured out that smartphones are the most frequent used devices for m-learning. In addition, informal learning is the most preferred procedure when it comes to m-learning. The omnipresence of smartphones provides unlimited access to knowledge, and learners can access information in different ways (e.g., informal, formal). With respect to the development of smart classrooms, digital devices are fundamental requirements. They function as virtual collaboration/communication tools and provide real-world scenarios for students (McQuiggan, Kosturko, McQuiggan, & Sabourin, 2015). Furthermore, m-learning can help to train a certain digital literacy, which is highly required by our modern knowledge society. Digital literacy implies the correct handling of available data as well as an appropriate usage of new technologies. By summarizing the characteristics of m-learning, it can be concluded that the approach leads to a more personalized and adaptive learning (Sampson & Zervas, 2013). While adaptive learning refers to its consideration of learner's individual prerequisites like context, social status, and needs, personalization means the possibilities of a personalized usage of mobile devices and involved applications (different languages and selection of preferred features).

2.2.2 Learning Analytics Definition and Features

As already mentioned in Sect. 2.2.1, mobile technologies have enhanced and improved the possibilities of learning and teaching significantly. Particularly, their contribution to a more personalized and adaptive learning is indispensable for today's educational system and for integrated smart solutions. Furthermore, it seems that personalization is directly linked to a better learning experience, because learners are able to choose their favorite methods according to their individual conditions (Ifenthaler, 2015). In this context it is important to mention that personalization is not only a one-sided process supervised by the individuals. It is also a procedure, which is built on the interaction between learners and technology. Particular interesting here is the amount of data emerging from the person-computer interaction. *Educational data mining* or *academic analytics* presents good options for analyzing virtual-produced data (Berland, Baker, & Blikstein, 2014). However, these models are only able to consider and evaluate information from the past. *Learning analytics*, on the other hand, use real-time data about learners like their individual behavior or context (Ifenthaler, 2015). While learning analytics are already used successfully in English-speaking countries (the USA, UK, Australia), only a limited number of researchers have implemented the approach in Germany yet (Ifenthaler & Drachsler, 2018). Besides the possibilities of real-time evaluations, learning analytics are utilized to visualize information about individuals (Macfadyen & Dawson, 2012; Schumacher & Ifenthaler, 2018). The benefits for involved stakeholders like students or teachers stem from the simplicity of these analytical tools. By considering special algorithms, the tools can help teachers to identify "at-risk" students and to select suitable interventions (e.g., feedback, reasons for poor performance) (Elias, 2011). Other benefits resulting from learning analytics are:

- Recommendations for learners (learning material, learning behavior) (Schumacher & Ifenthaler, 2018; Verbert, Manouselis, Drachsler, & Duval, 2012).
- Individual reflection of learning behavior (learn tracking) (Verbert et al., 2012).
- Diversity improvement and social collaboration (Gosper & Ifenthaler, 2014).
- Evaluation of influencing factors like emotions, cognition, etc. (Tempelaar, 2017).
- Pedagogical interventions (Ebner, Taraghi, Saranti, & Schön, 2015).
- Adaption of curricula for the target group (Ifenthaler, 2017b; Lockyer et al., 2013).
- Formative as well as summative evaluation of learning process (Macfadyen, Dawson, Pardo, & Gašević, 2014).
- Self-regulated and self-controlled learning (Pimmer, Mateescu, & Gröhbiel, 2016; Schumacher & Ifenthaler, 2018).

Nevertheless, the implementation of learning analytics in higher education institutions demand also trained staff and a well-equipped infrastructure. A current research showed that the majority educational institutions are only prepared poorly at this moment (Ifenthaler, 2017a).

Learning analytics include tools which can improve the universities' routine by the evaluation of learner's data. Therefore, the approach is strongly linked to the development of appropriate learning design (Ifenthaler, 2017b; Lockyer et al., 2013). The following five steps can be considered for a practical implementation of learning analytics into the curricula (Elias, 2011) (Figs. 10.1 and 10.2):

Time Horizon

STEP	ACTION
1 Capture	Data collection (learning behavior, motivation, etc.) of qualitative as well as quantitative sources
2 Report	Categorizing of data and learners information
3 Predict	Formulation of assumptions and hypothesis by analyzing the generated empirical basis
4 Act	Active interventions and creation of learning design
5 Refine	Monitoring of process and development of recommendations

Fig. 10.1 Five steps of implementing learning analytics into the curricula

Fig. 10.2 Screenshot of the MyLA app in German

2.3 Interim Conclusion (and Research Gap)

The literature review showed that smart solutions are highly beneficial for different stakeholders (lecturers, students) and that they play an important role according to a digital shift. Particularly, the development of wireless communication and innovative collaboration has contributed to on-demand learning. Although mobile devices and innovative learning environments (virtual, hybrid, blended learning) provide great potentials, they are rarely implemented to provide full potential for all involved stakeholders. In addition, a well-developed infrastructure, trained staff, and integration into the universities' strategy are indispensable. One step toward the right use of digitalization in higher education context will be the promotion of a certain digital awareness and a creation of transparency.

3 Project *Mobile Learning Analytics*

The project *mobile learning analytics* is a cooperation project of the Cooperative State University Mannheim and the University of Mannheim. It is part of the initiative *Digital Innovations for Smart Teaching—Better Learning* of the Ministry of Science, Research and the Arts of the State of Baden-Württemberg, Germany.

Within this project, two applications with the brand name *MyLA* (= My Learning Analytics) have been developed—an app for students and an additional dashboard for lecturers. Both applications will be presented in the following sections.

3.1 MyLA App

The MyLA app was built on web technologies, a so-called web application. The reason for this is a cross-platform usage on almost every smart device. Furthermore, the utilization with laptops and other personal computers enlarges the possibilities of this application. MyLA app consists of three main categories: *My Profile*, *My Learning*, and *My Progress*.

- My Profile: (1) Profile Data: Only anonymous data will be collected, like university, course, or lecture. For using the app, a user has to register with an individual username with a minimum of six characters. (2) Trophies: App users can collect several trophies for different actions within the application, for example, for making the first pinboard entry.
- My Learning: (1) Pinboard: This part facilitates the communication between students and lecturers. Via the pinboard the app users can express individual needs or needs occurring on course level. The short messages will be sent to the lecturer's dashboard, where he/she can react on. A special feature is the tagging. Before sending a pinboard entry, the user can categorize the message into a tag

(e.g., question, exam). Thus, the lecturer can filter all messages by using these tags. Furthermore, the students receive messages containing text, link, and file from their lecturers. Hence, the instructors may share exercises with their students. (2) Survey: The second part can support the feedback process during different periods (e.g., over a semester at university or a semester abroad). The student receives the published surveys from their respective lecturer. Now he or she can anonymously participate to give important feedback to the lecturer. Based on this exchange, the lecturer can also analyze how the course performs and if there is room for improvement.

- My Progress: (1) MyTracker: This evaluation feature enables an individual tracking of personal data, e.g., learning motivation and learning effort. App users can evaluate several variables at different time stamps. Based on the feature, students should be engaged to self-regulate and self-control their personal learning process. (2) MyTracker Stats: This section visualizes the MyTracker data using different colored charts. The user can track and analyze their individual development, where every variable has an own chart.
- Further parts of the app are imprint, privacy, use policies, frequently asked questions and app history (versions), contact, settings, app statistics (like date of registration and collected trophies), and several navigation elements (e.g., side menu and home button).

The aim of MyLA is to improve the communication between students and lecturers. Not only during the shared time at university but also during their physical absence from the institution. Moreover, the feedback process should be enhanced. The lecturers can publish surveys and gather feedback on different times (e.g., before a semester, while a semester, and after a semester) for starting interventions, if necessary. By implementing the digital instruments into learning and teaching processes, the situation for the involved actors can be improved. Additionally, the tracking function targets progressive feedback to students concerning their individual learning process. Special concerns, which occur with the usage of individual data, are privacy issues. Thus, the anonymity and pseudonymity are important features of MyLA. The only data that have to be saved are university, course, lecture, semester, and a self-given username. This should prevent the student's overcoming in contacting their lecturer and resultant in using the app.

3.2 MyLA Dashboard

The MyLA dashboard is built on web technologies as well as the app. The default usage is via personal computer (desktop), but it is also possible to use it on mobile devices. Generally, tablets are most suitable in comparison to smartphones because of their screen size and their grid display. MyLA dashboard consists of three grids on the home page: *Pinboard Entries*, *Survey Centre*, and *LectureTracker*. Additionally, the lecturer can manage his profile and has almost the identical further parts (like imprint, etc.) in comparison with the app.

- Short description of Fig. 10.3:

- Left side, Pinboard Entries; Middle, Survey Centre; Right side, LectureTracker.
- My Profile: The profile displays the conjunction between students and their lecturer. On the dashboard the lecturer has to select his university and course. Within the course he/she can register several (at minimum one) lecture/s with the respective semester. Furthermore, the lecturer has to place an access code for every registered lecture. The access code and the automatically given lecture number are important for the students to join a lecture. In MyLA app the students need those two inputs to successfully register in the lecture and use the app functionalities.
- Pinboard Entries: On this area of the dashboard, the lecturer receives messages from the students and can also respond to them. Furthermore, the instructor can mark them just as read. The second option is, e.g., for entries with informative character. The lecturer can filter the entries by the given filter buttons which are equivalent to the student's tagging (see My Learning in Sect. 3.1). Furthermore, the lecturer can see on the button how many entries of a certain category were submitted. Additionally, the lecturer can send messages to a certain lecture. Those lecture messages can contain text, link, and file.
- Survey Centre: This section gives lecturers the possibility to get feedback whenever it is wanted or necessary. Lecturers can use default questions or add own questions with options. After publishing a survey, only the instructor's selected lecture sees the survey and can respond to it. Then the lecturer gets the aggregated results of all responds.
- LectureTracker: Students have the possibility to track several variables like learning motivation or learning success over time (see My Progress in Sect. 3.1). The aggregation of student values is available on lecture level. The only transmitted data will be the number of participants and the average values of all variables divided by weeks.

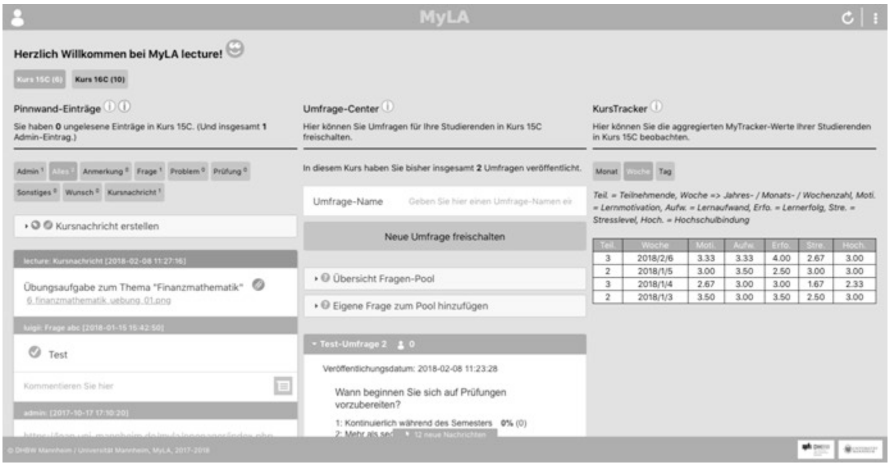

Fig. 10.3 Screenshot of the MyLA dashboard in German

MyLA dashboard's actual version is a communication and feedback as well as an analysis tool. With applying these functions, the lecturer can force the exchange with his students and enhance the feedback process. In further developing of app and dashboard, additional functions shall be implemented. The added functions shall be chosen with the feedback from lecturers and students. The aim of both tools is to improve the situation for both groups—students and instructors.

3.3 First Findings and Outlook

In spring 2017, the app was tested regarding its design, navigation, and further aspects. One hundred five students from both universities participated in the quantitative study. For the investigation and with respect to meeting general quality criteria of empirical research, a usability testing instrument was adopted (Pirnay-Dummer, Ifenthaler, & Spector, 2010). Furthermore, the project team conducted an additional eye-tracking study to investigate the use of the application. Within the qualitative testing, the participants had to solve three different tasks (e.g., navigation through the app) by using the app prototype. The two applications should be tailored to the potential users (i.e., students and lecturers). Therefore, workshops and information events had been taken place. The project *Mobile Learning Analytics* focuses on further research regarding mobile learning and learning analytics. With the two applications—consisting of MyLA dashboard and MyLA app—data will be collected. Further functionalities shall be identified, students and lecturers evidently need. Another big challenge of MyLA integration is the conviction especially of lecturers and also of students. Reasons for that might be the existence of a learning management system at the university or the apprehension of an additional time effort. Challenges have to be processed in a detailed way to reduce existent obstacles.

4 Long-Term Success of Smart Solutions

The future smart solutions in higher education can only work if stakeholders will be aware of possible benefits and risks. In the following sections, the opportunities as well as the challenges will be discussed from a perspective of the three main stakeholders (i.e., students, lecturers, and universities).

4.1 Opportunities for Stakeholders

Smart solutions that integrate mobile devices in learning processes have an important impact on future learning opportunities and scenarios. The potentials of using mobile devices in the context of higher education are only rudimentarily exhausted, yet. For example, a current study with 105 German participants showed that the respondents use apps for learning on average only 4 days per month. In comparison to this, the students utilized apps for other reasons almost every day (29 days per month on average) (Kuhnel, Seiler, Honal, & Ifenthaler, 2017). In this section, the opportunities of smart solutions will be discussed under consideration of different stakeholders.

For Students Mobile applications are independent from time and location. Moreover, learning materials and additional options for in-depth studying like videos are available in portable form via Internet access. Furthermore, the communication and feedback process can be simplified and improved (Torres, Infante, & Torres, 2015). Additionally, the applications can support collaborative learning like sharing materials and knowledge or discussing with peers and lecturers. Social media functions like commenting, connecting, and so on are further possibilities. To come along with this, learners can build a personalized learning experience based on all inputs and media offers (Gikas & Grant, 2013). Learning analytics (LA), for example, use digital traces which are produced while using learning systems. To fulfill the students' needs in learning and feedback management, Schumacher and Ifenthaler (2018) identified several features, which students expect most from LA. For example, the majority of the study participants wanted to integrate a self-assessment feature which is resemble to real exam conditions. Furthermore, they expect valid feedback and recommendations on learning materials to close their knowledge gaps.

For Lecturers Lecturers can also benefit from the advantages mentioned afore. Furthermore, instructors ideally detect at-risk students by using learning analytics technologies and can help their students almost in real time by planning necessary interventions. LA is also suitable to identify course materials that lead to problems or do not have any impact to students learning (Ifenthaler, 2017b; Mor, Ferguson, & Wasson, 2015). Another long-term aspect is digital literacy of the lecturers. This means the skills concerning the usage of digital technologies. There has been some positive relationship between digital literacy and the adoption of new technologies. Additionally, teaching self-efficacy is an important point, which relates to the integration of technologies in lecturers teaching (Mac Callum, Jeffrey, & Kinshuk, 2014). If those challenges can be coped with success, the lecturers can benefit from smart solutions regarding their expertise. Using digital technologies can also enlarge their possibilities in teaching processes.

For Universities Universities as educational institutions benefit from smart solutions. Analyzing and optimizing the impact of internal resources are important assets to universities. This data should be used to improve processes at institutions and optimizing the resource input. Further goals are improving learning and teaching processes, lower dropout rate, and higher success rate (Ifenthaler & Widanapathirana, 2014).

4.2 Challenges for Stakeholders

As already indicated in the introduction, digitalization and advanced technology have not only advantages for students, lecturers, as well as universities. They will also occur new challenges for all stakeholders. This section provides some possible challenges of smart learning environments.

For Students In general terms smart solutions should support the individuals during their learning process by analyzing data and providing personalized learning paths. In this context it has to be mentioned that only data from (recent) past and from digital sources are used. Hence, they might not be bias-free and lead to wrong interpretations (Ifenthaler, 2015). The upcoming challenges are dichotomous here: On the one hand, it has to be focused on the students' needs and not on what might be best for the universities images (Ferguson, 2012). On the other hand, transparency and the selection of data are indispensable aspects for preventing privacy and ethical issues (Ifenthaler & Schumacher, 2016; MacCarthy, 2014).

For Lecturers The lecturers have a particular role regarding digital enhanced learning scenarios. They interact between students and institutions. So, apart from their pedagogical job, they are subordinates under internal regulations (e.g., legislation and culture). Moreover, it is often criticized that instructors are educated poorly when it comes to digital media and new technology in the classroom (Gikas & Grant, 2013). Reasonable factors for this might be a lack of support for further trainings and of the encouragement to use innovating approaches by the institutions. The Horizon Report annually highlights the six trends, challenges, and developments with respect to digitalization for higher education. In the latest article, the authors argued that rethinking the role of the instructors and educating a certain digital literacy to overcome old patterns are serious problems (Adams Becker et al., 2017). Only if lecturers understand the added value new technology has for students, they will be able to spend more effort in the didactical realization and their own education. Particularly, the correct transfer of technical data into pedagogical interventions is of high importance for the implementation of a holistic approach (Ebner et al., 2015; Gibson & Ifenthaler, 2017).

For Universities Besides the difficulties to cope with the students, lecturers, and other involved stakeholders, universities have to face other conditions for implementing smart learning successfully. Primarily, a well-developed digital infrastructure involving, for example, wireless access to the Internet on the campus or available technical equipment might be a first obstacle for the institution. Considering the global situation, it can be derived that not every country has equal preconditions as the Western-orientated world (West, 2015). Thus, digitalization in the context of learning and teaching has been discussed under the consideration of social inequality. For universities this signifies to support, for example, more disadvantaged partner institutions. Working in a globalized world is equivalent to grow together with also regarding cultural terms. Gosper and Ifenthaler (2014) argued that diversity is enriching as well as challenging at the same time. In other words, if institutions want to be attractive for students and thereby competitive on long term, they have to offer intercultural opportunities for exchange (e.g., semester abroad, virtual collaboration, etc.). Hence, the implementation of smart learning is still new in the context of higher education; a lack of best-practice solutions and profound research is listed. Furthermore, the majority of initiatives (e.g., projects) to close this research gap usually end up in silo solutions. Only a strong embedded strategy for implementation, the determination of interim steps, and an ongoing evaluation are needed for achieving the objectives.

5 Approaches for Implementation

After discussing the opportunities as well as the challenges for the involved stakeholders, this section will shortly introduce two approaches for implementation of digitalization into higher education. Accordingly, a major challenge will be the avoidance of silo solutions and thus the reinforcement of a long-term success for smart solutions.

5.1 Technology-Enhanced Learning Complex

Higher education systems have a complex environment where different needs (students, lecturers, policy, etc.) are met and where various decisions have to be made. By ignoring these aspects when realizing innovation into the context of higher education, processes often fail. One option for a helpful assistance is seen and discussed in the technology-enhanced complex (TEL Complex) theory by several researchers (Laurillard, 2008; Scanlon et al., 2013). The approach covers different influencing factors, which are presented in the following figure (Fig. 10.4):

The TEL Complex model shows that the vision (e.g., particular example for including digital media into the learning and teaching process) illustrates the center. Around the core, the two components of *pedagogy* as well as *technology* are placed. As already mentioned afore, pedagogy is an indispensable parameter for a successful implementation. Apps (e.g., MyLA app) provide good opportunities for a combination of technical and didactical aspects. Moreover, approach complexity results

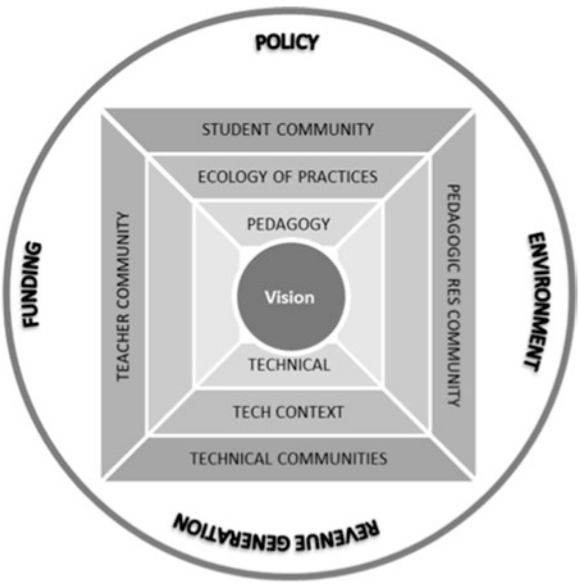

Fig. 10.4 TEL complex model (Adapted from Scanlon et al., 2013)

from the diversity of the involved actors. Thus, Keeley, Pikkel, Quinn, and Walters (2013) discussed in this content the correct quantity of engagement from students and lecturers. In addition, transparency and authenticity present dispositive variables within this context. Besides the *human factor*, *technology* constitutes the recognizable element, which is a prerequisite for the implementation of the shaped vision and can be seen as supporter for the pedagogical implementation. Furthermore, technology is also a driver for innovation. Without an ongoing improvement and development of new technical equipment as well as included applications, no stimuli will be given (Laurillard, 2008). The transition in the model is shown by the component *tech context*. Additionally, the *ecology of practices* has to be considered, too. Scanlon et al. (2013) mentioned in this context that a successful implementation of technology-enhanced learning formats depends on a variety of factors, which can differ between cultural, social, and infrastructural aspects. To give an example, the digital infrastructure in developing countries is usually worse in comparison to industrialized countries. According to the TLE approach, unequal conditions lead to another vision and thus to other periodization. Furthermore, there are four *communities*, which have to be taken into account when planning the realization of an innovation. In the literature, communities are frequently related to suppliers and customers (Keeley et al., 2013). In the context of higher education, the communities consist of, e.g., learner, lecturers, researchers, and further involved persons.

5.2 The Rapid Outcome Mapping Approach

The rapid outcome mapping approach (ROMA) is a holistic approach originally developed for the implementation of policy changes (ROMA, online). Likewise, to afore-presented TEL Model, ROMA considers change not as a linear process, but as a complex system. By focusing on three main topics (diagnose a problem, develop a strategy, develop a monitoring and learning plan), the approach represents a manual, which is flexible and dynamic in its usage. Furthermore, the three main areas are divided into different steps, which help to gain a better understanding of each. The following figure will give an overview of the approach:

As presented in Fig. 10.5, the first step is to clearly *define or redefine* the overreaching policy goals by *mapping the context*. The importance of defining precise problems is supported by the experts' recommendations for evaluation (ROMA, online). Besides specifying the strategic purpose, the *key stakeholders* should be identified and furthermore set into context with the objectives. By pointing out connections and spheres of influencing persons, assumptions for an appropriate strategy can be made (*identify desired behavior changes*). The *development of a strategy* is a next step. Young and Mendizabal (2009) recommend using a force field analysis for analyzing supportive as well as obstructive factors. Particular milestones can be also helpful for the implementation, and they can function as control parameters (see *develop a monitoring and learning system*). Another stage of the policy development is the inspection of the environment and the analysis of the available resources (*analyze internal capacity to effect change*). Only with a suitable infrastructure, the implementation can be successful on long-term view. Furthermore,

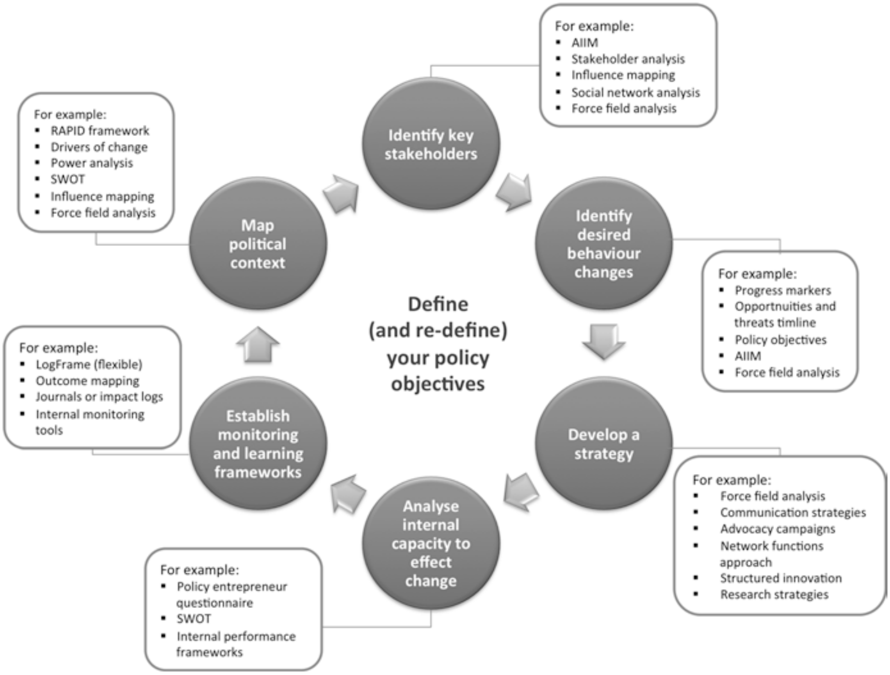

Fig. 10.5 The rapid outcome mapping approach (ROMA) (Adapted from Young & Mendizabal, 2009)

processes should be constantly monitored to contemporary react to changes, make necessary adjustments, and learn from the interaction (*develop a monitoring and learning system*). With respect to ROMA model, the project team had used a similar procedure (e.g., stakeholder and internal capacity analysis) for the development and implementation of the two applications.

The represented approaches—TEL complex model and ROMA—indicate two conceptual models to cope with the implementation of innovation in complex environments. Still, there is no standard solution, but the approaches display detailed and relevant information for higher education institutions. Particularly the development of a strategy, which is built under consideration of environmental influences and internal resources, seems to be a good choice for an appropriate implementation of smart solutions. Furthermore, the ROMA theory does also control the process and gives the recommendation for modification if changes occur.

6 Conclusion and Outlook

Smart solutions have great potential of enhancing the teaching and learning processes at universities. There are many opportunities in using smart solutions in class as well as during practical or internship semesters. However, there exist many challenges that have to be overcome through early interventions. One important aspect is the improvement of digital literacy among all involved stakeholders. Additionally, the technical infrastructure has to be strengthened, for example, through stable wireless Internet access. Furthermore, rigorous research in the area of mobile learning and learning analytics is necessary, especially in German-speaking countries. For instance, German higher education institutions have not reached the level of digitalization when compared to other industrialized nations like the USA or England (Schumacher & Ifenthaler, 2018). Furthermore, universities should implement a digital agenda in their corporate strategy, particularly to support research in the field of digital learning and teaching. By doing so, higher education institutions may actively prevent silo solutions and disorientation. One good example can be seen in the initiative "*Digital Innovations for Smart Teaching—Better Learning*," funded by the State Ministry of Science, Research and the Arts Baden-Wuerttemberg. Within this program, the aforementioned research project "mobile learning analytics" and nine other activities in the field of digital learning and teaching are supported to create evidence for innovative higher education learning environments. All projects are connected for frequent exchange and workshops, providing a platform for collaboration and mutual learning. To sum up, financial and contend-related support (e.g., best practices, guidelines, data privacy, etc.) are essential for the implementation of smart learning environments at higher education institutions. Moreover, higher education institutions should be more open for collaborations across boundaries.

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Chapter 11
Learning Analytics to Support Teachers' Assessment of Problem Solving: A Novel Application for Machine Learning and Graph Algorithms

Philippe J. Giabbanelli, Andrew A. Tawfik, and Vishrant K. Gupta

1 Introduction

For many years, education has often been administered using didactic- and lecture-based methods. In these settings, a teacher often disseminates information, and learners are tasked with memorization of information. However, many argue this form of decontextualized education fails to support learning transfer and engender problem solving. To address this challenge, theorists posit that learning should be situated within problem-solving contexts (Hmelo-Silver & Barrows, 2006; Jonassen, 1991). Instructional strategies that employ ill-structured problems are often referred to as inquiry-based learning. In these instructional strategies, learners are often presented with a problem that is representative of the types of issues that practitioners face. These problems are often characterized as being ill-structured, that is, the problems lack defined goals or explicit ways to achieve the predefined goal state (Herrington, Reeves, & Oliver, 2014). In contrast to well-structured problems that prescribe a set of correct answers, an ill-structured problem is often assessed on the viability of the proposed solution given the constraints, perspectives, and standards embodied in a context (Hung, 2015). The belief is that the ill-structured and problem-solving approach espoused in inquiry-based learning better generate more robust knowledge structures (Clariana, 2010; Ifenthaler, Masduki, & Seel, 2011; Kim & Clariana, 2015).

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This shift in education toward an ill-structured approach has implications for theory and practice. In contrast with multiple-choice questions that an instructor may use for assessment of a well-structured problem, ill-structured problems require learners to identify the relevant elements of the problem space and generate arguments about why a solution is viable and rationale (Ju & Choi, 2017). In addition, Eseryel, Ifenthaler, and Ge (2013) see an "effective learning process as one that facilitates transition of problem spaces of learners from the state of preconceptions or misconceptions to the state of comprehensive, causal explanations" (p. 449). As such, the multiple-choice approach often employed in the information dissemination model fails to meet the assessment needs of inquiry-based learning. Therefore, educators look toward alternative forms of understanding complex problem solving, such as concept maps (Fig. 11.1) which articulate concepts and their logical antecedents/consequents, because the creation of these artifacts affords learners opportunities to articulate their understanding of the problem space and the causal relationships between the concepts (Ifenthaler, 2010). Representing the problem space using causal maps is a critical cognitive process not only to the success of that problem solving, but also the refinement of the student's conceptual knowledge and problem-solving skills. In doing so, these mapping processes also help students construct the knowledge acquired into a conceptual framework for that problem (Jonassen, 2011; Weinerth, Koenig, Brunner, & Martin, 2014).

The shift in student's representation of knowledge creates challenges for assessment. Whereas well-structured problems are assessed by student's ability to reiterate the predefined answer, representations of solutions to ill-structured problems through causal maps necessitate a varied set of cognitive procedures for assessment. There are two broad categories of procedures. First, a causal map can be assessed

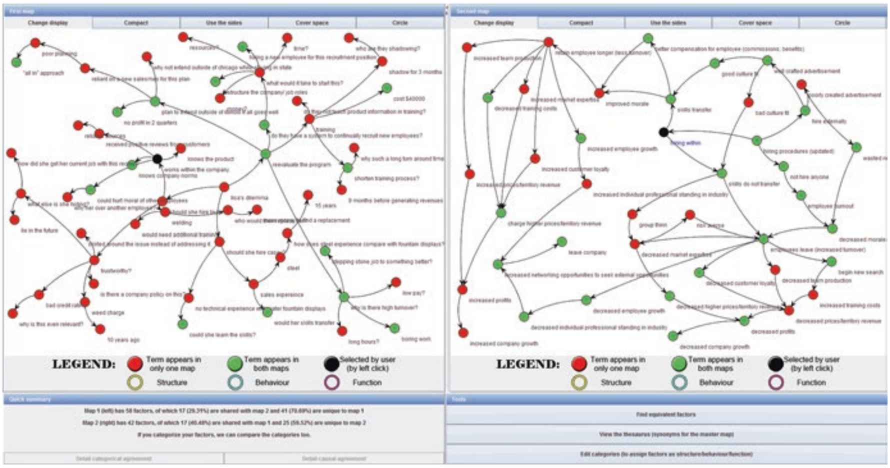

Fig. 11.1 A concept map is a *network* or *graph* where relevant concepts are captured as nodes (depicted as circles) with logical connections known as *links* to indicate antecedents and consequents (depicted as arrows). The first version of our ITACM software (Giabbanelli & Tawfik, 2018) allowed to compare a student network (*left*) with an expert network (*right*)

through a scoring method that favors certain structures. For instance, Kotovsky, Hayes, and Simon (1985) suggest that one way to understand complexity in problem solving is through the size of the problem space, measured by the "number of branches at each node and depth of search to a solution node" (p. 248). A metric can thus be developed where a student map with longer paths and more branching would score higher, indicating a more "complex" map. Such scoring methods are known as *referent-free*. Structural attributes favored in students' maps have included "parsimony, temporal flow, total links, connectedness" (Jeong, 2014, p. 240). Extensions to causal maps have also been proposed to bring in elements specifically for scoring: weighted concept maps examine the weight of propositions (i.e., links) (Chang, Sung, Chang, & Lin, 2005), while a "concept map+" distinguishes between types of links (Passmore, 2004). Second, a student's map can be assessed by comparison to a *reference expert map*. Ifenthaler suggested that providing an expert map and comparing it with student maps (e.g., for model-based feedback) can foster a better understanding of a problem (Ifenthaler, 2011). This potential was confirmed by experimental studies (Ifenthaler, 2012; Trumpower & Goldsmith, 2004). However, "hand scoring knowledge maps can be quite time-consuming" and often impractical for instructors (Trumpower, Filiz, & Sarwar, 2014, p. 229).

Learning analytics may be one way to address the challenge of assessment in ill-structured problem solving. Indeed, researchers continue to explore how learning analytics can resolve persistent issues in education, often from the student perspective. That said, many algorithms have been developed to automatically assess digital knowledge maps and challenges that teachers face (Trumpower et al., 2014). These algorithms operate typically at the level of individual nodes and links to find the ones present in both the expert and the student maps, or present in the expert map but missing in the student map (Trumpower et al., 2014). In parallel with the growing interest on comparing maps in education, algorithms have been developed over several decades at the intersection of pattern recognition and graph theory to address the related problems of map comparison, network alignment, and graph matching (Foggia, Percannella, & Vento, 2014; Vento, 2015). However, the uptake of such approaches in educational research has been limited.

This article explores how learning analytics can be leveraged to address the assessment challenge that educators face as they implement problem-solving strategies in the classroom. First, we detail how approaches in pattern recognition and graph theory (e.g., graph kernels, graph editing distance, graph embedding) can be used to go beyond comparing individual nodes or edges when assessing a student's map using a reference expert map. Second, to benefit the practice of problem-centered instruction and the field of education, we implemented these methods through a client-server software that supports instructors in comparing maps through several methods.

The remainder of the manuscript is organized as follows. In the section that follows, we provide a detailed background on how knowledge structures have been conceptualized and assessed in the form of causal maps for educational research. Then, Sect. 3 summarizes and emphasizes the relevance to educational research of methods for graph comparison from graph theory and machine learning. Sect. 4

presents a new software which implements these methods and provides instructors with opportunities to collaborate on assessments. Section 5 discusses the implications and limitations of these methods and implementation.

2 Background

2.1 Developing Knowledge Structures Through Ill-Structured Problem Solving

Well-structured problems possess all of the necessary information, solution strategies, and criteria for evaluation of the problem. Generally speaking, in these situations, problem solving often consists of problem representation and then a search for the correct solution (Ericsson, 2005; Simon & Newell, 1971). These problems are often employed in modern education because the predetermined nature of the solution affords efficiency in assessment. Alternatively, inquiry-based learning suggests that learners should be provided opportunities to solve problems that are representative of a domain. Specifically, students' learning is centered around real-world, ill-structured problems (Lazonder & Harmsen, 2016; Savery, 2006). These problems provide opportunities to work on complicated or complex cases that students may later encounter. Complexity is caused in part by a large number of variables in the problem space, high connectivity among variables, changes over time (i.e., dynamics), lack of clarity in the goal (i.e., intransparency), or multiplicity of goals (Clariana, Engelmann, & Yu, 2013). These problems provide students with a meaningful real-world context to structure their domain knowledge schemata and effectively retrieve it later when the need arises (Barrows, 1996; Schmidt, Rotgans, & Yew, 2011).

How learners conceptualize the problem space is a critical issue in inquiry-based learning. The problem space not only depicts the major concepts (variables) that have a role in the cause(s) or the solution of the problem, but also provides an underlying explanation as depecited by the causal relationships among the variables. For example, in medical education, problem space should "include[s] all the causal mechanisms that account for the patient's signs and symptoms" (Hmelo-Silver, 2013, p. 26), that is, the understanding of the problem is also described by the causal relationships among the variables that detail the mechanisms for why the problem occurs and how it can be solved (Eseryel et al., 2013). Furthermore, when students construct a problem space through causal reasoning, they are practicing scientific problem-solving process and consolidate their knowledge into a knowledge structure.

Knowledge structures consist of the problem space that explains the mechanism of how all the variables work together to manifest themselves as the symptom ("problem") (Dufresne, Gerace, Hardiman, & Mestre, 1992; Ifenthaler et al., 2011). Knowledge structures describe the degree to which an individual organizes information elements from memory. These include an individual's understanding of the facts, concepts, and their relationships embedded within the problem space. Theorists argue that strong knowledge structures facilitate subsequent learning when new information is presented (Ausubel, 1963; Ifenthaler et al., 2011). Furthermore, it is posited that retrieval is impacted by the construction of the knowledge structure, that is, a well-constructed knowledge structure facilitates efficient pathways when learners need to reference an idea. It is thus hypothesized that learning can be thought of as the degree to which learners alter their knowledge structures. As it relates to education, theorists contend that the contextualized nature and emphasis on problem solving in inquiry-based learning strategies facilitate the development of robust knowledge structures.

Proponents of inquiry-based learning suggest that the emphasis on ill-structured problems better bridge the differences that exist between knowledge structures of experts and novices (Hmelo-Silver, 2013; Jonassen, 2011). Whereas the knowledge structures of novices are characterized by misconceptions, disconnections, and surface-level understanding of the problem space, experts include a more complete, structural-level understanding. Moreover, experts' knowledge structures are often defined as a more holistic, schematic organization of information, whereby the concepts in the problem space are organized in a relational and semantic manner (Jacobson, 2001). In turn, this allows experts to approach problem solving from a decentralized way that supports causal reasoning (Hmelo-Silver, Marathe, & Liu, 2007). In contrast to experts, studies show that novice knowledge structures often focus on readily available and most salient concepts while tending to overlook more foundational concepts that are not as obvious (Ertmer et al., 2008; Hmelo-Silver & Pfeffer, 2004). In addition, novice explanations are often linear and focused on a single cause (Grotzer, Kamarainen, Tutwiler, Metcalf, & Dede, 2013; Tawfik, Gill, Hogan, York, & Keene, 2018a).

2.2 Assessment in Ill-Structured Problem Solving

An important part of problem-solving facilitation is the ability of educators to direct students toward the most relevant elements of the problem space. Given that networks can be depicted through nodes and links (Ifenthaler et al., 2011), concept and causal maps are becoming increasingly popular forms of assessment (Olney, Graesser, & Person, 2012). Clariana (2010) suggests there are four unique aspects as it relates to mapping of the problem space. First, the open-ended nature of ill-structured problems requires learners to go through the process of recalling and selecting which concepts (i.e., nodes) to include in a map. Upon completion, students must be able to engage in meaning-making about how their concepts are related. Doing so generates important insights about the structure of causations (when a directed link goes *from* a concept *into* another) and associations (when a link is undirected or two directed links are reciprocal). Causal maps also elucidate what learners choose to select from the problem space (extent of knowledge), the distance of those relationships (proximity), the links between the ideas (lexical association), and perceived final state of the problem representation (conditional knowledge) (Clariana et al., 2013).

Although concept maps may serve to understand student's knowledge construction, the ill-structured nature of problem solving and design of concept maps creates a significant challenge for educators. Indeed, research finds that educators cite assessment as a significant barrier, which precludes their proclivity to implement inquiry-based learning and ill-structured problem solving in the classroom (Tamim & Grant, 2013; Wijnen, Loyens, Smeets, Kroeze, & Van der Molen, 2017).

Challenges particularly arise at two steps of the assessment. First, variations in language (e.g., "cardiac arrest," "heart attack") can create an important confound that make assessment inefficient and impractical. This problem may be prevented from appearing in the first place when students are limited to using a complete list of concepts from the problem space, which may include "distracters" or "misleading" concepts (Ruiz-Primo, 2000). For instance, in participatory modeling studies, linguistic variability is limited by using a set of terms standardized through independent focus groups (Gray, Hilsberg, McFall, & Arlinghaus, 2015). However, imposing such limitations may produce two maps that look more similar than the individuals' knowledge structures (Lavin, Giabbanelli, Stefanik, Gray, & Arlinghaus, 2018). The alternative is to place no restriction on the use of concept names and then to go through an alignment phase in which educators identify equivalent terms either manually (Giabbanelli & Tawfik, 2018) or through algorithms (Fig. 11.2) such as recommender systems (Gupta, Giabbanelli, & Tawfik, 2018).

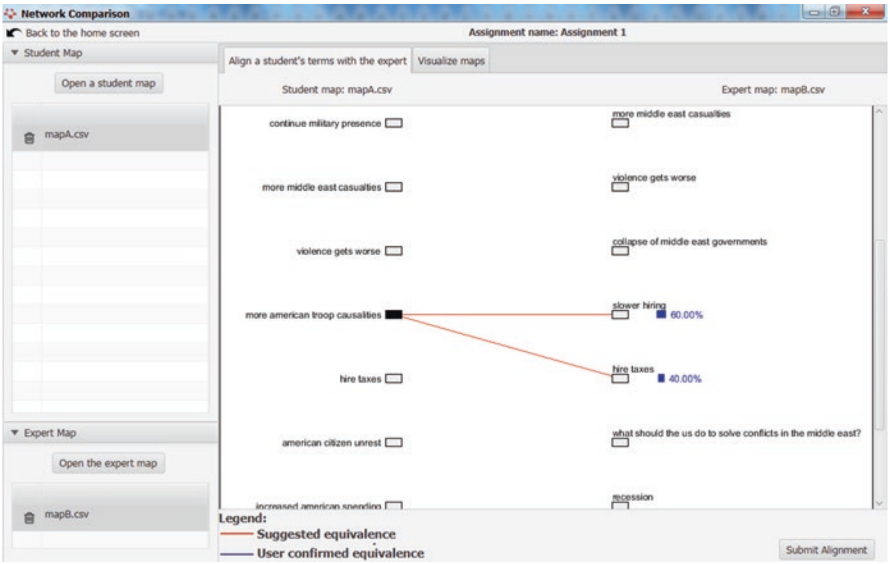

Fig. 11.2 When no restrictions are placed on concept names, linguistic variability can be resolved by aligning the names used by a student with the names used by the expert. As the alignment process can be time-consuming, we recently used interactive visualizations and recommender systems to support this process (Gupta et al., 2018)

Second, once variations in language have been resolved, educators have to compare maps structurally. Initial assessment approaches have focused on counting elements that are present in both the student and expert map or only in the expert map. For instance, such approaches can point out which links are shared and which links the student may miss (Trumpower et al., 2014). Other recent approaches employed learning analytics to better address these issues. For instance, HIMATT or AKOVIA (Ifenthaler, 2014) have treated causal maps as graphs, using structural metrics derived from graph theory, social network analysis, or network science. For these earlier approaches, the diameter of the spanning tree was proven to be a retest reliable measure (Ifenthaler et al., 2011). More recently, Lavin and colleagues demonstrated that specific types of centrality indices (i.e., metrics to score the importance of nodes) could be used to infer that individuals or groups would make similar predictions (Lavin et al., 2018). Other approaches using *structural matching*, *semantic matching*, *overlap measure*, and *propositional matching* have been detailed in the learning analytics literature (Krabbe, 2014). In sum, assessment approaches mostly employ tools from graph theory designed to measure structures in *one* map (e.g., diameter of the spanning tree), and then two maps were compared with respect to their individual measures. This is an indirect approach to comparison, using tools that were not specifically designed for this purpose. In contrast, graph theory (and particularly as it relates to machine learning) possesses many tools to specifically compare maps. Therefore, tools exist that can take in two maps and compute the distance between these maps. The next section seeks to address the paucity of graph comparison methods in assessment by providing a brief overview of these tools and their possible uses in learning analytics.

3 Using Graph Comparison Methods for Assessment

3.1 An Intuitive Introduction to Graph Comparison

There are three broad approaches to compare a student map with an expert map. While they are grounded in graph theory and machine learning, this section provides an intuitive overview of these approaches. Details and recommendations to formal specifications as they relate to learning analytics are provided in the following sections. Examples from assessment are reinforced with the metaphor of comparing houses.

First, we can measure the number of changes necessary to transform one structure into another. *Graph edit distance* (GED) accomplishes it by finding an efficient sequence of transformation. In the case of houses, we can compare their plans side by side and see what changes are necessary to turn one house into the other, such as adding a bedroom, removing a bathroom, or relabeling a bedroom as a home office. In the case of maps, we can add or remove nodes and edges or relabel a node's name. The output of the GED is a single number (i.e., the distance), which can be used for summative assessment. The process to compute this number is also of interest for formative assessment, as the student can see each difference with the target map and work along a suggested sequence of operations to bridge this gap. Similarly to the concept of solution path length (Hays & Simon, 1974), computing the GED produces a "solution path" (i.e., sequence of operations) to transform a student map into the expert map, and the final number characterizes this path by taking into account that some operations may be more significant than others.

Second, rather than doing a possibly long sequence of minute changes, we can ask whether "the big picture" is similar in two structures. The idea of *graph kernels* is to focus on the core of a structure. For instance, the core of a house could be the size of its rooms. We would thus compute the distribution of room sizes in both houses and compute the distance between these discrete distributions. Similarly to GED, the output of a kernel is a single number, but it measures the discrepancy between distributions of user-defined features. For example, taking the approach of Kotovsky et al. (1985), we could measure the distribution of the number of branches per node, as a proxy to a map's "complexity."

Third, we could apply a set of metrics to the structures and compare them based on the results for each individual metric. In the case of houses, one may measure the surface area and count the number of large open rooms that flow (as a means to characterize an open floor plan). Each house can then be plotted into a 2D space where the number of large open rooms is on the x-axis and surface area on the y-axis. The problem of comparing two houses thus becomes a matter of measuring the distance between two points in space. Consequently, the final result of a *graph embedding* is a single number comparing points in space. For a map, we can measure N features and plot the map in a space of N dimensions.

Within each approach, we have to state precisely what we value. For instance, in graph edit distance, is it worst when a student has a link that the expert does not have or misses a link that the expert has? In graph kernels, which structures are indicative of learning? For graph embedding, which features should we extract from a map? Finally, we need to select an algorithm that efficiently accomplishes the computations. There are dozens of algorithms to compute the graph edit distance, numerous ways to compare two distributions, and several methods to compare two points in space. The remainder of this section details each approach, including its implications for the assessment of digital knowledge maps in education and how to choose values as well as algorithms in this context.

3.2 Graph Edit Distance (GED)

There are two broad approaches to graph matching. On the one hand, we can require an *exact match*, when asking questions such as "are the student and expert maps identical" or "what is the largest part of the expert map that the student got right." However, these questions may not be of practical relevance (e.g., the student and expert maps are very unlikely to be identical), and the answer may support summative assessment more than formative assessment. In addition, these questions are, respectively, known as graph isomorphism and subgraph isomorphism, and solving them in a reasonable amount of time remains an active area of research (Arvind & Jacobo, 2005; Carletti, Foggia, Saggese, & Vento, 2018). For all these reasons, solutions such as graph edit distance (GED) have been developed to handle an *inexact match*, in which differences between maps are penalized rather than forbidden.

In graph edit distance, we look for an *edit path*, which can be defined as a sequence of operations that transforms the student map (source) into the expert map (target). Operations can be performed on edges (deletion, insertion) and nodes (deletion, insertion, relabeling). It is always possible to transform a map into another one: for instance, we could delete all of the students' nodes and edges and then add all of the expert's nodes and edges. We are thus interested in finding the *best* path. When all operations are viewed as equally important by the instructor, then the best path minimizes the number of operations (Fig. 11.3).

As the method is flexible, instructors can also state that some operations reveal more of a misunderstanding from the student than others. For example, studies suggest that students struggle to remove extraneous concepts from a problem space (Hmelo-Silver et al., 2007; Tawfik, Law, Ge, Xing, & Kim, 2018b). In addition, studies find that students focus on the surface-level characteristics rather than the less salient concepts that are more central to the problem (Ertmer et al., 2008;

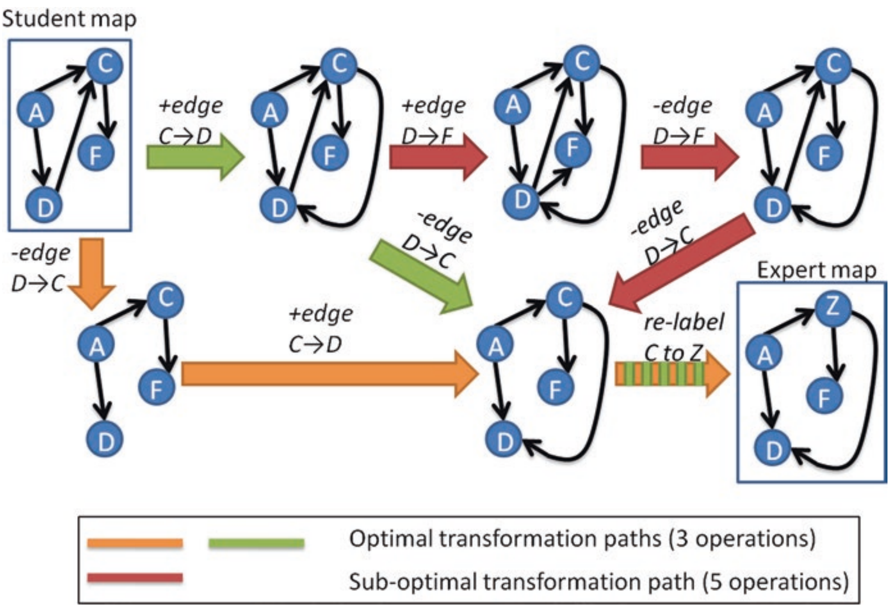

Fig. 11.3 A student map (top left) can be transformed into an expert map (bottom right) through sequences of operations, some of which are equally short (green, orange) and some go through unnecessary steps (red)

Jacobson, 2001). From a learning analytics perspective, the best path in these cases is to minimize the sum of the operations' costs. The costs of operations such as adding/removing nodes are usually set to a positive constant, and the same applies to edges if they do not have a label. The costs for relabeling have often been approached from a theoretical perspective (Sole-Ribalta, Serratosa, & Sanfeliu, 2012), where labels are seen as vectors of characters and pair-wise differences are computed between characters (e.g., "bad" and "sad" differ by only one, whereas "bad" and "not good" differ on all eight characters). In contrast, assessment is more focused on the semantic of the words. Methods in the learning analytics literature exist about how to automatically measure the strength of association between terms (Sen et al., 2014), but they have not yet been widely applied in the context of comparing maps, perhaps due to the paucity of use for graph comparison techniques in educational research. Our recommendation would be to resolve variations in languages before computing the GED. In other words, a preprocessing step would align terms as described in Sect. 2.2, and that would avoid penalizing for variations in language during the GED. All remaining differences in labels would incur the same constant cost.

Once the instructor has preprocessed maps (to resolve variations in language) and identified suitable costs, then the GED can be computed. In terms of supporting the teacher, this is useful for summative assessment (as the GED is a number summarizing how "close" the student got to the expert), and particularly for formative assessment as computing the GED shows how to transform the student map into the expert's. This is related to the concept of *action sequence* in educational research. In contrast to general guidelines or "one-size-fits-all" approaches to identifying general action sequences leading to accurate maps (Jeong, 2014), computing the GED can create an entirely personalized action sequence for a given student's map. Future research may explore whether these personalized action sequences do cluster across students and, if so, based on which individual characteristics. Clustering and sequential pattern mining would provide powerful methods toward this objective (Perera, Kay, Koprinska, Yacef, & Zaiane, 2008).

3.3 Graph Kernels

A graph kernel considers a graph as being made of an unordered collection of simpler patterns. The matching problem thus consists of extracting and comparing these patterns. The patterns are user defined; thus, they vary depending on the emphasis and context of each study. These techniques are particularly used to compare biological networks, and they are summarized in this context by Mueller, Dehmer, and Emmert-Streib (2013). Patterns have included "graphlets" (i.e., all subgraphs with 3, 4, or 5 nodes) (Shervashidze, Vishwanathan, Petri, Melhorn, & Borgwardt, 2009), which are similar to the concept of motifs and triad significance profile used in social networks and regulatory networks for biology (Juszczyszyn, Kazienko, & Musiał, 2008; Sanz, Navarro, Arbues, Marijuan, & Moreno, 2011), trees when comparing the structure of molecules (Mahe & Vert, 2009), and cycles, which have also been used for molecules (Horváth, 2005).

When it relates to teachers assessment of causal maps, patterns can be used to examine the level of knowledge construction exhibited by a student. In classifications of systems, independent nodes are at the lowest level of systems thinking, while edges can be slightly higher (Malhi et al., 2009; Meadows, 2008). When going even higher, we start looking at (feedback) loops, also known as cycles. A set of nodes are in a loop if, starting from any node in the set, we can follow a sequence of edges that ends at this node. Loops capture a student's understanding that "a change can be initiated everywhere in an event circle and after a certain time be read off as either cause or effect elsewhere in a system" (Skyttner, 2006, from p. 34 specifically). Studies have shown that loops were absent from many causal maps about a variety of problems even when they drive the dynamics of these problems in the real world (Axelrod, 1974). It is thus important when comparing the maps made by individuals to look at their cycles (Fig. 11.4). That is, a relevant kernel for assessment would be the distribution of cycles, which counts the number of cycles (y-axis) of each length (x-axis). In sum, comparing two maps would compare their distributions of cycles.

There are several important differences with using the GED described in the previous section. The GED takes a very detailed view of all the operations needed for the transformation: it measures what is different and tells the student how to fix it. This serves as more knowledgeable peer and source of scaffolding as students are alerted to gaps in understanding. When students become aware of their knowledge deficiencies, they are encouraged to reflect and later iterate their problem solving (Ge & Land, 2003; Hong & Choi, 2011; Jonassen, 1997; Tawfik, Rong, & Choi, 2015). The kernels would not give us an action sequence, but they would tell us the bigger picture of how a student "thinks" compared to the expert. For instance, the

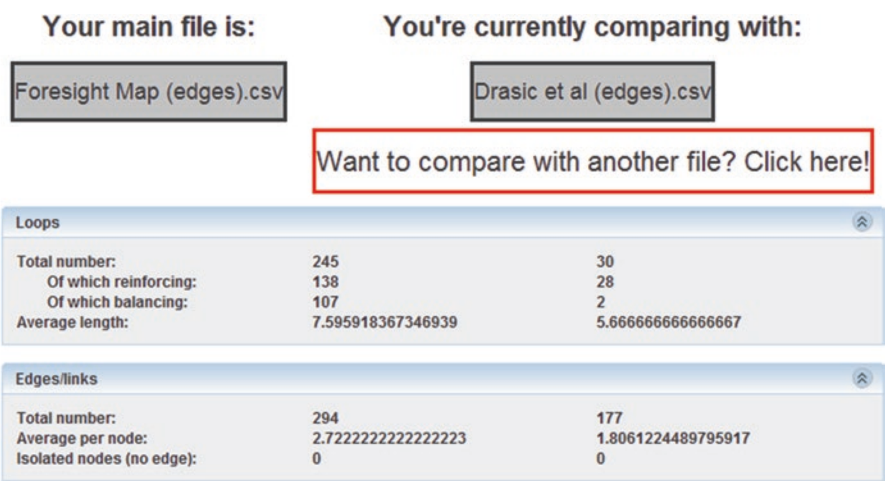

Fig. 11.4 Comparison of two maps in the software *ActionableSystems* on the basis of their loops (Giabbanelli & Baniukiewicz, 2018)

GED may tell the student to add four links because the expert has them. However, three of those links may be used to close a loop, and it is thus particularly important that they are present, whereas the fourth one only connects to a peripheral concept.

An action sequence could still be derived from kernels, for instance, by listing all the loops that the students missed and highlighting which specific edges have to be added for these loops. Similarly, we can list loops that the students claimed, but that expert does not endorse. An experimental study may compare whether this action sequence or the one generated by GED yields either more accurate maps or a better understanding of the problem.

3.4 Graph Embeddings

Several measures from graph theory have been mentioned in relation to the assessment of causal maps (Krabbe, 2014), including the diameter of the spanning tree, the number of components (i.e., disconnected parts of a map), or the density (i.e., ratio of edges present to the total number of edges that could connect the nodes). Each one of these measures produces one number. Comparing two maps by looking at each individual measure can be a challenge. For instance, are two maps similar if both have a single component but one is denser than the other? Would they be more similar if one was less dense but had a longer spanning tree? A composite score can be created to provide a single number based on a set of metrics. While this can be achieved by approaches such as taking the weighted sum of the underlying metrics, it raises the question of how to set appropriate weights to each metric and whether we should account for interactions between metrics to avoid double or triple counting. In contrast, learning analytics that espouse graph embeddings provide a mathematical framework. The idea is to "embed" an object (i.e., a map) into a vector space, where the distance between the embedded objects serves as proxy for the actual distance between the objects themselves (Hjaltason & Samet, 2003).

In the case of embedding causal maps for assessment, the instructor decides on N metrics to use. Each map is then transformed into a vector with N coordinates, whose values are the graph's scores on each selected metric. For instance, Fig. 11.5 shows how three maps can be positioned in a three-dimensional space based on their number of nodes, number of edges, and the average number of edges per node (i.e., average degree). Using only two or three metrics allows instructors to conveniently see each map as a point in space. When using four or more metrics, results can still be visualized, but the multidimensionality requires the use of techniques such as parallel coordinates (Inselberg & Dimsdale, 1990), which may be less intuitive.

Once the maps have been transformed into vectors based on selected metrics, the vectors can be compared. This can inform instructors on whether a student is heading in the same direction as the expert. For instance, a student may have several nodes, many edges, and a few cycles. If the expert has these elements in similar proportions but in a larger map, then we suppose that the student's structure is going

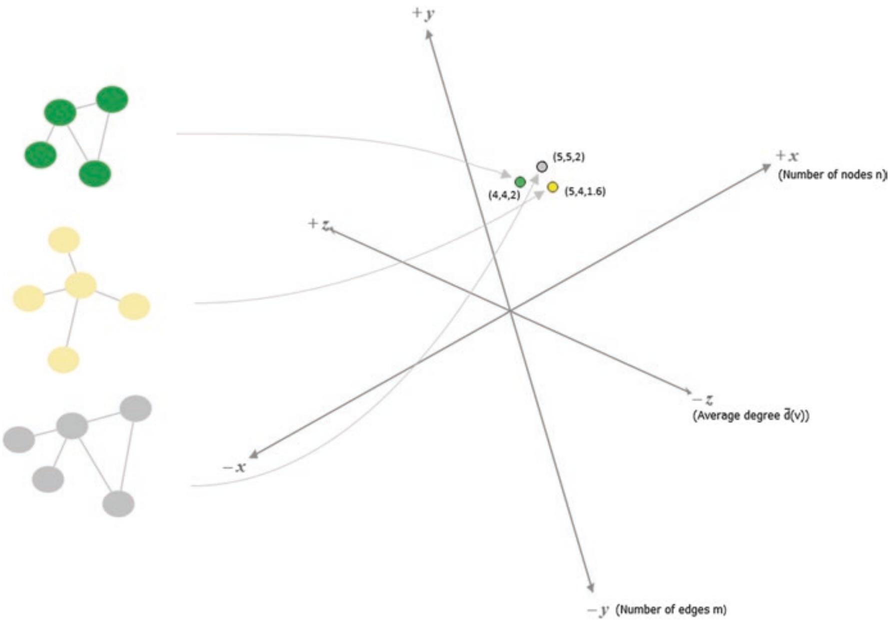

Fig. 11.5 Three maps are embedded as points in a three-dimensional space by measuring three attributes: the number of concepts/nodes, the number of connections/edges, and the average number of edges per node (i.e., average degree)

in the right way and will grow with additional problem solving iterations. Conversely, if the student has few edges and no cycles, then an intervention may be needed to set the student in the path to success.

4 Implementation

4.1 Influence of Previous Implementations

Our implementation grew out of the Incremental Thesaurus for Assessing Causal Maps (ITACM) software. The software was first released to assist with reducing linguistic variability when assessing maps (Giabbanelli & Tawfik, 2018), and the comparison then consisted of counting the percentage of factors whose names were equivalent in two maps (Fig. 11.1). The software has three broad limitations as it relates to supporting teachers during assessment of ill-structured problems. First, it did not allow for the comprehensive forms of comparison summarized in Sect. 3. Second, it was a desktop application, forcing users to either work independently or email files to other specific users. This stands in contrast with previous recommendations to "use software with a web interface or client-server architecture that allows to retrieve a concept map from different work places through the Internet"

(Krabbe, 2014, p. 279 specifically). Third, the reduction of linguistic variability was a labor-intensive process, where the computer was only able to recognize whether two terms were set as equivalent by the instructor previously.

The second release, ITACMv2 (Gupta et al., 2018), addressed the last two limitations. Taking a client/server architecture allows the software to support a community of practice. Given that educators struggle with the initial preparation of inquiry-based learning, allowing users to share maps with their peers allows to save time in terms of onboarding (Nariman & Chrispeels, 2015; Tamim & Grant, 2013). Rather than starting with a "blank slate" to redesign the curriculum, sharing resources using an open education research (OER) format allows educators to leverage expertise within their own learning communities, which allows dissemination of best practices within peer networks. The use of recommender systems also allowed instructors to identify potential equivalences between terms used by the student and the expert (Fig. 11.2), which results in a faster alignment process.

Our newest release, ITACMv3, addresses the last limitation by giving access to all three approaches to comparisons presented in this chapter.

4.2 Methods Selected for Each Form of Graph Comparison

Our implementation for the graph edit distance uses the beam search approach (Riesen, Emmenegger, & Bunke, 2013; Riesen, Fischer, & Bunke, 2014). Given a student map with N nodes and an expert map with M nodes, we can start by taking one of the student's concepts and identify the expert's concept to which it can be mapped (or aligned). There are M possibilities. We can continue the process with the next concept from the student, and there are still M possibilities as two concepts from the student may refer to the same in the expert. There are thus in the order of M^N edit paths. Finding the right one is similar to a game of chess, in which a very large tree is created to compute each possible move, the resulting board configuration, and each possible move within each configuration. Tree-search-based methods such as the A^* algorithm thus *estimate* the cost of each of the possible branches. Beam search is an improvement introduced by Riesen (2015) that further prunes the search tree. Five other alternative implementations are presented in Sect. 4.2 of Riesen (2015).

Our implementation for graph kernels uses cycles. Cycles are listed using a backtracking algorithm with labeling presented by Tarjan (Tarjan, 1973) and implemented in other software such as ActionableSystems (Giabbanelli & Baniukiewicz, 2018). There are alternative algorithms to list all cycles (Bax, 1994), but since causal maps are typically small graphs, we did not optimize the computation time. The important choice is on how to handle the distributions. That is, the problem of comparing two maps has been transformed into comparing the *discrete probability distributions* of their cycles. A statistical approach to measuring differences between these distributions is to use an *f-divergence*, which is a type of function. Specific functions include the Hellinger distance and the Kullback-Leibler divergence (known as KL-divergence). Both are bounded metrics: their output ranges from 0 (similar behavior expected) to 1 (distributions behave very differently). The KL-divergence is not a distance because it is not symmetric: the KL-divergence between the student map and the expert map may differ from the KL-divergence between the expert and the student. This lack of symmetry may prove problematic in the interpretation of results. Consequently, we used the Hellinger distance, which is symmetric. We compute it with a four-step process: (1) extract all cycles; (2) compute the distribution of cycles' length, where the x-axis is the length of a cycle and the y-axis is the number of cycles with this length; (3) normalize the distribution into the range [0, 1] so that it can be treated as probability distribution; and finally (4) apply the Hellinger distance to the two distributions.

Finally, for graph embeddings, we used three metrics: the number of nodes, the number of edges, and the graph density. The similarity between two maps is computed using the cosine similarity between their corresponding vectors. The maximum similarity is 1, obtained when two vectors have the same orientation, intuitively meaning that the two maps are "thinking in the same direction." Theoretically, diametrically opposed vectors have a cosine similarity of −1, but this situation cannot exist here since the metrics produce strictly positive numbers. Thus, the minimum cosine similarity is 0, when vectors are orthogonal.

Our interface is shown in Fig. 11.6. We recommend that instructors first align the terms to reduce linguistic variability (first tab), optionally inspect the maps visually (second tab), and then start to compare maps (third tab). Explanations are provided for each metric to aid with interpretability of results.

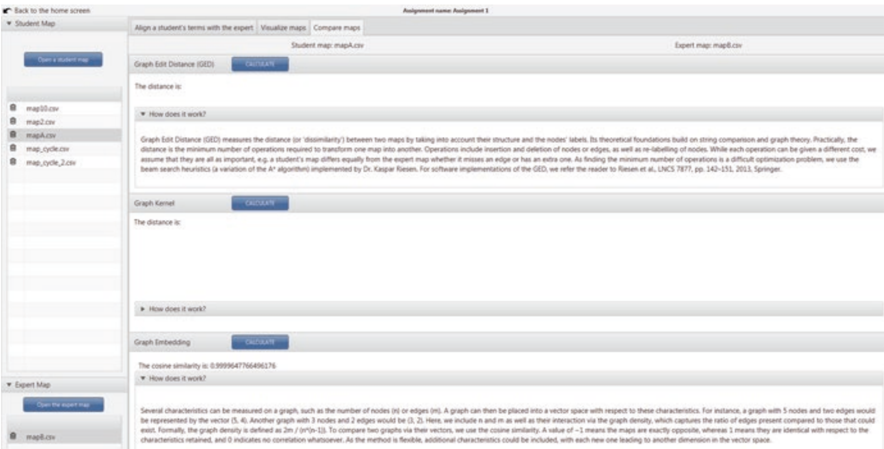

Fig. 11.6 The newest version of the ITACM software includes a "Compare maps" tab, in which educators have access to an implementation of graph edit distance, graph kernel, and graph embedding. Details of the specific implementation can be accessed by expanding the panel "How does it work?" within a metric

4.3 Verification

Standard processes in software engineering call for the *verification* of an implementation to ensure that it is free of bugs. In this section, we present verification test cases for the dual purpose of demonstrating that our software was built according to specifications and to exemplify the methods discussed in the previous section. Two test cases are presented per method for the sake of brevity, although our implementation was also subjected to additional cases and passed all of them successfully.

For the graph edit distance (GED), we considered that all operations had the same cost (0.5). In the first case (Fig. 11.7a), the sequence of operations with the lowest total cost consisted of three operations (two deletions of causal links and one addition of a causal link) leading to a total of 1.5. In the second case (Fig. 11.7b), five operations were required (two node additions and three additions of causal links), leading to a total of 2.5. The software correctly produced 1.5 and 2.5 in these two cases.

For graph embeddings, we create the distribution of cycle length. Figure 11.7f shows the distributions produced by our software for the test case represented by Fig. 11.7c. These distributions are then turned into proportions, that is, normalized

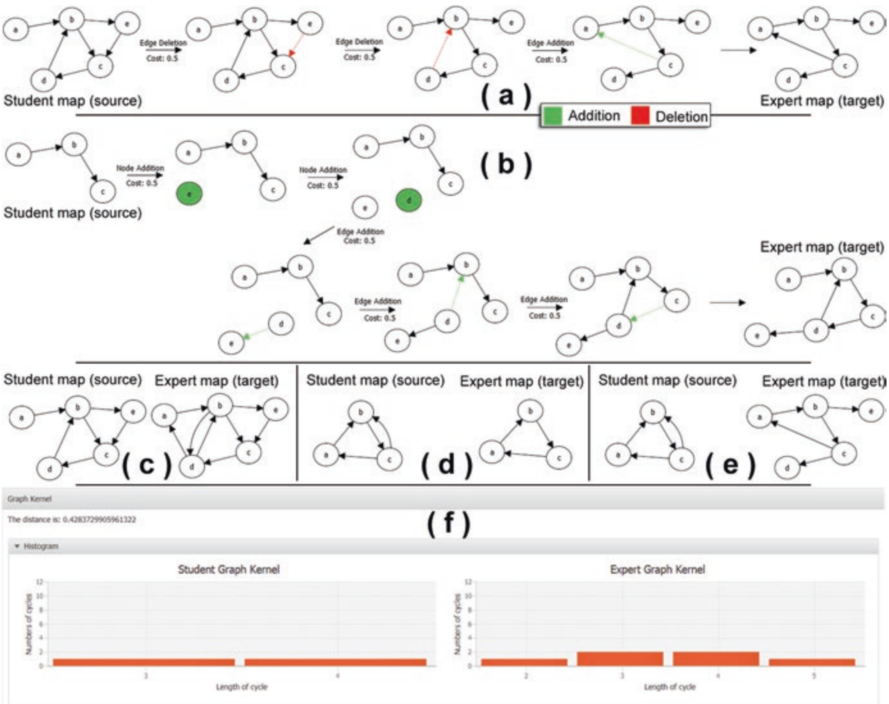

Fig. 11.7 Test cases and detail of steps for the graph edit distance (**a**, **b**). Test cases for graph kernels and graph embeddings (**c**–**e**), with a sample result for the graph kernel (**f**)

in the range [0, 1] as shown in Table 11.1. For instance, in Fig. 11.7d, the student's map has one cycle of length two; hence, each cycle accounts for half (0.5) of the total cycles in the map. Denoting the proportion of cycles of length i by s_i and e_i for the student and expert, respectively, then the student and expert maps produce the discrete distributions $S = (s_1, \ldots, s_n)$ and $E = (e_1, \ldots, e_n)$ where n is the length of the longest cycle. The Hellinger distance is:

$$H(S,E) = \frac{1}{\sqrt{2}} \left\| \sqrt{S} - \sqrt{E} \right\|_2 = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{n} \left(\sqrt{s_i} - \sqrt{e_i} \right)^2}$$

Applied to the test case shown in Fig. 11.7c, this equation results in:

$$\frac{1}{\sqrt{2}} \sqrt{\left(0+0+\left(0-\sqrt{0.16}\right)^2 + \left(\sqrt{0.5}-\sqrt{0.33}\right)^2 + \left(\sqrt{0.5}-\sqrt{0.33}\right)^2 \left(0-\sqrt{0.16}\right)^2 \right)}$$
$$\approx \frac{1}{\sqrt{2}} \sqrt{0.16+0.017+0.017+0.16} \approx \frac{0.59}{\sqrt{2}} \approx 0.42$$

which is the value displayed in Fig. 11.7f. The value for Fig. 11.7d is 0.54, also confirmed by the software.

Finally, for graph embeddings, we obtain a vector with three elements for each map: the number of nodes, the number of edges, and the graph density. If we denote by $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$ the student and expert maps, respectively, then we compute their cosine similarity as:

$$\text{similarity}(A,B) = \frac{A.B}{\|A\|\|B\|} = \frac{a_1 b_1 + a_2 b_2 + a_3 b_3}{\sqrt{a_1^2 + a_2^2 + a_3^2} \times \sqrt{b_1^2 + b_2^2 + b_3^2}}$$

In the case of Fig. 11.7c, we have $A = (5, 6, 0.6)$ and $B = (5, 8, 0.8)$ hence

$$\text{similarity}(A,B) = \frac{5\times5 + 6\times8 + 0.6\times0.8}{\sqrt{5^2+6^2+0.6^2} \times \sqrt{5^2+8^2+0.8^2}} = \frac{73.48}{\sqrt{61.36}\times\sqrt{89.64}} \approx 0.99$$

which is confirmed by the software. Similarly, the case in Fig. 11.7e results in 0.97.

Table 11.1 Computing and normalizing the distribution of cycle lengths for graph embeddings

		Student		Expert	
Test case	Cycle length	Total number	Normalized	Total number	Normalized
Figure 11.7c	2	0	0	1	0.16
	3	1	0.5	2	0.33
	4	1	0.5	2	0.33
	5	0	0	1	0.16
Figure 11.7d	2	1	0.5	0	0
	3	1	0.5	1	1

5 Discussion

5.1 Context of the Chapter

Ill-structured problems serve as the foundation of inquiry-based learning. These problems are defined as having multiple problem elements, unclear goals, and constraints. A learner must thus articulate multiple solution paths and criteria for the proposed resolution (Jonassen, 1997, 2011; Loyens & Rikers, 2011). In doing so, educators are able to go beyond the traditional, didactic forms of learning as they pursue higher-order learning outcomes (Herrington et al., 2014; Hmelo-Silver et al., 2007). Indeed, various studies cite the benefits of ill-structured problem solving afforded by inquiry-based learning when properly supported (Kim, Belland, & Walker, 2017; Lazonder & Harmsen, 2016; Walker & Leary, 2009).

The aforementioned instructional strategies have given rise to alternative forms of knowledge representation. Hung (2011) contends that students should be evaluated on their ability to "articulate the critical elements of the problem, their process for solving it, and the solution proposed and defend their proposed solution and the rationale, rather than whether they match predetermined answers" (p. 547). One evidence of how learners solve ill-structured problems is through causal maps, which require learners to articulate relationships consisting of the concepts' antecedents and consequents (Jonassen, 2011; Weinerth et al., 2014). Causal maps are especially beneficial because they provide insight into the connections that learners make between elements of the problem space, along with affording opportunities to depict multiple solution paths for ill-structured problems (Clariana et al., 2013; Jonassen, 2011).

Despite the purported benefits of inquiry-based learning, teachers face unique challenges in implementation (Hung, 2011; Wijnen et al., 2017). One emergent confound for educators is how to assess ill-structured problems accurately and efficiently. In terms of the former, ambiguity of assessment is impractical from a time management perspective. Research suggests that educators cite assessment as a primary reason for failing to sustain inquiry-based learning in the classroom (Nariman & Chrispeels, 2015; Tamim & Grant, 2013). To date, there have been a number of attempts to resolve the assessment challenge in inquiry-based learning using learning analytics. One approach is "referent-free," as the causal map of each student is assessed independently with respect to certain desired structures such as the total number of links (Jeong, 2014). The other approach assesses a student map using an expert map as referent. This is the approach studied in this chapter. Experimental studies have demonstrated that using a referent can foster a better understanding of the problem (Ifenthaler, 2012; Trumpower & Goldsmith, 2004), but a manual comparison of maps is too time-consuming and calls for the development of digital tools (Trumpower et al., 2014). Several such tools have been developed, but they are often limited in contrasting low-level features (e.g., number of links that a student has or misses vis-a-vis the expert) or an ad hoc set of properties (e.g., number of disconnected components within the maps). In contrast, graph theory and machine learning have created many algorithms specialized in comparing maps (Foggia et al., 2014; Vento, 2015).

5.2 New Insights

As noted earlier, the field of education is exploring new ways to leverage learning analytics to support higher-order learning outcomes in students. While much of the focus has been on the individual learner, there has been less of a focus on how learning analytics can be used to support the teacher. Our chapter has introduced three categories of algorithms for map comparison, with a focus on their applicability for the assessment of causal maps. We showed that graph edit distance (GED) provides both an estimation of the difference between maps (for summative assessment) and an action sequence personalized to assist a specific student in bridging the gaps with the expert map (for formative assessment). We discussed the benefits of graph kernels to assess systems thinking in students by extracting the distribution of feedback loops in their maps and comparing it with the expert's. Lastly, we examined the potential of graph embeddings to create a composite score and reveal whether a student is thinking in the same way as the expert. This may be most useful to provide feedback as the student gradually develops the map. We acknowledge that taking such approaches to assessing causal maps requires a leap forward, given that current software in educational research implement none of these approaches. We have thus provided one implementation (ITACMv3) for all three approaches, which educators can use within their own learning communities.

5.3 Future Work

While this chapter has detailed the potential for applying machine learning and graph theoretic techniques to the assessment of ill-structured problems, this application raises several questions both across techniques (e.g., how do we select an approach? can the software be used as it is?) and within each technique. Selected questions within both categories are now examined in turn.

Having exposed three different techniques to address the same assessment problem, educators may need to know which one to implement to best support study success. Despite the different theoretical underpinnings for the three techniques, one does not offer an obviously superior approach than the others. Consequently, establishing which one is the best would require an experimental evaluation in the form of a randomized controlled trial (RCT) where students are assigned to three groups, each receiving feedback with a different technique. As our software is the only one that implements all three techniques for the purpose of assessment, it would provide a de facto intervention tool for this RCT. Nevertheless, the tool itself should be extensively evaluated and changed where needed before being used. Indeed, usability testing would ensure that users do not experience barriers when using the tool for the specific assessment tasks that they face (Giabbanelli, Flarsheim, Vesuvala, & Drasic, 2016). While verification is about finding bugs and can be conducted solely by programmers, usability is about evaluating and improving the users' experience: it thus requires participants. Consequently, we would recommend usability testing followed by an experimental evaluation of all three approaches.

This will ensure that instructors have access to the tool that will provide a satisfactory experience and access to the right method to support study success.

We note that a major limitation to our tool is that students must provide causal graphs, as produced by tools such as Coggle or Actionable Systems (Giabbanelli & Baniukiewicz, 2018). The system would have a significantly wider reach if it could work with essays by first transforming them automatically into causal graphs. Learning analytics in the automatic analysis of text have demonstrated the growing possibility of extracting the structures of arguments from narratives or dialogues (Budzynska et al., 2014). As such techniques mature, they could eventually be integrated in our software.

Argumentation is multifaceted in that it requires learners to justify their claims using evidence. Moreover, argumentation essays may consist of an initial stance, counterargument, and rebuttals. Another limitation is that causal graphs do not include such forms of evidence. It may be that the expert and a student have different causal graphs because they reason based on a different set of evidence. Systematically suggesting that the student should embrace a structure "because the expert has it" may be less convincing and less flexible than examining how these structural differences arise from a different evidence base and/or a different use of the evidence. Approaches have been proposed to used evidential arguments (Bex & Bench-Capon, 2014) as part of argumentation frameworks, which support a more much complex analysis of the reasoning than the cause-rule effects employed in causal maps (Sedki, 2018). Transforming cause-rule effects into argumentation frameworks that also embed evidence is a long-term possibility for the automatic assessment of ill-structured problems.

In terms of specific methods, we explained that the graph edit distance can generate personalized action sequences. An open question is whether these personalized action sequences tend to cluster and for which student characteristics. This may assist instructors in better analyzing the learning journeys of groups of students. It could also assist with the identification of more homogeneous groups of students with whom the instructor could perform specific activities, as shown in the design of group-level interventions in health (Giabbanelli & Crutzen, 2014). An open technical challenge is to estimate the semantic relatedness (Sen et al., 2014) of terms used by students and the expert, such that the action sequence can deliver better explanations than merely asking students to change a concept's name.

While our chapter contrasted three techniques, they may also be used synergistically. For instance, the action sequence produced by GED would justify operations such as "add/remove a concept/causal link because the experts has/doesn't have it." Graph kernels can provide a higher-level view on why the student needs to perform operations such as adding causal links (e.g., because they close a loop and give rise to certain dynamics). Further exploration into these approaches would allow researchers to explore additional assessment approaches to assist teachers using learning analytics.

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Author Contributions PJG designed the project and supervised VKG. PJG and AAT wrote and revised the manuscript. VKG wrote the software.

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Chapter 12
Utilizing Learning Analytics in Small Institutions: A Study of Performance of Adult Learners in Online Classes

Ellina Chernobilsky and Susan Hayes

1 Introduction

The changing landscape of higher education calls for changes in how institutions use their existing infrastructure, understand and adapt to changing population of learners, and plan for strategic improvements in their long-term plans. These revised understandings call for the use of available data that various systems on university campuses inevitably collect. The use of these data is ever-increasing, and we, as a field, are still learning to harness and understand how to best use these data. Using such data to make decisions in postsecondary education, known as learning analytics, is evolving and becoming embedded in university operations (Picciano, 2012).

While large institutions, with state support or large endowments, have resources and man power to collect, organize, and then use the data, the situation may be very different in small, private not-for-profit organizations that cannot easily allocate the resources for such massive enterprise-level engagements. To stay competitive, however, this becomes a necessity in small and large institutions alike. In this paper, we show how one small liberal arts private university uses data to understand its current academic position and to chart the way to the future.

There are many reasons why higher education institutions decide to use learning analytics (Shacklock, 2016; van Barneveld, Arnold, & Campbell, 2012). The use of learning analytics in our university is necessary to better understand the roadblocks to student success (as defined by grades) and the issues of retention. This is driven by two specific objectives to help students achieve success and to increase operational efficiency of the institution. While we are limited in our resources and the ability to mine the data, nevertheless, we see learning analytics as an opportunity to increase our understanding of the students we serve and what institutional changes

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may be required in order to serve the students more successfully. Specifically, we are interested in student retention, especially, that of adult learners.

Leitner, Ebner, and Khalil (2017) identify short- and long-term trends for the higher education field. Among those trends is the adjustment to social and economic factors which afford the changes in what the students can do. Learning analytics is an important tool to better understand such factors. Learning analytics also helps to understand what change is necessary and how to impart these changes, especially for small universities where resources and infrastructure are at a premium.

Since the size of the datasets that the small institutions are generating is not on the same scale as the sets generated by large institutions in the same time period, we believe that working with small-scale data sets and growing them over time might help small schools to develop such models of student success that would be generalizable specifically to small institutions. Understanding what learning analytics can and cannot do for such schools becomes then particularly useful.

1.1 Learning Analytics and Data Mining

The use of databases to manage student biographical, financial, and academic data, as well as using learning management systems to manage the instructional and course information, while also using security card systems to track access to campus services resulted in proliferation of data that higher education institutions continuously collect about students and student behavior when learning (Piety, 2013). These data, if organized and studied properly, can provide a plethora of information and can help institutions in making decisions, both academic and strategic in nature (Romero & Ventura, 2013). In the last decade, in order to use the massive amounts of data, researchers and practitioners began engaging in the use of various techniques collectively known as learning analytics and data mining.

Romero and Ventura (2013) define educational data mining as an interdisciplinary field concerned with the research, development, and application of computerized methods to study large data sets in education. A related concept to data mining is learning analytics or a set of tools, technologies, and platforms that help shape understanding of learning and provide information for subsequent decision-making in order to improve institutions of learning and, ultimately, to help students succeed (Wagner & Ice, 2012). As such, postsecondary educators and support staff use learning analytics to collect and study data, both digital and analog, to understand what data may tell us about student learning and how this understanding might feed into learning outcomes (EDUCAUSE Learning Initiative, 2011). In an attempt to understand the level of focus learning analytics takes in postsecondary education, van Barneveld et al. (2012) propose a definition they adapt from Bach's (2010) work. They define learning analytics as "the use of analytics techniques to help target instructional, curricular, and support resources to support the achievement of specific learning goals" (p. 8). For the purposes of this chapter, we use this very definition of learning analytics.

Long and Siemens (2011) differentiate between learning analytics and academic analytics in that academic analytics is more general in nature and covers all levels from national to institutional. Learning analytics, in contrast, is more fine-grain, focusing on the data generated and analyzed specifically for department and course level improvements, Long and Siemens propose.

All research in learning analytics can be classified into one of the four types (Boyer & Bonnin, 2017). One such type focuses on recommendations and notifications to the users of the educational systems; another deals with educational data mining. The third type is primarily concerned with data visualization, whereas the last research cluster is focused on statistical analyses in learning analytics. Mattingly, Rice, and Berge (2012) rightfully note that analytics is a part of a still developing field and, as such might change noticeably in the future. Mattingly et al. warn that ethical issues must be carefully considered when engaging in learning analytics activities. Decisions on who owns and can access and use student data are to be made for any (big) data research (Slade & Prinsloo, 2013), especially if students can be identified by name at any point in the mining process. Slade and Prinsloo classified the ethical issues into three categories: (1) location and interpretation; (2) informed consent, privacy, and the de-identification of data; (3) the management, classification, and storage of data. All of these issues are difficult to address at smaller institutions, where students can be identified easier and in which the resources, human and financial, dedicated to data analysis and storage, are tight.

In 2011, IBM's *Analytics for Achievement* paper outlined eight categories of instructional applications where using learning analytics can be helpful (IBM, 2011). Of these, the primary interest to us is the ability to disaggregate student performance by specified characteristics such as major, year of study, GPA, and so on with the goals of improving retention and learning outcomes in our programs and/or courses. Picciano (2012) reports that student attrition in US colleges and universities has been an issue in American higher education for decades. Despite significant efforts and attention this issue received on all levels, high attrition rates, ranging from 22% at 2-year public institutions to almost 61% at private nonprofit organizations, persist (Picciano, 2012).

Chen (2015) argues that theory has been an important concern in the field of learning analytics. Dawson, Mirriahi, and Gasevich (2015) make an argument that learning analytics helps advance theories of learning and contributes to pedagogy and epistemology. Through these contributions, eventually, researchers who work in the field will devise their own theory where learning analytics is a main tenet.

Currently, there are various frameworks that learning analytics research can rest upon. One of them, proposed by Scheffel, Drachsler, Stoyanov, and Specht (2014), offers quality indicators for learning analytics grouped into five broad clusters: objectives, learning, measures of learning, data, and organization. The first three indicators deal with educational and pedagogical concepts not directly connected to learning analytics. These are important to consider, however, because attending to these concepts affects learning and outcomes. Data-related cluster includes the issues related to transparency, ownership of data, and data privacy and security. Organizational cluster of the framework focuses on the stakeholders, implementation of learning analytics into the organizational processes, and structure and organizational change factors.

One of our institutional goals is to explore data with a possibility of designing a notification process that would move the university from information processes to optimization processes (Boyer & Bonnin, 2017). This will help academic support staff detect issues early and to alert the student and the instructor if/when necessary. To approach this strategically, we, as an institution, use learning analytics for three specific goals outlined in the *Horizon Report* (Johnson et al., 2016). We use analytics to diagnose the problems and then lean on it to propose the solution. In our work, we are subscribing to Scheffel et al.'s (2014) model, and in this paper, we are specifically looking to understand what the learning analytics can help us see in the case where the size of data is limited due to small enrollment numbers. The purpose of this chapter, therefore, is to report on one university's efforts to use learning analytics to understand performance of adult learners in online undergraduate courses.

1.2 Online Learning

The roots of online learning can be traced back to earlier forms of distance learning when students were not always present physically. Correspondence courses were the traditional approach. Later, with the development of television and other more advanced technologies, the delivery formats evolved (Casey, 2008). In the mid-1990s, online course delivery via the Internet began, developing further as learning management systems were developed (Casey, 2008). Today, online learning is an integral part of higher education landscape and has a range of formats from MOOCs to small close access classes in a variety of platforms. During the 2011–2012 school year alone, about 7.4 million undergraduate students (32 percent) and about 1.3 million graduate students (36 percent) took at least one distance education class (NCES, 2015). Means, Toyama, Murphy, Bakia, and Jones (2010) stipulate that a replacement of face-to-face instruction with the online option may be considered successful only if such instruction provides online learning without sacrificing the achievement in the course (p. 3). For the institutions of higher learning, offering online courses frees up space, both classroom and parking, as well as creates flexibility in academic scheduling and in providing academic support. In addition, it offers faculty the options of using andragogy approaches in teaching. This makes online learning attractive to many students, especially working adults, as learning online offers convenience and choice that traditional face-to-face classes do not. This is especially important for those learners who balance work, school, and family (Kauffman, 2015).

Means et al. (2010) identify three key elements that describe online learning: replacement of face-to-face instruction or its enhancement; different, online-specific, pedagogical approaches; and the various types of communication that online teaching and learning can offer. In the current research, we were concerned with the replacement application, i.e., fully online courses. In our case, however, the situation is more complex, as traditionally, our institution has accelerated and semester-long online offerings.

There has been a long debate concerning the effectiveness of online learning. Recently, Nguyen (2015) explored the effectiveness of online learning by synthesizing the work done previously. Nguyen pointed out that while different studies see different results of the effectiveness of online learning, the majority of such studies find that online learning is at least as effective as the face-to-face education. One argument for not seeing the differences is that students essentially self-select to be in online or face-to-face class and that may contribute to the no difference seen in the results.

Stack (2015) reports on a quasi-randomized study that explored whether delivery systems (online vs. traditional) resulted in achievement differences. Stack controlled for supervised conditions during the exam times and for such important factors as gender, academic ability, effort, and amount of time used for studies by using the first hour exam as a control variable. The results of Stack's study indicate that there were no differences in the course achievement between those students who took an online section of the course and those who took traditional face-to-face section.

Kemp and Grieve (2014) caution that to consider online learning as a unitary concept is simplistic when it is examined on its own or when compared to general face-to-face learning. Kemp and Grieve state that each modality is complex and has multiple factors affecting success. Nevertheless, looking into the difference between the two types of offerings helps us, as a small campus, understand what might work for our students.

One of the flexibilities that makes online education so attractive is an opportunity to take courses in a variety of formats. One such option that may be particularly attractive is an accelerated option. Tatum (2010) defines accelerated learning as a compressed process of education. This can mean shortening the course of study without changing the total hours or Carnegie units, reducing the number of hours in a semester, or doing both. Accelerated learning has been around for many years (Seamon, 2004). The terms "accelerated" can be used in relation to a course in a program or study (Donaldson, 2001; Mealman & Lawrence, 2000) or the timing the course is offered as it can refer to summer sessions (Anastasi, 2007), intersessions (Geltner & Logan, 2001), weekend courses (Messina, 1996), and, currently, more and more often, accelerated online courses (Collins, Kang, Biniecki, & Favor, 2015; Millett, Stickler, & Wang, 2015; Shaw, Chametzky, Burrus, & Walters, 2013).

The outcomes in regard to student achievement in semester-long and accelerated programs and courses seem to be comparable to each other (Anastasi, 2007; Shaw et al., 2013; Tatum, 2010) or better in accelerated courses (Sheldon & Durdella, 2010). At the same time, Akyol and Garrison (2008) found that accelerated courses have greater social presence. That is because the courses are shorter and the learners must interact more with each other and with the instructor (Anastasi, 2007). Other benefits of condensed or accelerated offerings are that faculty provide faster feedback (Lee & Horsfall, 2010), students feel less isolated from peers (Chametzky, 2018), and experience reduced anxiety (Pino, 2008). The combination of these benefits along with the quicker progression through the program reduces the likelihood of dropping out from the program (Bowen, Chingos, & McPherson, 2009; Geltner & Logan, 2001). This particular option may be more attractive for older, mature learners who want to enter and exit the programs quicker to attain educational and career goals at their own pace.

1.3 Adult Students

Adult learners, often labeled as nontraditional students, are usually identified as students who are over 25 years old and who have one or more characteristics such as having dependents, being single parents, working full or part time, and having life or work experience outside of college or university (De Vito, 2009; Lambert et al., 2014). Ross-Gordon (2011) suggests that instead of being nontraditional, this population is slowly becoming a norm in college and university enrollment reports. Servicing adult learners requires a shift in teaching practices that includes understanding of andragogy (Henschke, 2011; Knowles, 1980; Samaroo, Cooper, & Green, 2013) as well as shifts in scheduling the courses and the availability of support services (Rhodes, 2001, as cited in Alhassan (2012)).

De Vito (2009) suggests that institutions have responsibility to enhance adult learning programs. De Vito also acknowledges that one of the barriers to adult learning is the issue of accessibility in traditional higher education, which addresses such issues as times and locations of the course offerings. Since most adult students work and have families, attending school competes with other life obligations and commitments. One way to address this discrepancy is to offer ways for adult learners to attend classes at the pace comfortable to them which often means asynchronous, fast-paced courses online.

Dropout rates for adult students attending higher education institutions, whether face-to-face or online, remain high. In their study of factors that influence adult learners' decisions on whether to drop out of the online learning or to persist, Park and Choi (2009) concluded that there were two significant predictors to the decisions to persist in online learning. These predictors were the perceptions of university support and relevance of the courses to the lives and work of the adult learners. Park and Choi further elaborate that these predictors are linked to the classes for which adults register. Park and Choi state that learners are more likely to drop out of an online course if they perceive that the university does not support them or if they perceive the course as not being related to their own life or work.

1.4 Retention Issues

Despite all these benefits, online classes continue to display serious retention issues, which need to be addressed (Bawa, 2016). Attrition rates have always been higher in online learning as compared to face-to-face instruction (Carr, 2000).

Bean and Metzner (1985) proposed that four factors influence the attrition of nontraditional students. These factors are student background, environmental factors, and academic variables such as study habits and course availability and academic and psychological factors. Cochran, Campbell, Baker, and Leeds (2014) found that the strongest predictor of student withdrawals is academic experience. Like Levy (2007), Cochran and colleagues saw that seniors are less likely to withdraw from an online course than freshmen and sophomores. Cochran et al. also saw that prior course withdrawals from online courses and student GPA are the two other factors that significantly affect the retention in online courses.

More recently, Bawa (2016) pointed out that attrition of students in online programs and courses is related to misconceptions about online learning (e.g., it is easier, it requires less effort, does not interfere with the current lifestyle), financial factors, issues of motivation, and technological constraints. At the same time, Bawa indicated that instructors too maybe at fault: the instructors who do not understand the specifics of online students and who lack technical and pedagogical knowledge will contribute to student dropout rates from the online programs.

It is clear that the type of course (face-to-face or online) students choose for their studies may affect their success. When considering the differences between traditional and adult learners in online settings specifically, research shows that adult students have higher dropout rates (Park & Choi, 2009). To investigate this phenomenon more completely, the authors posed the following research question for this study: How do adult students perform as compared to the traditional students in various online course formats? As the data were mined, other more specific questions began to emerge. Specifically,

- Were students (traditional or adult) excelling in the fast-paced accelerated courses as compared to the semester-long courses?
- Does taking multiple online courses either at the same time or consecutively result in better online performance as measured by the final grades earned?
- Is retention in online courses as measured by the withdrawal rate different for the two populations?
- Do traditional and adult students do equally well in different courses: core, either foundational or enriched, and other courses offered in online environment?

2 Methodology

2.1 Setting

The university where the study took place is a small, liberal arts and professional studies university serving 2206 undergraduate and graduate students in 2017–2018 academic years. The school offers traditional education with on-campus residence halls, learning facilities, extracurricular opportunities, and support services.

All students in undergraduate degree programs are required to take courses in the core curriculum (45–49 credits in total) in addition to the courses in their intended majors. The foundational core curriculum (36–40 credits) is intended to introduce students to the breadth of liberal arts disciplines and to develop the fundamental skills of writing, critical thinking, and information literacy. The enriched core curriculum (9 credits) is intended to deepen students' understanding of Roman Catholic and Dominican heritage, ethics, and global and cultural perspectives. All students, regardless of the mode of delivery of the degree program, must take the required core curriculum courses in order to graduate.

In the Fall 2017, 1603 undergraduate students attended the university. The total number of adult undergraduates (23 years of age or older) dropped steadily over the last decade; at the same time, the number of traditional undergraduates grew. In 2006, 705 adult students accounted for 42% of the entire undergraduate student body. By 2012, that number declined to 460 (29%). In an attempt to attract more adult undergraduate learners to the university and to better ensure they were retained, the school developed online courses in various programs and within its core curriculum that delivered to all undergraduate majors. The university also added new fully online undergraduate degree programs. The same year, the university added more online undergraduate courses in an accelerated 7-week format as opposed to the original 14-week format, again to better meet the needs of adult students.

Despite the addition of the new programs and formats, the share of adult students continued to decline, and in 2017, the number of adult undergraduates enrolled was 231 (14%). In order to better retain undergraduate students, the faculty requested that institutional research staff begin to mine online course performance data to better understand the trends, detect problems, and, possibly, propose a solution. This analysis could help faculty and academic support staff devise strategies to improve academic achievement and persistence.

2.1.1 Online Courses at the University

The university in this case study defines online courses as those that meet exclusively online without any physical face-to-face time on campus. The instructors have a choice whether to include any synchronous meeting times but are encouraged to offer courses in asynchronous format. At the time the data were collected, all courses were taught using Blackboard Learning Management System. Regardless of the length of the course (full semester or accelerated), each course is run in a module format. Faculty have freedom to identify the number of modules, the number of learning outcomes, and what each module contains. The faculty are encouraged to use Quality Matters best practices when designing their courses. The university offers support to faculty in course design through the Office of Online Education. While in the course, students have access to online tutoring, technical assistance, and the library.

2.2 Data Sources

This cross-sectional research study used course and student data across four semesters during the 2015–2016 and 2016–2017 academic years. Only fall and spring data were considered for the purposes of equal comparisons, as summer semesters are shorter. Only fully online courses were included, although the university also offered one course in a hybrid format during the time period.

The privacy of data was preserved since the researchers did not use any personal identifiers such as names and student ID numbers. Certain assumptions about the integrity of the data have been made while working with the data set. Specifically, the data were assumed to be accurate and independent.

The dataset consisted of data points from 70 online undergraduate course sections conducted during the 2015–2016 and 2016–2017 academic years. Thirty-nine of those courses were offered in an accelerated 7-week format, and 31 were the semester-long 14-week courses. The 70 course sections spanned 16 disciplines, namely, art history, biology, business, computer information systems, communications, English, health science, history, mathematics, music, philosophy, political science, psychology, sociology, Spanish, and theology. Fourteen of the course sections were noncore courses, 39 were foundational core courses, and 17 were enriched core offerings. Spring 2017 was the semester with the highest number of undergraduate online courses offered and the largest enrollments. One explanation for the increase was a change in the criteria that allowed undergraduates to qualify for enrollment in online courses. Table 12.1 summarizes the course format and course registration information by each of the four semesters in the dataset. A total number of registrations for all the courses in the set was 574.

Most of the courses were offered in a single section during a semester, with the exception of two sections of introductory biology courses in Spring 2016 and 2017 and introductory Spanish courses in Spring 2016 and 2017 semesters. Interestingly, all four biology sections were offered as accelerated courses, whereas the two Spanish sections offered in Spring 2016 were accelerated, and two sections offered in Spring 2017 were offered in the semester-long format. Furthermore, there were two disciplines that switched from semester-long to accelerated and vice versa between semesters within the dataset. These were an introductory course in art history and an enriched, 300-level course in theology.

Of these 574 course registrations in the dataset, 307 registrations were in accelerated courses and 267 were for semester-long courses. In both formats, traditional students outnumbered adult students (Table 12.2).

Three hundred thirty unique students made up the 574 course registrations in the dataset. Of those, 103 were adult undergraduates, and 227 were traditional under-

Table 12.1 Summary of dataset

	Course format			Course registrations		
Semester	Accelerated	Semester-long	Total	Adult	Traditional	Total
1516 FA	8	9	17	31	47	78
1516 SP	13	6	19	79	42	121
1617 FA	5	7	12	31	85	116
1617 SP	13	9	22	166	93	259
Totals	39	31	70	307	267	574

Table 12.2 Course registrations by course format and student type

	Student type		
Course format	Adult	Traditional	Total
Accelerated format	128	179	307
Semester-long format	127	140	267
Total	255	319	574

Table 12.3 Number of courses by student type

	Adult	Traditional	Total
Single course	40	149	189
2–4 courses	49	76	125
5 or more courses	14	2	16
Total	103	227	330

graduates. Seven adult students in the dataset were enrolled in one of the university's fully online academic degree programs. Of the 330 students who took online courses in the period studied, 189 students were single course registrants, i.e., these students took one online undergraduate course over the 2-year period. Forty of these 189 students were adults, and 149 of these students were traditional undergraduate students. Of the remaining students, 125 took two, three, or four online courses across the four semesters (regardless of the format), and 16 took five or more online courses during the four semesters, regardless of the format (Table 12.3).

2.3 Data Preparation

After the raw data were downloaded as a large batch file from the university's student information system, extensive sorting and recoding of several variables were performed before meaningful analyses could be undertaken. The raw data from the student records included student type (traditional or adult) and grade received (on an A–F scale, converted to quality points on a 0.0–4.0 scale). The course information included course delivery type (accelerated 7-week or semester-long 14-week), course discipline, year, and term of course. A variable was created calculating the total number of online courses completed per student during the time period. Another variable was created to categorize the type of course, i.e., if the course was a foundational core course, an enriched core course, or a course outside of the required core curriculum.

Frequencies and means of final grades were calculated for all course registrations in the dataset. Withdrawals were not included in the calculation of final grade means. Once the figures were grouped by subgroups (course format, student type, number of courses taken, content course type), differences in performance were noted. *T*-tests and one-way ANOVAs were conducted to determine if the observed differences were statistically significant.

3 Results

Initial frequency results indicated that overall, 47% of students earned an *A*, 9% earned an *F*, and 6% withdrew from online undergraduate courses during the 2-year time period. Students in the accelerated courses had a lower withdrawal rate of 3%

as compared to 10% withdrawal rate for semester-long courses. The share of *A* grades and the share of failing grades were similar for both formats.

Additionally, the researchers observed that adult students had a higher failure rate, as compared to traditional undergraduate students. As 14.5% of adults earned failing grades in their online courses, just 4% of the traditional students received a grade *F*. Throughout the semester, but after the add/drop period, 7% of adult students and 6% of the traditional students withdrew from the online courses they were initially registered to take. Finally, as can be seen in Table 12.4, adults earned fewer *A* grades as compared to the traditional students, 38% and 55%, respectively. As expected after reviewing the frequencies, the mean final grades for adults (2.72) were lower than the mean of the final grades for traditional students (3.31). This difference was statistically significant, confirmed by an independent samples *t*-test, $t(535) = -5.694$, $p < 0.001$. No statistically significant difference was found comparing the mean final grade for online courses (3.04) and accelerated (3.07) among all students.

This important finding, that adult students were not performing as well as the traditional students did, provoked more analysis. The next logical step was for researchers to examine the differences of both course type and student type combined on final grades. Table 12.5 provides the summary of these results. Frequency distributions indicated that adults lagged behind in performance compared to traditional students in both accelerated courses and semester-long courses. Only 3% of traditional students earned an *F* in an accelerated 7-week course, while 16% of adult students earned an *F*. Researchers also observed large differences in failures and withdrawals between adults and traditional students in the semester-long formats.

Researchers analyzed the means for these four groups of students to further examine the finding that adult students lag behind traditional students in both formats. Results from an independent sample *t*-test comparing the mean of adult students in accelerated courses ($M = 2.64$, $SD = 1.41$) to the mean of traditional students

Table 12.4 Frequencies and means of final grades by student type and course format

	N	*A* (%)	*F* (%)	*W* (%)	Mean	Std. deviation
All adults	255	37.6	14.5	7.1	2.72	1.40
All traditional	319	54.9	4.1	5.6	3.31	1.01
All accelerated	307	47.9	8.8	3.3	3.04	1.22
All semester-long	267	46.4	8.6	9.7	3.07	1.24
Total	574	47.2	8.7	6.3	3.05	1.23

Note: Means exclude withdrawal grades

Table 12.5 Frequencies and means of final grades by student type and course format combined

	N	*A* (%)	*F* (%)	*W* (%)	Mean	Std. deviation
Adult accelerated	128	37.5	16.4	2.3	2.64	1.41
Traditional accelerated	179	55.3	3.4	3.9	3.32	0.98
Adult semester-long	127	37.8	12.6	11.8	2.81	1.39
Traditional semester-long	140	54.3	5.0	7.9	3.30	1.05

Note: Means exclude withdrawal grades

($M = 3.32$, SD = 0.98) were statistically significant, $t(294) = -4.922$, $p < 0.001$. However, a *t*-test did not confirm a difference among adult students in semester-long courses ($M = 2.81$, SD = 1.39) and traditional students in semester-long courses ($M = 3.30$, SD = 1.05). The next step was to perform within-group analysis.

The differences between the four groups, namely, adults who took accelerated format courses, adults in semester-long courses, traditional students who took accelerated online courses, and traditional students who opted for semester-long courses online were tested with a one-way ANOVA. There was a significant effect of course format on student type at the $p < 0.001$ level for the three conditions, $F(3, 533) = 11.203$, $p < 0.001$. Post hoc comparisons using the Tukey HSD test indicate that the mean grade for the adults in accelerated courses ($M = 2.64$, SD = 1.41) was significantly different than the traditional students in accelerated courses ($M = 3.32$, SD = 0.98). Within-group comparisons indicated that there were no differences between adults taking semester-long courses and accelerated courses. The same is true for traditional undergraduate students.

Researchers mined further to determine what other variables within the dataset could impact final grades besides course format and student type. Final grades also varied between the two types of students when number of online courses, regardless of format, was included in the analysis, provided in Table 12.6. Adult students who enrolled in a single online course during the four semesters had a 12.5% failure rate and 18% withdrawal rate. Traditional students who took a single online course during the time period did better than adult students who took just one online course, with 64.4% earning *A*s and a low failure and withdrawal rate (5% and 3%, respectively). Similar differences in achievement were visible between adult and traditional students who took two, three, or four online courses in the period of time studied. Roughly a quarter of adult undergraduate students (21.5%) earned failing grades. However, those traditional and adult students who took five or more online courses had similar rates of success.

Mean final grade calculations also highlighted the weaker performance in the courses detected in the frequency calculations of final grades of adult students as compared to traditional students. Adult students who took one, two, three, or four online courses on average did worse as compared to traditional students who took one, two, three, or four courses online. Those adults who took five or more courses on average did better than traditional students in the same category.

Table 12.6 Frequencies and means of final grades by student type and number of courses combined

	N	*A* (%)	*F* (%)	*W* (%)	Mean	Std. deviation
Adult, single course	40	35.0	12.5	17.5	2.79	1.44
Traditional, single course	149	64.4	4.7	3.4	3.42	1.00
Adult, 2–4 courses	130	36.2	21.5	6.2	2.45	1.54
Traditional, 2–4 courses	158	45.6	3.2	8.2	3.23	0.98
Adult, 5 or more courses	85	41.2	4.7	3.5	3.09	1.03
Traditional, 5 or more courses	12	58.3	8.3	0.0	3.02	1.31

Note: Means exclude withdrawal grades

This finding of adults again lagging required further testing. Results from a one-way 2x2 ANOVA indicated statistically significant differences between final grades among the six groups. There was a significant effect of online course experience on student type at the $p < 0.001$ level for the six conditions, $F(3,533) = 10.09$, $p < 0.001$. The post hoc Tukey HSD test indicated that the mean grade for the adults who completed 2–4 online courses ($M = 2.45$, SD = 1.54) was significantly different than the mean grade for the traditional students who completed 2–4 online courses ($M = 3.23$, SD = 0.98). However, the mean grade for the adults who only took one online course *(M* = 2.79, SD = 1.44) was not significantly different from the mean grade of the traditional students who only took one course ($M = 3.42$, SD = 1.00).

A subset of these data afforded the researchers the ability to compare student performance measured by final grades in those courses that were offered in both accelerated and semester-long formats. Two Spanish sections offered in Spring 2016 were accelerated ($n = 15$ students), and two sections offered in Spring 2017 were offered in the semester-long format ($n = 15$ students). An introductory course in Art History was offered as a semester-long course in Fall 2015 ($n = 4$) and in the accelerated format in Spring 2016 ($n = 6$). A 300-level enriched core course in Theology was offered in Fall 2015 and 2016 in the semester-long format ($n = 17$) and in Spring 2016 in the accelerated format ($n = 8$). Frequency tabulations indicate a large difference in high academic achievement, as measured by the number of *A*s, between the two course formats in Theology. Both formats resulted in high failure rates in the Art History course, 33% (accelerated) and 25% (semester-long). The Spanish course offered in the accelerated format had a higher failure rate of 33% as compared to the semester-long format (7%). Table 12.7 delineates these results. Although the Ns for these groups were admittedly low, the researchers ran independent sample *t*-tests comparing the mean final grades for each format. The results were not significant.

Another variable of interest within this dataset that researchers could examine was to compare the differences across the kinds of courses, not just course formats. Courses were organized into three categories: foundational core, enriched core, and courses outside of the core. Table 12.8 depicts the differences in final grades across these course content areas. It is evident that the courses within the foundational core curriculum had the highest failure rate (13%) and withdrawal rate (8%), as compared to enriched core courses, where the failure rate was 2% and withdrawal rate

Table 12.7 Frequencies and means of final grades for courses offered in both formats

	N	*A* (%)	*F* (%)	*W* (%)	Mean	Std. deviation
Spanish 101, accelerated	15	20.0	33.3	6.7	1.68	1.60
Spanish 101, semester-long	15	20.0	6.7	6.7	2.55	1.11
Theology 319, accelerated	8	37.5	0.0	0.0	3.09	0.93
Theology 319, semester-long	17	64.7	5.9	5.9	3.55	0.99
Art history 122, accelerated	6	66.7	33.3	0.0	2.67	2.07
Art history 122, semester-long	4	75.0	25.0	0.0	3.00	2.00

Note: Means exclude withdrawal grades

Table 12.8 Frequencies and means of final grades by course content type

	N	*A* (%)	*F* (%)	*W* (%)	Means	Std. deviation
Enriched core courses	168	60.1	2.4	3.6	3.45	0.85
Foundational core courses	344	39.2	12.5	8.1	2.79	1.36
Courses outside of core	62	56.5	4.8	3.2	3.37	1.02
Total	574	47.2	8.7	6.3	3.05	1.23

Note: Means exclude withdrawal grades

was 4% and courses outside of the core, with 5% and 3% failure and withdrawal rates, respectively. The lower grades scored in the foundational courses were also apparent in the mean calculations. Similar to the other subgroup analyses, means of final grades were calculated after the frequencies, removing the withdrawals. The mean final grade for foundational core courses was 2.79 (SD = 1.36), lower than mean final grades for enriched core courses and courses not within the core curriculum [$M = 3.45$ (SD = 0.85); $M = 3.37$ (SD = 1.02), respectively].

To test these differences in means, a one-way ANOVA was conducted. Results indicated that the difference in the final grades means among the three course content groups (foundational, enriched, and outside of core) was statistically significant. There was a significant effect of course content type on final grade at the $p < 0.001$ level for the three conditions [$F(2, 534) = 18.981$, $p < 0.001$]. Post hoc comparisons using the Tukey HSD test indicate that the lower mean grade for students in foundational courses ($M = 2.79$, SD = 1.36) was significantly different than the grades in both the enriched core courses ($M = 3.45$, SD = 0.85) and the noncore curriculum courses ($M = 3.37$, SD = 1.02).

4 Discussion

These results allow us to answer the research question that we posed at the onset of the study as well as the sub-questions that emerged as the data were mined.

The major question that was posed at the onset of this research was whether adult students perform any differently from traditional students in the various online formats. The results suggest that on average, adult students are not succeeding in online courses at the same rate as traditional undergraduate students. The rates of failure are higher in both accelerated and semester-long course formats. In addition, adults do not perform better when they take multiple online courses either simultaneously or in sequence.

Since it may not be entirely clear why this may be the case, a question of why this is happening may be a compelling one to ask. However, this question is outside of the scope of research for this study and is a good future research opportunity for the university. Despite not offering an explanation as to why the performance is low, the results may offer an insight into one point of contention. Faculty are often reluctant to offer accelerated courses to students arguing that this online format is harder for the students, that students need time to get used to the course and to absorb the material, or that it is impossible for students to do well in the shortened courses. The results indicate that students perform somewhat equally in either format. Thus, the answer to the question of the success in the online courses does not lie in the type of format that students choose but has to do with other factors. This includes but is not limited to the issues of online pedagogy, faculty readiness and motivation to teach online, faculty and student engagement, and commitment to online teaching and learning. These constructs, although hard to measure in online formats, must be the focus of future endeavors.

One of the sub-questions asked whether the students do better in faster-paced courses. Success data, as measured by the final grade, indicate that both adult and traditional students did not perform any differently in the two online formats.

Another question of concern was whether taking multiple classes online, either in sequence or simultaneously, results in better online performance as indicated by the final grades. The results indicate that students who take multiple online classes, whether at the same time or sequentially, on the whole do not perform better than students who only take one online course. The exceptions are those students who take more than five online courses in a sequence. One can argue that when students take online classes sporadically, without a plan, students do not take these courses seriously. This view aligns with Bawa (2016) who spoke about such misconceptions as online courses being easier or less demanding. When students sign up for courses with this mindset and then find out that this view does not hold true, such a discovery might lead to decreased motivation, effort, and engagement in the course, or lead the students to withdraw from the course. Students who commit themselves to taking online courses systematically, however, may lack those misconceptions and, as a result, may be better positioned to succeed by being more motivated and prepared to engage, and to exert effort to do well.

The final question of interest in this work was to find out whether the retention rate as measured by the withdrawals is different for the two populations of students studied. While the results indicate that the overall withdrawal rate of adult students is somewhat higher than that of traditional students, one interesting point is evident when the comparisons of students who took a single course are made. These results indicate that the withdrawal rate for adults who take only one course is much higher (17.5%) than that of traditional undergraduate students (3.4%). While this might mean that more research is necessary, an argument that aligns with Cochran et al. (2014) can be made. Cochran and colleagues found that academic experience and readiness are strong predictors of persistence in a course of study. One can argue that traditional students tend to attend school full time, regardless of how many online courses they take. Adult students are at a disadvantage in this regard. Many of them have an interrupted academic experience, and many of them take classes on a part-time basis. This means that their academic experiences and overall academic baggage, so to speak, may be different. As such, these students may require different teaching approaches as advocated by Knowles (1980) and different university supports as suggested by Park and Choi (2009). One of the arguments Park and Choi advance is the relevance of content to the learner. It may be the case that adult learners do not see the relevance of the core courses to their lives and, therefore, do not put as much effort in them as compared to the classes they perceive as really important. More studies, probably of qualitative nature, are necessary to understand this issue further.

While these findings are discouraging, they do provide some food for thought. More questions were generated as a result of this work than were answered. Future research could look into the relevance of the core curriculum to the nontraditional adult population. Such issues as pedagogical approaches within accelerated and semester-long courses could be explored as well as issues related to student motivation and commitment to taking online courses, especially multiple online courses at the same time, should be studied further. Another possible investigation into understanding the success of adult learners specifically is to compare the success data as measured by the final grades in face-to-face formats as opposed to the online formats.

4.1 Implications

The results of this study were shared with academic affairs leadership, faculty, and academic support staff on our campus. It was clear to us, as researchers, that the study, although not perfect, has some clear implications to the institution. In particular, the following four questions were identified for the institution: (1) what are some student services decisions that we need to consider to help adult learners succeed?, (2) what are some enrollment and marketing decisions that we can make based on these data?, (3) what are some professional development opportunities for faculty that need to be considered in order to turn the tide?, and (4) what are some curricula and pedagogical adjustments that should/need to be considered if we are to continue to serve the adult population? While these questions do not have immediate answers, the stakeholders on campus should begin considering these questions while also collecting more data and considering other sources of data that may provide better answers.

The four questions outlined above may serve as long-term guides to the change. There are also immediate adjustments that have been made based on the data. For example, to address the issue of readiness, adult undergraduates are now required to take a quiz to determine how ready they are for online learning. The results of the quiz are then discussed with their professional advisor who then offers tips on improving online learning strategies to increase the likelihood of success.

Another finding that was uncovered through these analytics is the performance of students in foundational core courses. The foundational core curriculum is crucial in the development of writing, critical thinking, and information literacy skills of students. These skills are necessary for making progress within the degree program, as well as in entering and succeeding in the workplace. The finding that the foundational core courses within this study have high rate of failures and withdrawals is important to consider and think about.

4.2 Limitations

This study has a number of limitations that should be considered in future research. First of all, the study did not take into consideration a number of student characteristics that may affect performance in online courses. These include but are not limited to student prior experience with online courses, level of comfort with technology, amount of time devoted to studies, and student class level. Other variables related to courses that may also affect performance include faculty type, differences in instruction, and level of rigor. These too were not considered.

One of the biggest and hardest to overcome limitations in this study is that no actual student online engagement data were available to us. As researchers, we would have welcomed the opportunity to study what exactly and how the students have done in their online classes. Access to actual course data would have allowed the researchers to study teaching approaches, student responses to prompts, interim assessment grades, and other data normally stored within a typical Learning Management System (LMS). We could not use these data however. One reason was faculty permissions. Another is the limitations of this particular LMS. In addition, on a small campus, it is much easier to put the names of the students one sees in the Learning Management System with faces on campus, which feeds the concerns about privacy and ethics as Slade and Prinsloo (2013) bring up in their work.

Another limitation is the one that concerns the size of the dataset. In this paper, we argue that working with 574 course registrants constitutes big data for small institutions. Researchers working in large institutions have access to thousands of records at a time, and each semester the sets increase, sometimes exponentially. As Chernobilsky, Jasmine, and Ries (2016) point out, small-scale projects rarely result in massive data sets that traditionally are used in educational data mining and learning analytics. Engaging in data explorations, however, is equally important to large and small institutions. We, thus, argue that for small institutions like ours, the size of the data set is not a limitation but a reality of life. We believe that the size of the data set may not be as important and should be considered in relation to the overall size of the institution as long as the data set helps answer the questions addressed. Sometimes, working with smaller numbers may be a way to begin understanding an issue, as our study indicates. As the set grows, mining it further might provide an opportunity for predictive modeling and other more sophisticated decision-making tools available in the realm of educational data mining and learning analytics.

5 Conclusions

The researchers in this study sought to understand adult student success in semester-long and accelerated online courses. Although this research, at its conclusion, posed more questions than it answered, the researchers argue that learning from small data sets may be just as valuable as learning from the large sets of data. Small institutions by virtue of their size cannot collect large data sets easily. Working with smaller sets for these institutions is just as valuable, however, as working with massive data sets is for the large institutions when trying to understand issues of importance. Future investigations should consider a variety of data sources such as face-to-face comparisons, other kinds of demographics, prior educational experiences, and student experiences once in an online course. This case study showed how one small institution considers available data to learn about online performance of adult students. As a result of this study, the university has renewed its commitment to using learning analytics in understanding its student population.

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Part III
Learning Analytics Case Studies: Practices and Evidence

Chapter 13
Empowering Teachers to Personalize Learning Support

Case Studies of Teachers' Experiences Adopting a Student- and Teacher-Centered Learning Analytics Platform at Three Australian Universities

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1 Introduction

1.1 Students' Success and Teachers' Roles

Ensuring student success is a multifaceted challenge facing higher education institutions worldwide, particularly in light of pressures such as the massification, commodification, and diversification of higher education. We adopt Kuh and colleagues' definition of student success as "academic achievement, engagement in educationally purposeful activities, satisfaction, acquisition of desired knowledge, skills and competencies, persistence, attainment of educational objectives, and postcollege performance" (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006, p. 7). Student engagement is viewed as a key indicator of student success as the extent to which students engage in educational activities is likely to determine whether they will succeed in their studies (Kuh et al., 2006). Key mechanisms that support student engagement include improving the quality of student-staff relationships,

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encouraging timely help-seeking behavior, and clarifying expectations (e.g., Kahu & Nelson, 2018; Krause & Coates, 2008; Zepke & Leach, 2010). A sense of success in the early stages of students' university careers is also critical in building persistence and downstream academic achievement (Tinto, 2006). Lizzio (2006) has characterized five 'senses of success', including students' needs to feel capable, connected, purposeful, resourceful, and competent in terms of navigating academic culture. While 'engagement' and 'success' are necessarily broad, what is abundantly clear from the literature is the key role that teachers[1] play in fostering the abovementioned factors.

Krause and Coates (2008) point out that "[s]tudent perceptions of the learning environment and the commitment of academic staff to supporting student learning have a profound influence on student satisfaction and sense of belonging" (p. 501). A teacher's role in developing relationships and trust with students can powerfully impact on their engagement and academic achievement (Bryson & Hand, 2007; Reason, Terenzini, & Domingo, 2006). This has been encapsulated in the idea of 'relational pedagogy', which espouses that the "positive messages that are implicit when academics give time and support to students are significant in helping students feel that they are both worthy of their place and able to succeed in the university" (Pearce & Down, 2011, p. 492). Despite the commodification of higher education, the human relationships that exist at the core of learning and teaching are still critical but increasingly forgotten.

The unfortunate side effect of burgeoning class sizes and the concomitant sense of anonymity in today's higher education contexts undermines this central tenet of student success (Bryson & Hand, 2007). How students perceive these exchanges with their teachers has a positive impact on academic achievement, engagement, satisfaction, and retention (Farr-Wharton, Charles, Keast, Woolcott, & Chamberlain, 2018). Importantly, this conceptualization emphasizes the need for individualized communications: "Keeping the channels of communication open between the instructor and student is essential to enhancing the quality of exchanges. Students need to perceive that there is ready access to the instructor" (Jacques, Garger, Thomas, & Vracheva, 2012, p. 9). An example of these exchanges is feedback, known in the assessment literature to be another critical touchpoint between students and teachers (Hattie & Timperley, 2007). Timely, specific, goal-oriented feedback that clarifies standards and develops positive motivation and self-assessment strategies help to foster students' self-regulation and improve learning (Nicol & Macfarlane-Dick, 2006). The challenge in the context of higher education today is, of course, to scale these exchanges that provide learning support without losing the timeliness and personalization aspects. Proposed methods for such scaling increasingly include software (e.g., Pardo, 2017) that allow for teachers to measure student achievement in greater numbers and inform future teaching designs and approaches.

[1] We use "teachers" in this chapter to refer to educators who design and deliver learning experiences for students. This includes coordinators who have additional responsibilities such as broader curriculum design and ownership, as well as tutors (or teaching assistants) who work under coordinators.

Ostensibly, this is one of the promises of the field of learning analytics (LA), which purports to have a "[f]ocus on informing and empowering instructors and learners" (Siemens & Baker, 2012, p. 253). This field typically focuses on big data available from digital learning systems, algorithmically analyzing behavioral "user events" in the form of logs of interactions and being concerned with combining logs from different data sources (Pardo & Dawson, 2016). An important issue here is that LA can be characterized as taking a computational view of learning, missing out on its relational and humanistic aspects. Some authors have rightly warned that the 'learning' in LA is being forgotten in favor of the 'analytics' and that a return to the root of learning and teaching including considering pedagogical intent and context, and involving students and teachers as the key stakeholders, is essential (Gašević, Dawson, & Siemens, 2015).

1.2 The Contexts of Teaching and the Learning Analytics Needs of Teachers

Perhaps symptomatically, reports from around the world suggest laggard adoption and implementation of LA by teachers. Recent reports on Australasian LA adoption and implementation have highlighted that, as the primary implementers of any LA tool, teachers need to be involved in designing LA approaches that "are sensitive to their environments, meeting and extending their pedagogical requirements, and ensuring flexibility" (Colvin et al., 2016, p. 19). In this context, and in keeping with the relational pedagogy outlined above, a key need seems to revolve around actions that involve personal connections with students, which balances the automation of computers with the humanistic approach of teaching (West et al., 2015). Notably, this report highlighted that teachers "still have to make sure that it [communication and feedback] is personalized and meaningful for students" and that teachers need LA tools with "some ability to modify it to their own requirements because each course and each cohort of students may differ" (p. 20).

The learning and teaching landscape in any institution, faculty, and indeed course[2] is unique and influences the uptake of any innovation, especially LA (Ferguson et al., 2014). Several factors can impact adoption, but some are particularly relevant to teacher- and student-centered LA:

1. Faculty resistance to change and workload issues are examples of social and cultural context that need to be understood and addressed (Macfadyen & Dawson, 2012), including concerns around needing to adapt to new tools and approaches, and change existing practices.

[2] "Course" is defined in this chapter as an individual component of an academic program that a student takes, usually lasting a semester. For example, it is referred to as a "unit of study" at the University of Sydney, a "subject" at the University of Melbourne, and a "course" at the University of New South Wales.

2. A large proportion of learning and teaching activities typically occurs outside the online space (not just outside the confines of a learning management system [LMS]) and often involves human interaction (West et al., 2015), presenting challenges for capturing and using the right data in the right place.
3. The lack of available tools that properly address the needs of teachers and students (Colvin et al., 2016) and a lack of bottom-up support and sharing that is driven by LA users (teachers and students) who have personally experienced tangible benefits, potentially causing stalling or retraction of interest (Liu, Rogers, & Pardo, 2015).

From these challenges, it may be surmised that a potential solution for teacher adoption is LA software that (simultaneously, in one place) assists them in capturing and working efficiently anywhere and in real time with a wide and flexible range of meaningful data, addresses their felt needs while reducing workload, and can yield immediate, shareable benefits. Existing LA tools are predominantly based on dashboards or mail merge (Lawson, Beer, Rossi, Moore, & Fleming, 2016; Tanes, Arnold, King, & Remnet, 2011; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). However, these single-purpose LA tools that just present a dashboard or just allow databasing and creation of mail merge emails may be effective in addressing parts of the whole 'data lifecycle' that teachers must manage through the course of a semester or year but fail to address its entirety nor the three challenges noted above. For example, dashboard tools are typically view-only, do not afford direct-to-student or two-way communications, and even sophisticated reporting outputs may be seen as a workload imposition with little or no benefit (Macfadyen & Dawson, 2012). Additionally, mail merge tools typically do not afford data collection processes or predictive analytics.

In an example of a consolidated LA workflow, Pardo and Dawson (2016) outlined a multistep lifecycle for LA which was geared toward improving learning practice; their process involved (1) data capture and combination from logs and other sources such as demographics, (2) data visualization and analysis through reporting interfaces, (3) algorithmic generation of models for prediction of learning outcomes, and (4) interventions at various levels of the university enterprise ranging from students and teachers to directors and administrators. Here, we contend that this conceptualization is still too computational and does not sufficiently involve teachers throughout the cycle nor address their barriers to adoption identified above. We therefore propose a reconsideration of this lifecycle that is more humanistic and meaningfully addresses teachers' and students' immediate needs in a wide range of contexts, in order to shift the conversation from single-purpose LA *tools* to multi-functional LA *platforms* that may address these needs in an integrated way:

1. Data collection—the *right* data needs to be gathered from both online *and* face-to-face learning and teaching environments. This does not necessarily need to include system logs, nor demographics.
2. Data curation—all relevant data need to be accessible in one place. The teacher, with their understanding of the pedagogical and pastoral contexts of their course,

should be the one making the informed decisions about what data to curate and when.
3. Data manipulation and analysis—the 'raw' data may need to be transformed or otherwise manipulated before it can yield a useful representation of information or be used to inform subsequent action. This does not necessarily need to, but could, involve any automated or algorithmic processing.
4. Actions enabled by the presence of data—providing learning support to students needs to occur in a timely way, account for individual student needs, and consider the classroom climate (Hattie & Timperley, 2007). Personalized support delivered by an electronic system (e.g., via email or a web page) helps to address this, but empowering the entire teaching team with relevant data when interacting with students face-to-face and online is also important.
5. Closing the loop and evaluation—feeding students' engagement with, and perception of, personalized support back into the system so that teachers can use it to improve their approach.
6. Reflection—prompt and guide reflection on teaching and support practices by providing easy access to relevant representations of data.

Taken together, these needs and challenges speak to the importance of personalizing the learning environment. The term "personalized learning" encompasses a wide range of approaches that, broadly speaking, seek to tailor the content, support, and pathways that students receive based on some information known about each student (Alli, Rajan, & Ratliff, 2016). By amplifying the intelligence of human teachers with the agility of software (Baker, 2016), LA can help teachers leverage student data to provide timely, pedagogically meaningful, and tailored support. In completing the above LA lifecycle, teachers also change their practices based on data about students and the impact of support they are provided. We contend here that this personalized learning is therefore not just about *personalization* (tailoring) but also *person*-alization (humanizing) students' learning experience by teachers.

We next introduce an LA platform that was developed to address these issues, followed by the experiences of three Australian institutions—the University of Sydney, the University of Melbourne, and the University of New South Wales (UNSW) Sydney—which are at different maturity levels of its adoption and implementation. As part of this, we discuss the context in which each institution is using the platform and the rationale behind its adoption. Finally, we synthesize the impact of the platform on teachers and their students, discuss a series of implications for practice, and conclude with future research directions.

2 The Student Relationship Engagement System (SRES)

Teachers lack the requisite combination of tools to fully control the personalization process for their students through the "data lifecycle" outlined above. To this end, the Student Relationship Engagement System (SRES; www.sres.io) is a unique LA

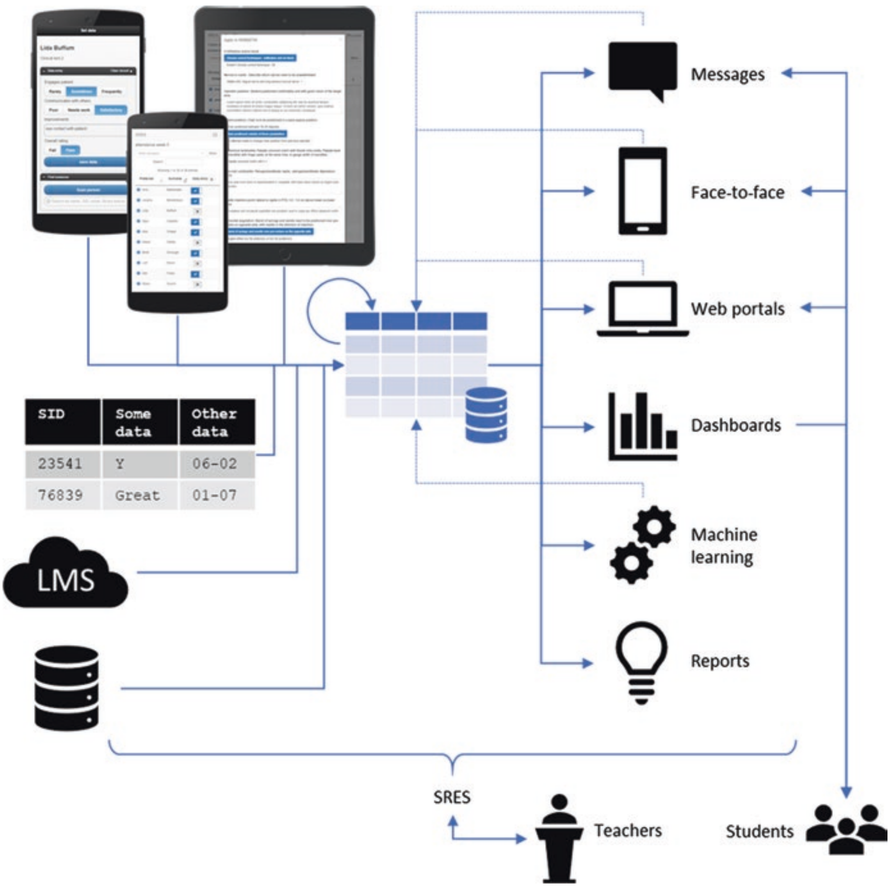

Fig. 13.1 Schematic of the Student Relationship Engagement System (SRES) as a multifunctional learning analytics platform. Data are collected and curated (left half) into a database that is unique for each course (center). Data can be manipulated, analyzed, and used in many ways (right half), some of which feed more data back into the system (thin dashed lines). Students interact with the SRES through a number of modalities and can also feed data back directly into the system (double-ended arrows). Teachers are in full control of all these stages of the learning analytics data lifecycle, accessing the SRES through a web interface

platform, housing a wide range of flexible and highly customizable tools, which has been developed to give teachers full control over the data lifecycle and to empower them to use data in ways that suit their specific teaching contexts (Fig. 13.1). The SRES addresses our proposed LA data lifecycle by providing a platform where teachers have ownership and control over each stage.

1. Data collection—teachers can import most kinds of electronic data into the SRES (keyed by a unique student identifier) or set up data synchronizations with databases or LMSs. Importantly, they can also build simple mobile web app interfaces within the SRES to collect data from face-to-face learning and teaching

environments (e.g., in-class attendance, participation, or assessment data). Similar web interfaces ("portals") can also be presented to students so that they can enter relevant information directly into the system.

2. Data curation—all collected data can be curated into "lists" (essentially a database, usually one such list per course) within the SRES and made accessible online to other teaching staff within the course in real time. A key factor here is that teachers are in full control of the columns (attributes, fields) in their lists.
3. Data manipulation and analysis—spreadsheet-like data manipulations can be performed directly within the platform, including using rules that can range from simple to complex depending on teachers' needs. They can also visualize data by creating custom dashboards and apply machine learning algorithms (clustering, decision trees, and association rule mining) to uncover hidden patterns in large datasets to better understand how students are engaging and succeeding (Liu, Taylor, Bridgeman, Bartimote-Aufflick, & Pardo, 2016). Predictive models can also be built and applied using teacher-selected attributes. All of these manipulations and analyses can be performed by teachers without any coding, simply by selecting relevant columns and operations via a graphical user interface.
4. Actions enabled by the presence of data—teachers can provide personalized online support to students by sending customized emails or pushing personalized web page content ("portals") to a student's LMS. They can also use data to inform face-to-face actions, such as presenting relevant data to teaching assistants at the point of contact to contextualize teaching activities to address identified learning needs. Custom dashboards can be shared with other teachers and even students. Customizable reports can also be designed to automatically inform members of the teaching team about students who meet teacher-defined criteria.
5. Closing the loop and evaluation—teachers can see who has opened emails sent from the SRES, how many times, and whether links have been clicked. This can inform the need for further action, such as follow-up communications either online or face-to-face. Teachers can also capture feedback about whether their message has been helpful to students by enabling a function that allows students to vote and provide qualitative feedback explaining how and why.
6. Reflection—by variably combining the custom visualizations, closing-the-loop information, machine learning insights, and by virtue of having all relevant data in one place, teachers can evaluate the impact of their actions and better understand the characteristics of their student cohorts. Based on this, they may, for example, adjust future approaches to student learning support in terms of recipient pool and messaging.

In stark contrast to other LA approaches and tools, the SRES gives precedence to teacher intelligence and small (but meaningful) data over predictive algorithms and big data. It enables teachers to design an LA approach that is contextualized to their unique learning and teaching situation. This may include collecting and curating traditional student engagement and performance data such as attendance, LMS use, tutor feedback, and grades but may also include nontraditional information such as

Fig. 13.2 Key functionality of the SRES mapped to the six stages of the proposed LA data lifecycle

those that students proffer about themselves, such as their preferred name, photo, and details such as their background and interests. The flexibility of the SRES affords teachers the ability to leverage a wide range of data to suit the needs of their teaching practices and student cohort. Together with the functionality built into the platform, teachers are given control of the whole data lifecycle (Fig. 13.2), enabling them to obtain and use contextually meaningful academic engagement and success data to foster relationships with, and provide support to, their students.

3 Institutional Case Studies

3.1 Methodology

To conduct a cross-institutional study, three Australian universities who currently have access to the SRES platform were selected: the University of Sydney, the University of Melbourne, and UNSW Sydney. Between these institutions, the maturity of adoption of the SRES varied, with the University of Sydney being the first developers and adopters, giving teachers more time to adjust to and implement the platform (Vigentini et al., 2017). Across all three cases, however, the research sought to investigate the following broad questions which applied regardless of the maturity of adoption:

1. Why did teachers choose to adopt the SRES?
2. How did teachers use the SRES to support student success? (That is, what data did they select, how did they use these data, and why?)
3. What are teachers' perspectives and experiences of the impacts and effectiveness of the SRES on them and their students? (For instance, on students' engagement, satisfaction, and success?)
4. What are students' perspectives of the personalized support messages received from teachers via the SRES?

The mixed-methods methodology for the investigation focused primarily on semi-structured interviews and informal feedback with teachers (including coordinators, lecturers, and tutors), supplemented with qualitative and quantitative data from the SRES platform including percentage of emails opened and responses from students regarding the helpfulness of communications received through the SRES. This approach was taken because it is often difficult to establish the impact of a *platform* which can be applied in many different ways for different purposes; in the context of LMSs, Coates, James, and Baldwin described this issue as being "not the provision of features but their uptake and use that really determines [a platform's] educational value" (2005, p. 26). The diversity of uses (and indeed teachers and students and their individual characteristics) also precluded predominantly quantitative measures of impact, even though they may be possible for more focused programs (Dawson, Jovanovic, Gašević, & Pardo, 2017).

While these research questions were used across all three institutions, the highly customizable nature of the platform meant that it was not possible to compare courses within institutions, nor across institutions. Currently across the three universities in this study (Fig. 13.3), the SRES houses teacher-selected data for over 43,000 students (2017 count, over 72,000 projected for the entirety of 2018). These

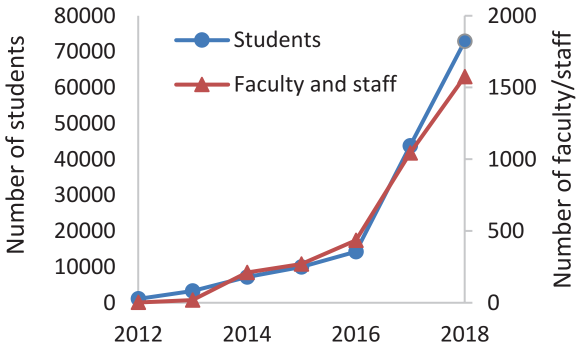

Fig. 13.3 Combined adoption measures of the SRES at three Australian institutions. Figures for 2018 are projected based on half-yearly data

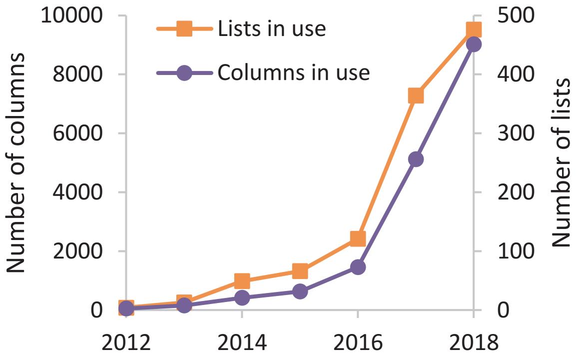

Fig. 13.4 Combined use measures of the SRES at three Australian institutions. Figures for 2018 are projected based on half-yearly data. The database structure of the SRES allows teachers to create "lists" (typically one per course) with students and create relevant "columns" in these lists to house data of their choosing

data relate to students across 360 lists (2017 count, 470 projected for 2018), each list typically representing a single course (Fig. 13.4). Across these lists, 5100 columns (2017 count, 9000 projected for 2018) contain data about students, each of which has been selected by teachers for use. While a large sample size usually lends itself to more impressive statistical outcomes, in the context of the SRES, this primarily resulted in an overwhelming diversity of variable uses and users. Therefore, this study sought a more holistic understanding of how teachers were using the platform and the reported impacts of this on students. The case studies start with a wide-ranging snapshot of its use at the University of Sydney, the original developers of the platform where it has been used by an increasing number of teachers since 2012. More focused perspectives are then presented for the University of Melbourne and particular courses at UNSW Sydney.

3.2 *Case Study 1: The University of Sydney*

The SRES was developed in 2012 by two teachers in the Faculty of Science responsible for coordinating large first-year units with up to 2000 students per semester. After being used primarily within the Faculty of Science for the first two years, it spread organically across other areas including Arts and Social Sciences, Business, Engineering, Health Sciences, and Medicine. It now reaches over 50% (in 2017, over 32,000 unique students) of the entire university's student cohort, almost 5,000 weekly users (students, teachers, and support staff), and over 1,500 registered faculty and staff users. In these diverse settings, teachers' adoption of the SRES has extended from enhancing teaching and learning to streamlining administration and course coordination.

A recurring theme from interviews was the use of the SRES to capture student attendance and participation grades. Many reported collecting attendance at face-to-face sessions such as tutorials and laboratory classes. Compared to traditional practices of using paper-based rolls that were often lost or sometimes entered at the end of the semester, the SRES allowed teaching teams to record data and act upon it throughout the semester. Many teachers viewed attendance as an important indicator with both their personal experiences and empirical studies indicating a correlation between student attendance, participation, and performance (Credé, Roch, & Kieszczynka, 2010; Newman-Ford, Fitzgibbon, Lloyd, & Thomas, 2008). As one coordinator explained, "it tends to be the case that if you don't turn up you just don't have the opportunity to ask as many questions and really sort of nut out those ideas. Earlier in the degree attendance is a lot more important because they're picking up the basic concepts that they need for the rest of their degree, and possibly for the rest of their lives." Having access to attendance data in the SRES allowed teachers to identify students who were not engaging, with many using this information to generate personalized emails, reminding students of attendance requirements and offering support where required.

Interestingly, others provided additional reasons for collecting attendance data, noting that the process of collecting this data was in itself an opportunity to engage with students. The change in tools and process meant that instead of calling names from a paper-based roll, teachers would move from student to student scanning their student ID using the SRES mobile web app. Some teachers reported that this process allowed them to learn the names and faces of their students more quickly, while some reported this as an opportunity to provide feedback to students about their progress. In these situations, the technology caused a change in practice which helped to strengthen teacher-student relationships.

To achieve a similar goal, some teachers reported directly collecting information from their students through the SRES at the beginning of semester. They noted the positive effects of having this information, such as work experience, interests, career trajectory, and even student photos, with one coordinator reporting, "that really helped with our tutors because they felt like they had this photo there that they could immediately see who their students were, and then they also had something interesting about them that they could use to memorize who they were as well. They found that really useful." Some used this information to inform their teaching practices as it allowed them to contextualize these based on the cohort of students. One tutor with students from a range of majors used this information to structure class discussions based on the different background knowledge and unique perspectives of individual students present. They found this to be a more positive experience, stating, "because I could go directly to a person who I already knew had background—whether it be through their major or through their work experience—I was able to generate a much smoother discussion in class." Reflecting on students' perspective of this experience, they reported, "their perception was here's a teacher who actually knows all about me already. They've taken the time and the effort to understand me as an individual."

Coordinators reported using face-to-face data in conjunction with data from a variety of online platforms, including the LMS and external discussion boards such as Piazza. For example, having access to last log-in date and discussion board usage allowed coordinators to identify whether students were actively contributing, passively viewing, or not engaging at all. Combining multiple data sources in the SRES allowed coordinators to identify students who were at risk of lower performance. The focus on this combined dataset was primarily in the early weeks of the semester, including the weeks leading up to the census date (when students can unenroll without financial penalty). One teacher reported using this information prior to census to send personalized emails to students who were at risk, advising them and offering support. Interestingly, they reported a reduction in the number of students who dropped out, stating "we used to have maybe 30, 40 people drop out minimum. Now we can have a handful" (cohort size 800–1300). Another teacher using the SRES in a similar way reported a halving of the year-on-year withdrawal rate in a first-year cohort of 270, without any other changes made to the course except the introduction of the SRES.

In addition to capturing and acting on face-to-face and online participation data, the SRES was used heavily for providing personalized assessment feedback. As with attendance, many teachers increasingly used the SRES to mark and provide feedback for in-class assessments such as presentations. To do this, course coordinators or learning designers built forms within the SRES, which were then used by markers on a mobile-friendly SRES web app that enabled live data collection. Teachers then used these data to build personalized feedback via email, text message, or through a web page embedded into the LMS. This involved creating conditional text and piping entered data into templates, as with mail merge approaches. Some teachers reported grouping students based on performance (such as low, medium, and high) and sending feedback that was customized to each of these groups. Others reported much more complex processes in which students were assessed against a detailed set of criteria and would receive highly personalized emails with feedback comments tailored to their performance against each criterion. In addition to receiving feedback, they would also receive suggestions for improvement.

The use of the SRES for assessment feedback not only allowed for more efficient marking processes but also resulted in more timely and detailed feedback to students. Providing more immediate feedback was seen as important, particularly where assessments built upon each other or required the application of similar skills. As one coordinator reflected, "We've moved from, I'd have to say, not the best feedback mechanisms up to now very prompt feedback on any submitted work. So that the students, before they have to complete their next submission task, have an opportunity to improve." The personalized nature of the feedback was also well-received by students, with one coordinator noting, "I routinely get emails back from students who believe I have personally sent them that email. Who believe that I have taken the trouble to individually engage with them and give them that feedback. I get thank you emails, and I get questions about the email that I sent, from time to time. Not a huge number, but enough to give me a good indication that that's the way that they seem to be received." Some coordinators also emphasized the benefit of having timely access to assessment grades for their course as this allowed them to quickly identify trends, including areas where further instruction was required for all students to address learning gaps. From here they were able to communicate this to tutors and ensure that subsequent classes focused on bridging these gaps.

In addition to using the SRES to provide personalized feedback to students' assessment tasks, some teachers also utilized the SRES to contact students who were not performing well and may have needed support. For students who had not submitted, some coordinators used personalized emails to remind them of the requirement to submit, to negotiate deadlines, and to remind students of the process to make arrangements for missed assessments. For students who had submitted but were not performing to the level required, coordinators often sent emails recommending they attend additional workshops or engage with support services. While many wanted to provide support and encouragement to other students, time constraints were a major challenge which impeded their ability to do so. As one teacher reflected, "we're very good at sending complaint emails when things go wrong, but when things go well we don't tell people and people need those spontaneous good emails," Another teacher noted, "reinforcing the good ones—there's immense value in that and we forget that group, often. We don't give them enough praise and recognition." Interestingly, one coordinator did report using it to identify high performers in order to email them about opportunities for further study.

While many see the value in adopting the SRES, for tutors, the support of the coordinator was an important factor in being able to implement and use the SRES within a course. One tutor reported, "I had a whole lot of fights with the [course] coordinator to get SRES into the [course]." To overcome this resistance, they initially trialed it with one class of students on a limited basis and then rolled it out across all classes. The workload generated by sending emails was also a point of reflection for staff. Some teachers mentioned challenges engaging with students despite the personalized nature of their emails, reporting that they perceived that often students did not even open them. In contrast, others reported an increase in the responses received from students as a result of sending emails through SRES. Despite the increase in workload, many teachers actually commented on this positively. As one noted, "[f]rom a workload perspective, yes, it is generating a whole lot more [email responses from students] that you wouldn't otherwise have. It's actually really quite productive [at engaging students] that way." Another reflected, "Care [for students] overrides the [additional] time."

This sentiment was echoed in student comments, which were volunteered directly to the platform in response to personalized messages. These allowed the platform to accurately capture students' perspectives and therefore allowed teachers to close the loop and start reflecting on their support approaches:

- "Thank you for the feedback! Understanding the breakdown of marks and feedback in such detail really helps prepare for other [assessments] and next year placement. Thanks for the semester!"
- "Just let me know teachers do concern [sic] about my study and my learning outcome, and helpful advice to do better."

- “It is really helpful, thanks for encouraging me onto the rest of the semester, I was losing it and I thought I might just give up. But thank you very much and I will keep up the good work!!!!!!!!!!!!!”
- “This message shows me which part I can do better in final exam and makes me feel the professor is kindness.”

At the University of Sydney, the SRES has provided teachers with a practical platform to work with student data on attendance, assessment, participation, and engagement in face-to-face and online environments. This has led to tangible benefits including improved student feedback and engagement as well as administrative efficiencies, which together has gradually helped to overcome faculty resistance. Additionally, small communities of practice have formed within and between departments, where learning designers and faculty worked together to share success stories and help provide on-demand support. Despite the challenges some teachers have experienced, the involvement of teaching staff in the design and development of the SRES over the years has also improved the extent to which it has been adopted and used across the university. As one participant noted, “the selling point is that it was made by a teacher. Because teachers know what teachers need.”

3.3 Case Study 2: The University of Melbourne

The second case study involves teachers from the Faculty of Science at The University of Melbourne, a large research-intensive university, who piloted the use of the SRES from early 2017 (Vigentini et al., 2017) and as such are still relatively new adopters of the platform. Melbourne’s adoption began with a conference presentation piquing interest, leading to the joint initiative between the platform’s Sydney developers and the academic faculty leadership team at Melbourne. Melbourne was further supported in the implementation of the platform by an information technology specialist, who had her role shifted to help support the SRES. Participants in the SRES pilot were coordinators from five courses ranging from Mathematics, Biology, and Chemistry, and all courses had over 300 students enrolled. The structure of the courses often included multiple lectures each week as well as additional tutorials and workshops. Assessment typically included a large examination component (e.g., 70–80%) with the remaining assessment linked to assignments and laboratory work. Within all the courses that participated in the study, coordinators noted that they believed student engagement could be improved. Yet despite these ongoing concerns, coordinators felt they had few routes to improve engagement or understand what other measures, apart from attendance, could be designed and implemented to better track student engagement.

Participants were drawn to trial the SRES for a multitude of reasons. One reoccurring reason stated by participants to use the SRES in their course was dissatisfaction with the existing LMS’ functionality. While the SRES was originally designed to supplement the LMS rather than to replace it, participants noted that using the SRES decreased the amount of time they spent using the LMS. One coordinator noted, "[t]he systems we've got at the moment are a bit old, a bit clunky… we needed a better system for recording data, [the SRES] seems to be an improvement over what we've got at the moment."

However, the SRES' appeal was not only a sleeker interface. Participants also mentioned that they were motivated to participate in a system that could improve student support. The ability to send personalized emails to students, a function not available on the current LMS, intrigued participants. One noted, "I wanted the students to feel like we were really interested in their progress, so to be able to personalize an email to them and point out what support was available to them if they were struggling, I really like that idea…." Another participant voiced similar motivations for using the SRES, "It just sounded like a way we could interact with the students on a more personal level, we've heard comments, and we try to reach out to as many as we could, and [with the SRES] now if there are at risk students we could sort of go, 'Hey, you are at risk'."

Yet despite the appeal of personalized emails, many participants in the pilot did not fulfil their hope of using the email function available through the platform. When asked about how they used the platform, many coordinators only used it for rudimentary functions, such as recording attendance or marks. However, this finding not only did not match participants' original motivations for using the platform, which were often far loftier, but also was subsequently modified by many participants who still wished to use the personalized email function in future semesters. One participant explained, "[w]hen I started using the SRES the semester was already underway, and you got to brief tutors about how to use the system and so on, so by that point it felt a bit too late… also partly because you know I've got a hundred other things going on in a semester, and partly because it's also with so many tutors it is a bit of an effort to hunt down tutors to get them to input their data."

Further complicating the research was the ad hoc way that many coordinators piloted the email function within their teaching design and course delivery. One teacher noted, "I sent an email to basically the bottom quartile of the class… picked a point where I thought anything above that seemed reasonable." He emailed those students regarding their current mark and reminded them to do their assignments and attend tutorials and offered consultation times. In response, some students emailed thanking him for letting them know or for noticing, although he also received some emails saying that students' assignment marks were missing from tutors who had yet to input them.

In fact, a common issue that arose in interviews about the SRES was the lack of engagement from tutors, rather than students. As the courses had such large student enrolments, some coordinators had close to 40 tutors during the semester. For the data to stay up to date, all the tutors needed to take attendance using the SRES web app (and if by hand, they would later input it into the system) and enter all student grades in a timely manner. However, this goal was difficult to achieve and cumbersome to enforce. As one participant said, "When you have 40 tutors in a [course], there's always going to be some that haven't entered their data on time, no matter how many times you drum it into them."

Implementation challenges related to tutor responsibilities and ad hoc emailing were further compounded by the lack of available time for coordinators to familiarize themselves with the system. Despite these challenges, students who did receive messages were generally positive about the extra support and care. Students who were asked to comment on whether the email was helpful or not wrote comments such as:

- "It was personal and gives me faith in the care our lecturers and coordinators have in us. It also included additional helpful information just in case."
- "Great appreciation to that, like a hopeless person just found a guiding star! Thanks."
- "It was highly encouraging and sends a positive message to the student about the staff's commitment to their success."

Additionally, the use of the SRES may have contributed to changing teachers' perspectives on student engagement, teaching design, and possibly motivate teachers' attitudes and future behaviors about student engagement and LA. For example, in one course, the tracking of marks and attendance made the coordinator realize that students were unconcerned about marks and attendance as long as the minimum requirement was achieved so they could sit for the exam. This revelation led the teacher to rethink his approach and use the email function in the future to help understand why students may not come to lectures and/or tutorials.

The use of the SRES also motivated some coordinators to more deeply consider how student engagement could be measured to improve their teaching design in the future. For example, one participant, when asked about how the SRES impacted them, noted that "[t]he SRES has made me think 'wouldn't it be good if we knew this?'," while another participant mentioned, "[y]ou know, you need to do some analysis to have evidence for making a change… and you need data for that." One participant, who noted that they did not really utilize the platform to its fullest potential, further mentioned, "I'd like to know more about the platform, I think we can improve, I think we can do more."

Teachers at the University of Melbourne adopted the platform to provide more personal support for students and to ease the process of data collection and curation primarily from face-to-face environments. These two purposes were interlinked, with data availability affording targeted support; an unforeseen but encouraging effect was that this also triggered further reflection on selecting and applying relevant data to enhance learning and teaching. Despite only having used the SRES for a short period of time, teachers started to see positive impacts in terms of workload efficiencies and improved student feedback, although there were issues around compliance by more diverse teaching teams.

3.4 Case Study 3: The University of New South Wales Sydney

UNSW Sydney also started piloting the SRES in early 2017. There were three elements that catalyzed its implementation here: (1) a fertile landscape incentivizing the personalization of student experience, supported by an ambitious strategic plan (the “2025 Strategy,” grounded on four key domains: “Communities,” “Feedback and Dialogue,” “Inspired Learning through Inspiring Teaching,” and “Being Digital”); (2) a certain flexibility to support innovations in learning and teaching afforded by a strategic and systematic review of over 800 courses over 5 years; and (3) a forward-looking team in the portfolio of the Pro-Vice-Chancellor Education, with the expertise to support early adopters of educational technologies.

Yet, a cautious and thorough approach was developed in order to provide effective support for teachers involved in the project. The starting point of the implementation was the invitation of several coordinators to participate in the project, focusing on large first-year courses. In the initial round, four large courses expressed interest, but only two decided to continue; these two were characterized by a higher level of resilience to uncertainty and innovation (with a potential to accept and learn from failure and suboptimal processes): a first-year Marketing course (800+ students) and a first-year Biology course (250+ students), both repeated over the two semesters in the year).

An important element behind the choice of courses is the belief at this university that the focus on the first-year experience departs from the traditional transactional model of education delivery, instead of offering a multicomponent model with multiple value creators that focus on student experience. In this sense, it is envisaged that *personalized* learning pathways and communications are customized using LA and iteratively inform learning design. This is intended to address critical concerns that are particularly salient for first-year students, including interaction in group work, ambiguity in communications, and assessment anxiety. By scaffolding students in personalized ways, the strategic aim is to enhance students’ educational experience and improve performance.

With this backdrop, the two courses adopted very different approaches: the Biology course took a simplistic path, adding the SRES as the tool to enable more detailed feedback after the mid-semester exams. In a sense, this established a baseline for the implementation without disrupting the normal running of the course but gave an opportunity for the teachers to identify data to offer students a more detailed account of their performance which they would not normally get for exams. In this case, only the two course coordinators were involved in the process: they negotiated the scope of the implementation and selected the metrics of interest, keeping in focus only the provision of better feedback to students.

The personalized report received in students’ inboxes after the mid-semester exams gave specific details about the areas requiring improvement and additional targeted resources, enabling them to adjust their modes of learning. The student response (in semester one 2017, emails were sent to 1005 students; 81.4% opened the emails with some up to 30 times) was overwhelmingly positive with 99.8% of the students indicating via a survey link at the bottom of the email that it was helpful. Similar results were obtained in the second mailing. The following comments exemplify their views:

- “This email was helpful in highlighting specific areas of weakness and will allow me to fill in gaps in my knowledge!”
- “It told me exactly where I went wrong, now I can improve in that area, thanks [teacher name]!”

- “The feedback was detailed and constructive- advised on what areas could be improved on instead of a generic feedback relating to the entire cohort.”
- “Thank you for providing me feedback on the areas that I am weak on, please continue to do this. I will use this to revise and improve in these areas.”

The coordinators were surprised by the response from students and were quickly convinced about the effectiveness of the approach: “I could not believe that students would open and go back to the email 30 times! …even if the amount of feedback provided is limited, the students are appreciating the fact that the message is directed to them.”

The Marketing course adopted a more holistic and systematic approach, integrating several tools in the course including the use of an external resource from the textbook publisher (McGraw-Hill Connect and LearnSmart), a unique approach focusing on individual characteristics for personal development and team formation, and the SRES as an essential component to provide logistic support in the collection and curation of key behavioral and performance attributes during the course (including attendance, class participation, and team presentation outcomes). Although the main focus of the integration and adoption of the SRES was an administrative one, because of the nature of the discipline (marketing), the coordinator was convinced about the potential benefits of the SRES for the running of the course and for the use of data. In this case, all the tutors as well as the course coordinator contributed by using the SRES in their daily activities. For example, all teachers logged attendance and class participation in the same place via the SRES web app, saving much time from manually aggregating separate spreadsheets.

In the first run of the course using the SRES, the coordinator praised the simplicity of being able to visualize a snapshot of what happened in the course by the end of each week. Using the SRES visualization tools, the coordinator could easily generate a real-time report. Further, the fact that information about engagement with the external tool was brought back into the SRES meant that she could also appreciate how students valued the resource. The ability to see what students and tutors were doing in near real time also meant that she started to question the importance of attendance at lectures and of engagement with the ecosystem in the course. This sort of reasoning, partly prompted by the disciplinary context, reflects the effectiveness of marketing channels in the consumer journey to purchase and draws a parallel to the student journey (Bucic, Vigentini, & King, 2018). This thinking drew the course team to experiment with the modes and level of “nudging” (i.e., the frequency and timing of messages) in order to test whether there was a perceived difference in “teacher’s presence.” Comparing the way in which messages were sent (high frequency, about once per week in semester one vs low frequency, at the start and around key assessment points in semester two) showed that students receiving more frequent and consistent relevant messages rated their satisfaction with the course to be much higher than when they were just prompted occasionally.

Both cases provided strong evidence that students appreciated the teacher’s presence or simply the fact that their teachers cared about them. This was associated with higher satisfaction with the courses and, at least in the Marketing course, was also associated with an improvement in performance compared with the previous instances of the course without the SRES. Combined with the ability to collect and curate face-to-face and electronic data (e.g., assessment outcomes, attendance, participation, and online tool use) as well as visualize and act on this data, all in a single platform, this helped teachers overcome resistance to change. As seen in the other case studies, teacher engagement with the SRES also enabled some reflective practice.

4 Discussion

4.1 Empowering Teachers to Personalize Support for Student Success

The work presented here sought to investigate one LA solution to a sector-wide issue: maintaining the personalization of higher education in the face of massification, commodification, and diversification. As student numbers grow, along with tuition prices, and emerging new cohorts of students, higher education is pressured to find new ways to support student engagement and success. The platform discussed in this chapter, the SRES, seeks to enable teachers to provide personalized and timely support and feedback to students which would not be feasible at scale using traditional approaches.

The case studies coordinated across three very different institutions provided systematic data on the adoption, implementation, and use of the SRES, showing how the platform offered teachers the ability to collect, curate, analyze, and act upon data that was meaningful to their specific teaching context, as well as close the loop for reflection on changes to practice. To teachers, the two most important differences between the SRES platform and other extant LA tools have been (1) the ability to precisely select and use data that is relevant to them and (2) being able to efficiently perform operations at scale on the data from a single software platform. Many teachers at the three universities placed strong emphasis on collecting attendance and assessment data, and many also used the SRES to curate data from other sources including online systems and richer metrics from face-to-face classroom interactions. The unique web interface also afforded both students and teachers the ability to input information directly into the SRES, such as allowing students to enter information about themselves and teachers to efficiently enter attendance, participation, grades, and feedback.

In contrast to existing (often manual) practices, the SRES has empowered teachers to engage in more systematic and targeted support actions throughout the semester. The most common actions from the platform have been to personalize messages to students for a wide range of purposes including offering support to students considered “at risk,” reminding students of attendance and assessment requirements, providing tailored feedback, and alerting high achievers to the possibility of advanced study. Other actions have included customizing face-to-face teaching and learning activities to the backgrounds and interests of learners by leveraging data curated in the SRES. Interestingly, many teachers commented that their workload when using the platform was not necessarily reduced (at least not at first), although their time was more "productive"; this has helped to alleviate a key barrier to adoption (Macfadyen & Dawson, 2012).

Another contributing factor to overcoming change resistance has been the positive outcomes for both teachers and students from the personalized, *person-alized*, and timely nature of actions taken by teachers empowered by the SRES. These outcomes included more open channels of communication, increased help-seeking behaviors from students, feedback that allowed students to improve performance on subsequent assessments, and increased retention rates. The impact on student satisfaction has been reflected in the positive feedback teachers have received from their students. Although the diversity of ways in which this LA platform was used across the three institutions precluded a typical quantitative impact study, the mixed-methods data including teacher interview responses and student perception data together suggested that the SRES positively impacted students' outlook on the level of personal support provided for them, and perhaps even their engagement with the material and eventual academic performance. The SRES has therefore helped to enhance teachers' "relational pedagogy" (Pearce & Down, 2011) to promote student success. Of course, effect is hard to generalize as the use of the platform was sometimes part of a range of changes made to courses by teachers, and the cohorts were different. At the same time, the case studies started to show that the platform not only provided an opportunity to enhance the student experience, but given interest, time, and effort from teachers, there is great opportunity to delve into action research of how students learn and engage with support.

4.2 Implications for Practice

This chapter set out to investigate the experiences of teachers at three Australian universities implementing a humanistic LA platform. A number of ideas from the LMS implementation and adoption literature are instructive here to help frame implications for LA practice.

First, it is important to keep in mind that learning technologies (including LA) are not neutral technologies but rather can impact teacher's expectations, desires, behaviors, and, thus, their teaching design (Coates et al., 2005). The technology itself has a powerful role in influencing and shaping teaching practices. Second, even though an LMS may provide various functions for enhancing online learning and teaching beyond the transmission of textual content, the way teachers use the technology may be mismatched with students' expectations or needs (Lonn & Teasley, 2009). Third, these varied functions open the possibility for teachers to reconsider their practices as their use of (and comfort with) the technology progressively evolves (West, Waddoups, & Graham, 2007). Using these three perspectives in the context of the case studies, we highlight three general implications for LA practice.

4.2.1 Learning Analytics Needs to Address Actual Needs

Adoption of the SRES has spread throughout the University of Sydney where it was developed, to the University of Melbourne, UNSW Sydney, and to teachers in other Australian institutions. In contrast to many top-down implementations of LA, the bottom-up nature of the SRES has assisted with its widespread adoption primarily due to being designed by teachers for teachers. By helping teachers to collect and use meaningful data relevant to their context to provide timely learning support to students, the SRES addresses pedagogical and pastoral needs of personalization and relationship building (Kahu & Nelson, 2018; Zepke & Leach, 2010) and removes some of the usual barriers to LA adoption such as one-size-fits-all approaches, opaque predictive algorithms, and a disconnect between analysis and action (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017). Other barriers removed have led to greater veracity and workload efficiency (Macfadyen & Dawson, 2012) in data entry, analysis, and communication with students. It has not only empowered teachers with the capability to increase the number and quality of exchanges with their students (West et al., 2015), but more importantly it has allowed them to humanize these exchanges and also support nonelectronic interactions. This has helped to mitigate the sense of anonymity (Bryson & Hand, 2007) that is associated with large cohorts of students. At the same time, the SRES has streamlined some of the most burdensome administrative aspects of unit coordination, allowing teachers to focus more attention on pedagogical and pastoral care for students.

Together, these contribute to the critical "usefulness" factor highlighted in the literature on LA (Ali, Asadi, Gašević, Jovanović, & Hatala, 2013) and LMS (West et al., 2007) adoption and address the need for innovations to present a "relative advantage" to existing approaches as argued by Rogers (2003). In the face of institutional culture and workload pressures contributing to the lack of LA adoption by teachers, being able to demonstrate the relative advantage of LA and its compatibility with their needs is crucial (Macfadyen & Dawson, 2012). Bringing data and a range of tools together into one platform for academics who are interested in their students empowers them to reflect on how their practice affects students but also enables them to reflect on the effectiveness of their practice.

4.2.2 Start Small but Provide for Growth

Addressing elements of teachers' immediate perceived needs helps to underpin strong teacher buy-in. However, it is also important to negotiate the implementation space to ensure that the technology does not get in their way but rather blends in with their practice facilitating the running of courses. The case studies suggested that teachers' contexts and approaches were nuanced, needing an LA system that was customizable and flexible and could support multiple learning designs and teacher perspectives. For example, while the SRES platform is capable of quite complex data collection and analysis, many teachers included within the study found its most simple functions to be the most meaningful for them: collecting attendance and sending personalized messages. This is not to say that these are purely perfunctory; indeed, many studies have suggested a close association between these and student success (Credé et al., 2010; Newman-Ford et al., 2008; Pearce & Down, 2011). Also, this does not indicate that the other functions of the platform are not useful or meaningful, although it does affirm that the system design needed to include both simple and advanced functionality to allow teachers to apply functions as they chose and felt comfortable with. This concords with LMS adoption literature where instructors would start to use simple features that addressed their immediate goals, and then experiment with other functionality as they grew more comfortable with, and confident in, the platform (West et al., 2007).

A risk here is that teachers will not progress from rudimentary applications of the technology, and the technology becomes a shackle rather than an enabler. In the LMS space, this may present as teachers continuing to use the largely textual platform to didactically transmit written content to students and codify learning in terms of achievement in preprogrammed positivist quizzes (Coates et al., 2005). This potential shackling was clear in some interviews where, although teachers had every intention to explore richer functionality beyond attendance tracking, they did not have the workload capacity or the knowledge to be able to experiment in this way. Part of this involves teachers overcoming the initial learning curve with all technology such that this investment can pay time dividends and permit further experimentation. Another part is gaining an understanding of how the technology may be better applied. When combined with initial rudimentary applications, this may be sufficient to drive teachers to richer uses; as one interviewee noted, this is a "…foot in the door. Because once you realize that you can efficiently keep track of people and just use it almost as an administrative tool, then you start to see what else can be done with it… Once I see that it can do that, then oh, I can also – and then you start to get into the more sophisticated functions. There's that classic thing about any piece of software and the user interface – you want it to be accessible to your new user, to your basic level." The same interviewee emphasized that "sharing success stories" as part of his community of colleagues was an integral part of this, as discussed in the next section.

4.2.3 Foster Communities

Combining top-down support with bottom-up adoption may assist to expand the uptake of LA throughout higher education institutions. In our case studies, teachers were empowered by having the customizable platform, although there was scope to further empower them by fostering communities of practice through which they could share different ways in which the SRES might helpfully personalize support and feedback. Learning by members of an organization is often informal, relying on colleagues who are geographically close or in similar roles (Boud & Middleton, 2003). This is particularly true for university teachers, who primarily rely on informal conversations with peers to grumble about teaching issues and share solutions for improving teaching practices (Thomson, 2015). As there is a strong tendency for teachers to interact and share ideas just with others who are similar to them, top-down support may provide the opportunity to foster a more heterogeneous community of users. As the type of user expands from innovators to early adopters and the use of the SRES moves from ad hoc trials to more strategic and systematic use, the need for support is also likely to expand. Communities of practice that form around interested teachers and support staff can then aid the sharing of information and the spread of innovation (Wenger, 1998). At the University of Sydney, these communities are starting to form within faculties where early adopter teachers and learning designers are promoting the platform, training their peers, and self-organizing support from the central learning and teaching unit. At UNSW Sydney, both course coordinators were awarded teaching excellence awards from their respective faculties for the ability to lead teaching in their disciplines and experimenting with digital tools capable of improving the student learning experience; this serves to raise the profile of such innovations and pique colleagues' interest.

The importance of a learning and teaching support unit (either within a faculty or centrally) was an understated feature in all three case studies. In the three institutions, this unit variably comprised staff with learning design, educational technology, and/or software development expertise, which was crucial in supporting academics in using the platform (Vigentini et al., 2017). In some cases, these units were also instrumental in connecting various data sources to the SRES so that relevant student data was available. Because these institutions shared a common open-source codebase for the platform, the designers and developers in these units formed an informal cross-institutional community of practice. This allowed not only the sharing of practice but also the development of new approaches and software functionality, which in turn benefited all involved.

4.3 Conclusion and Future Directions

Traditional LA, with its focus on single-purpose tools such as dashboards, visualizations, or mail merge, may not only stifle the richness and depth of support and relationship building that is integral to effective teaching but may also inadvertently suppress the development of teachers' collection and application of student data. Although the SRES is a more holistic platform, it is not immune: a fixation on capturing and tracking attendance (even though it may be pedagogically and contextually meaningful) may limit teachers' conceptualization and the use of student data. However, at least at the University of Sydney where SRES adoption is more widespread, we are observing a subtle progression from rudimentary to richer applications, which has been afforded by the flexibility of the platform and communities of teachers sharing success stories. In future work, we seek to analyze this progression of sophistication, consider how teachers' aspirations compare with their actual usage, and determine the factors that lead to evolving uses of student data by teachers to continue to personalize the learning experience.

Personalized messages were one of the intermediary steps in this progression of complexity, requiring teachers to apply data to tailor this form of support and feedback, which itself required teachers to collect and curate the right data. Previous research has suggested that there may be some discrepancies between how teachers compose message-based support and what is impactful for students in terms of content (e.g., motivational vs informational, summative vs formative) and nature (e.g., tone and orientation toward performance or outcomes) (Tanes et al., 2011). With the SRES allowing teachers to be more nuanced and granular in the triggers and content for each personalized message, it will be interesting to explore these in terms of their nature and content, and the extent to which they are being personalized. Some future analyses will also explore the interaction between students' personal characteristics (e.g., personality, emotional intelligence, and learning approaches) and behavioral observations (from both engagement and performance) with the messages received.

Beyond direct student-facing impacts such as personalized electronic communication and data-augmented face-to-face interactions, our interviews also revealed how using the SRES to enhance student engagement and success could prompt teachers to reconsider their broader teaching approaches and learning design. This seemed to be related to their use of the platform indirectly increasing their awareness of the measures of student engagement and success, and the implications for their existing practices. At the micro level, the affordances of the technology have led to changes in how teachers interact with students during face-to-face classes, nurturing positive teacher-student relationships. These impacts warrant further investigation, such as identifying archetypes of users and uses, investigating how teachers' own learning may be associated with each of these, and examining appropriate ways to measure impact that are specific to the type of use. Further studies are also planned at the course level to identify the impact of specific SRES affordances, such as the impact on student belonging of using the SRES web app to capture student attendance. After all, LA as a human activity is intensely contextualized, and its ultimate goal is to optimize learning and the environments in which it occurs, through empowering teachers' human judgment (Siemens & Baker, 2012).

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Chapter 14
Predicting Success, Preventing Failure

Using Learning Analytics to Examine the Strongest Predictors of Persistence and Performance in an Online English Language Course

Danny Glick, Anat Cohen, Eitan Festinger, Di Xu, Qiujie Li, and Mark Warschauer

1 Introduction

Given the increasing recognition of English as the lingua franca for business and communication in the global economy, a growing number of developing countries are making significant investments to improve English language learning (ELL). Yet, often constrained by both economic and human capital resources, national efforts to develop students' English language proficiency in developing countries often remain ineffective. Typical challenges include a shortage of qualified English teachers, lack of teacher certification or training, limited access to high-quality language learning resources, and poorly designed English curricula (Ministério de Educación Perú, 2016a; OECD, 2015). While policy frameworks in many Latin-American countries (e.g., Peru, Ecuador, Costa Rica, and Mexico) require teachers to have an English proficiency level of B2 (upper intermediate) or better on the CEFR[1] (Common European Framework of Reference for Language) scale, many English teachers perform well below these standards (see, e.g., Cronquist & Fiszbein, 2017).

[1] The CEFR is an international standard for describing language ability ranging from A1 (basic) up to C2 (proficient).

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In view of these challenges, online language learning has increasingly been viewed as a possible way to remove the barriers associated with traditional English language learning by providing low-cost, quality education (e.g., Glick et al., 2016; Sife, Lwoga, & Sanga, 2007). Recent studies suggest that technology-mediated language learning implemented in developing countries has a significant, positive impact on students' course grades and course completion rates compared to traditional face-to-face instruction (Bai, Mo, Zhang, Boswell, & Rozelle, 2016; Banditvilai, 2016; Glick et al., 2016; Rios & Cabrera, 2008). While online learning is a promising approach to deliver more desirable learning outcomes, many students struggle in such settings, especially students lacking certain personal attributes – such as being goal-oriented and self-disciplined—that are essential for successful online study (Appana, 2008). Therefore, to improve persistence and performance in online courses, it is important to have a better understanding of student online learning behavior and student engagement in online courses.

This study employs a learning analytics approach framed in Ryan and Deci self-determination theory (SDT) (1985, 2000) to examine the strongest predictors of persistence and performance in an online English language course. Deci and Ryan's SDT argues that all humans have intrinsic needs to be self-determining or autonomous (i.e., experiencing a sense of agency or control), as well as to feel competent and connected in relation to their environment. SDT states that environmental conditions that support perceptions of autonomy and social relatedness improve motivation, thereby positively influencing learning outcomes. Thus, the purpose of this study is to investigate how autonomy, competence, and relatedness, as defined by Deci and Ryan, may predict student persistence and performance in an online English language course by analyzing a large dataset collected from a pre-course student readiness survey, the course learning management system (LMS) log files, as well as data collected from the course Facebook page.

Previous research with regard to student persistence and performance in *traditional* learning environments has found that learner autonomy, competence, and sense of relatedness have a positive effect on student performance and persistence (e.g., Black & Deci, 2000; Vansteenkiste, Lens, & Deci, 2006). However, research examining the SDT with regard to students' persistence and performance in *online* courses is scarce.

Based on a sample of 716 Peruvian university students enrolled in an online English language course, we present evidence on the effects of an online ELL course on university students' learning outcomes. The aim of this study was to use learning analytics framed in SDT to examine the strongest predictors of persistence and performance in an online ELL course.

The results of our study provide important implications for policymakers, online teachers, administrators, and instructional designers in the postsecondary arena in developing countries as they consider whether and how to implement online learning to better reach their goals of promoting English language proficiency.

2 Research Background

2.1 Challenges in Peru's English Language Education

Peru has made considerable efforts to improve English language learning through policies and programs, resulting in more students having access to ELL. However, despite considerable efforts and investments in English language education, the quality of Peru's English language system remains low. The English First English Proficiency Index (EF EPI), which ranks 72 countries and territories based on online English proficiency tests taken by more than 950,000 test takers, put Peru in the bottom half – ranking it 45th out of 72 countries (EF English Proficiency Index, 2016).

One major barrier to improving ELL is the quality of Peru's English teachers. A UNESCO study assessing the proficiency of 3356 English teachers in Peru found that about 33% of the teachers have an English proficiency level of A1 (low beginner) on the CEFR (Ministério de Educación Perú, 2016b). Another area of concern is the lack of accreditation of Peru's pre-service English teaching programs. While there are many options throughout Peru to pursue an English teaching degree, a growing number of nonaccredited programs continue to enroll and train pre-service teachers. Specifically, only 34 out of 285 pedagogical institutes of higher education (11.9%) that offer English teaching programs were accredited in 2016 (Cronquist & Fiszbein, 2017).

Recent reports show that a serious shortage of high-quality English teachers in Peru (Cronquist & Fiszbein, 2017) constitutes a serious bottleneck for ELL programs. Even more worrying is the fact that Peru's demand for English teachers will continue to grow over the next 5 years. English is one of the subject areas receiving more time in the new school day in Peru (Ministério de Educación Perú, 2017), which has increased the need for qualified English teachers. The Ministry of Education, in its national English plan, aims to recruit and train over 30,000 additional English teachers over a period of 8 years (Ministério de Educación Perú, 2016b), a goal which seems very ambitious for a country where nearly 90% of its pre-service training programs failed to gain accreditation in 2016. Given the fact that nearly two-thirds of Peru's teachers are unlicensed or have low English proficiency levels, online learning programs may provide an attractive alternative.

2.2 Enhancing English Instruction in Developing Countries Using Online Courses

Online learning is a growing trend and derived from efficiency, economic, organizational, pedagogical, and operational considerations (Bakia, Shear, Toyama, & Lasseter, 2012; Lee, 2016; Massengale & Vasquez, 2016). Online courses provide access to a wide range of audiences and, in some cases, improve teaching and learning processes (Macfadyen & Dawson, 2010; Roby, Ashe, Singh, & Clark, 2013). They may offer an enjoyable and effective learning environment if they emphasize solid content, interaction, and clear structure (Driscoll et al. 2012). Studies have found that students perceive the ease of access to varied, high-quality, and up-to-date learning materials as benefiting their learning in an online course (Palmer & Holt, 2010). In addition, integrating social networks can contribute to a sense of community among learners and develop pedagogical values (Erdem & Kibar, 2014) as well as reduce loneliness and motivate students to persevere in their studies (Yuan & Kim, 2014). Furthermore, online courses provide more autonomy and enable students to learn at their own pace, as they allow flexibility of time and location (Lim, 2016; Rodriguez, Rooms, & Montañez, 2008).

Prior research has shown that online learning is particularly beneficial to learners in developing countries where language learning resources are limited. In a large-scale study in Mexico, it was found that, compared to traditional face-to-face instruction, blended learning has a significant, positive impact on students' course grades and course completion rates (Glick et al., 2016). Rios and Cabrera (2008) found that students who used an online environment improved their language skills more than the students who learned face to face. Bañados (2006) found similar findings with Chilean students who significantly improved their speaking, listening, pronunciation, grammar, and vocabulary. Similarly, Iranian students who learned in online environments outperformed students taking the same course face to face (Barani, 2011; Marzban, 2011; Vahdat & Eidipour, 2016).

Online courses offer many benefits for students (Baker & Yacef, 2009; Cohen & Nachmias, 2006; Zakrzewska, 2009); however, there is growing concern regarding the persistence and engagement of students in such courses, as well as with the high dropout rates compared to face-to-face courses (Cheng, Kulkarni, & Klemmer, 2013; Clay, Rowland, & Packard, 2009; Levy, 2007; Nistor & Neubauer, 2010; Otter et al., 2013; Park & Choi, 2009; Willging & Johnson, 2009). Moreover, previous studies indicate that lack of persistence which is reflected in low engagement and poor self-regulation is an important factor leading to attrition among students in online courses and inadequate academic achievements (Angelino, Williams, & Natvig, 2007; Otter et al., 2013; You, 2016). Learning analytics, therefore, seems to have the potential to overcome the abovementioned challenges associated with online learning by understanding the learners' behavior during the learning processes (Gašević, Dawson, & Siemens, 2015).

2.3 Learning Analytics for Predicting Success in Online Courses

The development of online courses has led to enormous amounts of information regarding the learning process. Students' interactions with online learning activities as well as with their peers and instructors are captured automatically in the log file records of the course LMS (Levi-Gamlieli, Cohen, & Nachmias, 2015), without interfering with the learning process (Cohen & Nachmias, 2012). These log data can be retrieved and analyzed in order to identify patterns of learning behavior and provide insights into education practice. This process of mining and analyzing data on learning has been described as learning analytics (Gašević et al., 2015). Siemens and Gašević (2012, p. 1) defined the study of learning analytics as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."

Learning analytics has been used to study teaching and learning processes (Gašević, Dawson, Rogers, & Gasevic, 2016); diversity among learners and usage patterns, which could be used to predict achievement (Ai & Laffey, 2007; Lu, Yu, & Liu, 2003; Romero & Ventura, 2007); the utilization of information accumulated in log files to identify students at risk of dropping out with low achievement (Santana, Costa, Neto, Silva, & Rego, 2015); and the provision of identification tools for instructors (Cohen, 2017). In addition, intervention programs (Campbell et al., 2007; Dietz-Uhler & Hurn, 2013; Romero, López, Luna, & Ventura, 2013) and warning systems to identify at-risk students have been developed using learning analytics (Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Macfadyen & Dawson, 2010).

Predicting student success or failure is a challenge due to the many factors that may affect student performance, including demographics, pace of progress, amount of content viewed, activities in discussion groups, and task performance and achievements (Johnson, Becker, Estrada, & Freeman, 2015). Some claim that learning behaviors that reflect self-regulation are the primary predictors of student success or failure in courses. You (2016) found that students' regular study, late submissions of assignments, number of sessions (the frequency of course logins), and evidence of reading the course materials significantly predicted their course achievement. In addition to self-regulation, collaborative learning activities have been found to be a relevant predictor of student performance as well. For example, the cooperative activity level of students in the first weeks of a course was found to predict course drop out (Nistor & Neubauer, 2010). Gašević et al., (2016) found that the number of logins and the number of operations performed in discussion forums and resources were significant predictors of academic performance.

The literature shows that predicting student learning success has been one of the most frequent tasks associated with learning analytics (Dawson, Gašević, Siemens, & Joksimovic, 2014). However, there remains a significant absence of theory in the research literature that focuses on LMS variables as key indicators of interaction and success (Gašević et al., 2016). Furthermore, learning analytics needs to build on and connect better with the existing body of learning and teaching research knowledge (Gašević et al., 2015). In this study, we address these issues, and in what appears to be a first attempt to frame data analytics methods in a motivational theory in an ELL context, we link learning analytics (based on observed behavior in the log files) to a theoretical model based on the motivation to learn (SDT). In addition, a holistic approach that combines data collected from three different sources—a student readiness survey, LMS log files, and Facebook logs – is applied.

2.4 *Self-Determination Theory*

As in traditional learning environments, in online courses, student engagement and persistence are strong predictors of learning outcomes (Campbell et al., 2007; Goldstein & Katz, 2005; Mandernach, 2009). One of the main factors influencing persistence and success in a course, whether it is conducted face to face or online, is student motivation (Allen & Bir, 2012; Hartnett, George, & Dron, 2011; Järvelä, Volet, & Järvenoja, 2010; Miltiadou & Savenye, 2003; Muilenburg & Berge, 2005).

Motivation is a central factor in learning. Students are motivated by past and current reinforcements, which are related, among others, to purpose, self-efficacy, values, and areas of interest (Schunk, 2012). Motivation is a presumed internal force that stimulates an action and determines its direction and influences what we learn, how we learn, and when we choose to learn (Schunk, 2012). According to SDT, a learner's motivation is determined by the degree of responsiveness to three basic needs: *autonomy* (the degree of learner control over the learning process), *competence* (sense of ability and efficacy), and *relatedness* (the perception of social belonging).

Autonomy Autonomy is the feeling of choice or the sense of control that learners have over the learning process (Ryan & Deci, 2000). The autonomous learner is self-regulating (Driscoll et al., 2012), takes responsibility for his/her learning, and defines the goals, content, and pace of his/her learning (Holec, 1981). Active and autonomous involvement of students in their own learning increases motivation to learn and improves learning effectiveness (Dickinson, 1995) and thus can have a positive impact on success and achievement (Giesbers, Rienties, Tempelaar, & Gijselaers, 2013). In an online learning course, learners have freedom to determine their learning pace and pathway (Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers, 2009) by utilizing a range of learning strategies such as time management and goal setting. The literature shows that the ability to manage one's time, to work out contingency plans, and to set goals is a strong indicator of autonomy (Andrade & Bunker, 2009; Ho & Crookall, 1995).

Competence Competence is the feeling that one has the relevant skills to achieve a goal. Competence is measured by the learner's ability to cope with the tasks of the course (Ryan & Deci, 2000) and the degree to which he/she experiences feelings of efficacy and a sense of achievement (Baard, 2002). In a learning environment, learners can express competence by challenging tasks in a way that enables them to examine and expand their academic abilities and by allocating time for reflection to improve their learning process. Teacher feedback and assessment can also be used to measure competence.

Relatedness Relatedness is the sense of belonging and connectedness to the persons, group, or culture disseminating a goal. In a traditional learning environment, students feeling respected and cared for by the teacher is essential for their willingness to accept the proffered classroom values (Ryan & Deci, 2000). The sense of belonging is also important in an online learning environment and can be expressed in activities such as online discussion groups. Studies have shown that the more the learners find online discourses to be valuable, interesting, and enjoyable, the greater the frequency and the quality of their participation in discussions (Järvelä et al., 2010; Rienties et al., 2009; Xie, Debacker, & Ferguson, 2006).

When these three needs are met, there is an optimal environment for functioning and growth (Deci & Ryan, 1985). Thus, conditions supporting individuals' basic psychological needs for autonomy, competence, and relatedness are argued to foster high-quality forms of motivation and engagement in activities, including enhanced performance, persistence, and creativity (Giesbers et al., 2013; Ryan & Deci, 2000).

3 The Study

Based on a sample of 716 Peruvian university students, the primary aim of this study is to employ a learning analytics approach framed in Deci and Ryan's self-determination theory to examine the strongest predictors of persistence and achievement in an online English language course.

3.1 Research Variables

This study utilizes data collected from three different sources: a pre-course student readiness survey, course LMS log files, and activity reports from the course Facebook page.

3.1.1 Independent Variables

We classified the independent variables into two categories: variables related to students' online learning behavior, which we labelled *behavioral variables*, and variables related to students' learning strategies and online readiness, which we labelled *readiness variables*.

Seven behavioral variables emerged from the LMS log files and Facebook activity reports. Description of these variables is presented in Table 14.1.

Eighteen readiness variables emerged from the student readiness survey. These variables were classified into three categories. The first category, *competence*, includes items that describe students' learning strategies and skills (V1–V5, V12). The second category, *autonomy*, includes items that describe activities related to students' sense of control over the learning process (V6–V11, V14–V15). The third category, *relatedness*, includes variables that describe different aspects of social interaction (V13, V16–V18) (Table 14.2).

Table 14.1 Description of student behavioral variables

Variable name	Description	Range
V1-Behav: Average score on unit quizzes	Average score on quizzes in the learning units	0–100
V2-Behav: Midterm exam score	Student grade on the midterm exam	0–100
V3-Behav: Facebook engagement rate	Number of messages, comments, and likes posted on the class Facebook page	0–18
V4-Behav: Email activity	Number of emails sent by each student	0–23
V5-Behav: Time spent in course	Total time each student spent in the course in minutes	0–2316
V6-Behav: Time spent trend[a]	Trend line of time spent studying during the course (slope)	−22–12
V7-Behav: Quiz score trend in course units	Trend line of quiz scores in the learning units during the course (slope)	−19–6

[a]Trend is calculated according to the values along the units from the first unit to the last. Its value is the slope value of the progress according to the LINEST function which calculates the statistics for a line by using the least squares method to calculate a straight line that best fits the data

Table 14.2 Description of student readiness variables

Variable	Survey statement/question
V1-readiness	I am certain I will be able to master the skills taught in this course
V2-readiness	I am certain I can figure out how to learn even the most difficult course material
V3-readiness	I believe I can do almost all the work in this class if I don't give up
V4-readiness	What was your high school grade point average? (Decoded)
V5-readiness	What grade do you expect to get in the online English proficiency course that you are about to take? (Decoded)
V6-readiness	When I make a schedule for my coursework, I stick to it
V7-readiness	I never give up even if the course material is difficult
V8-readiness	I can ignore distractions around me when I study
V9-readiness	I keep a record of what my assignments are and when they are due
V10-readiness	I plan my work in advance so that I can complete all my assignments on time
V11-readiness	Planning the order of class tasks and following a schedule is easy for me
V12-readiness	I am quick to get caught up with my coursework if I start falling behind
V13-readiness	When studying for this course, I plan to set aside time to discuss the course material with a group of students from the class
V14-readiness	I plan to work hard to do well in this class even if I don't always like what we are doing
V15-readiness	On average, how many hours per week do you plan to spend on all aspects of this course?
V16-readiness	I am comfortable asking my instructor and classmates to clarify concepts I don't understand well
V17-readiness	I believe that participating in a course Facebook page would help me learn
V18-readiness	I believe that participating in a synchronous online class would help me learn

3.1.2 Dependent Variables

Three dependent variables were defined for this research: student persistence, achievement, and motivation. Persistence was measured using the behavioral variable *Average Completion of Unit Materials*, which is the amount of course materials completed by the student during the course. The second outcome variable, achievement, was measured using students' grades on the final exam, which is an online test covering the teaching points from all the units in each course. The test was developed by a leading learning and assessment company specializing in creating and administering high-stake exams. The test covers four skills (listening, reading, speaking, and writing), and it reflects grammar and vocabulary covered in the course. The test is scored on a 100-point scale. Finally, motivation is an index calculated as the mean score of ten items measuring student motivation in the pre-course student readiness survey. Table 14.3 presents these items. The reliability analysis revealed high scores for this motivation sub-questionnaire ($N = 10$, $\alpha = 0.953$).

3.2 Research Context

This study was conducted at a private university in North Peru. The university enrolls roughly 13,500 students annually in 20 degree programs, 10 of which are delivered online. About 88% of the enrollees come from low or middle socioeconomic backgrounds. Each student is required to take 20 courses of 1 month each to fulfill their degree requirements: five courses at pre-beginner level (Levels 1–5), five at beginner level (Levels 6–10), five at pre-intermediate level (Levels 11–15), and five courses at intermediate level (Levels 16–20). The courses are moderated by certified EFL teachers, who receive training in online teaching methodologies.

Table 14.3 Motivation questions from the readiness survey

Variable	Survey question
Motiv1	I'm really looking forward to learning more English
Motiv2	I enjoy learning English
Motiv3	I think learning English is very interesting
Motiv4	I think that learning is important
Motiv5	English courses are important for my future
Motiv6	I think what we are learning in the English course is important
Motiv7	The language skills we are going to acquire in this course are really important
Motiv8	Having a good level of English is important
Motiv9	Being able to communicate fluently in English is an important aspect of who I want to be in a few years
Motiv10	I would classify myself as someone who is generally self-motivated and always gets things done on time

Note. Cronbach's alpha = 0.953, $N = 10$ items

The student-to-teacher ratio is approximately 32 online students for every 1 teacher. Students can choose between regular and intensive courses. Typically, students in the regular track finish the course requirements within 2 years.

The online course, which is the focus of the current study, is an interactive learning environment developed by a leading technology-mediated English language learning and assessment provider. The course combined 4 hours a week of online instruction with monthly Skype meetings, class discussion forums, email communication, and a Facebook page. Each course consists of eight units that include learning material and quizzes or written assignments. Students who completed less than 30% of the course assignments were classified as dropouts. Only students who completed a minimum of 70% of the assigned course materials were allowed access to the final test. The final grade in the online course was based on the student's score on the final test. The final grade was assigned on a 100-point scale, with a grade of 75 required to pass and continue on to the next course.

3.3 Sample Description

The course participants were 716 Peruvian undergraduate students enrolled in online English language courses offered during the fall semester in 2017. Over two-thirds of the enrollees came from low or middle socioeconomic backgrounds. 22.9% of the students felt that online courses were more difficult than face-to-face courses. 16.8% of the students had slow Internet connections, and 13% of them were first-time online learners. 7.1% of the students were not using social media regularly.

3.4 Method and Procedure

This study employs quantitative methods to analyze data collected from three different sources: a pre-course student readiness survey, LMS log files, and Facebook activity reports, which were exported to an Excel spreadsheet.

- The student readiness survey was a mandatory prerequisite for all students enrolled in the online English language course. The online readiness survey used in this study was adapted from Wladis and Samuels' (2016) e-learning readiness survey questions, which were developed by faculty and staff at a large community college in the USA. The items on this survey are based on instruments used at other community colleges and those identified in the research literature. Each item on the survey was assessed for content validity by e-learning staff and faculty. Additionally, a number of items on the student readiness survey used in this study were adapted from Pintrich, Smith, Garcia, and McKeachie's (1991) *Motivated Strategies for Learning Questionnaire* (MSLQ[2]), which was developed

[2] The MSLQ is in the public domain; therefore, permission to use this instrument is not needed.

to measure the types of learning strategies and academic motivation used by college students. The survey used in this study includes 18 five-point Likert-type scale items. Sixteen out of eighteen items (items 1–4, items 6–14, and items 16–18) were adapted from Wladis and Samuels' (2016) and Pintrich et al. (1991) pre-course surveys. One item in our survey (item 15) was adapted from Maki and Maki's (2003) student readiness survey. Finally, one item (item 5) was included in our survey to reflect a large body of research which has shown that students' self-efficacy beliefs may predict academic achievement (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Komarraju & Nadler, 2013).
– Student log files were exported from the course LMS to an excel spreadsheet in a tabular, student-level view with student behavioral data (V1–V7 in Table 14.1). Student data were stored in a password-protected LMS. Special attention was given to information security and privacy aspects.
– The data from the Facebook page were retrieved through a designated code, written in C#, which utilizes the Facebook graph API and retrieves data from the Facebook feed into CSV files. It contains the following data: Number of likes, number of comments, messages, and replies posted on the course Facebook page.

An additional program was developed in C# to merge the information retrieved from the three different data sources and cross-reference the student names to associate data to students. To compensate for naming variations, a designated algorithm was developed to match the student names by comparing text strings in the student names. The LMS consists of 3–4 text values for each of the students enrolled and was used as the baseline for building up the complete students' grid. The algorithm in the program used a comparison method to check the other data sources, so that if at least two text strings in the complete name were matching, the reference would be made. A manual review was conducted afterward to verify correct matching. Finally, the merged data were entered into SPSS version 24.

3.5 Statistical Analyses

To examine the strongest predictors of persistence and achievement in an online ELL course, three steps of statistical analysis were carried out. The first step involved conducting factor analysis using the 7 behavioral variables (see Table 14.1) and the 18 readiness variables (see Table 14.2). This enabled us to identify common themes in the data and to examine whether the emerged factors would fit into the three motivational attributes in Deci and Ryan's SDT. The second step in the statistical analysis involved running a Pearson correlation among the emerged factors and the three dependent variables: persistence, achievement, and motivation. Finally, stepwise multiple regression was used to determine the overall fit of the model and the relative contribution of each of the predictors to the total variance explained. It is hypothesized that the emerged factors will affect student persistence, achievement and motivation.

4 Findings

This study includes 25 independent variables classified into 2 groups: 7 behavioral variables and 18 readiness variables related to students' learning strategies and online readiness. Descriptive statistics of the behavioral variables are presented in Table 14.4. As shown, average unit quiz score (V1) and midterm exam score (V2) means were quite high (> 80). Interestingly, although the mean of average unit quiz score (V1) was high, the average quiz score trend (V7) was negative. This may suggest that student motivation was higher during the first few weeks of the course and, as the course progressed, student motivation dropped slightly, which may have led to decreased scores during the second half of the semester. This may also suggest that the level of course difficulty increases as the course progresses, which may explain the negative average quiz score trend.

Descriptive statistics of all readiness variables are presented in Table 14.5. Results of the competence-related variables (V1–V5, V12) show that, on average, students have a fairly strong belief that they have the ability to master the skills taught in this course ($M = 4.08$, SD = 0.79) and are fairly certain they can learn even the most difficult course material ($M = 4.12$, SD = 0.81). Results of the autonomy-related variables (V6–V11, V14–V15) indicate that students, on average, believe they have a fairly good sense of control over the learning process. If students make a schedule for their coursework, they tend to stick to it ($M = 3.82$, SD = 1.0), and they do not usually give up even if the course material is difficult ($M = 4.31$, SD = 0.81). Finally, results for the relatedness variables (V13, V16–V18) show that students are fairly comfortable asking their teacher and classmates to clarify concepts ($M = 3.9$, SD = 0.94) and believe that participating in the course Facebook page will help them learn ($M = 3.89$, SD = 0.99).

To identify common themes, a factor analysis with a varimax rotation using the standardized values (z-scores) of the 7 behavioral variables and 18 readiness variables was conducted. The results of the factor analysis are presented in Tables 14.6 and 14.7. All the correlation coefficients, except one, are greater than 0.9, indicating that there is no problem of multicollinearity or singularity in the data. The results of the behavioral variable analysis are presented in Table 14.6. The variables that load highly on Factor 1 (unit score trend, average unit score, and time spent trend) relate to unit score. Therefore, this factor was named *unit learning outcomes*. The variables that load highly on Factor 2 (Facebook and email activity) relate to the number

Table 14.4 Descriptive statistics of behavioral variables ($N = 716$)

Variable name	Range	Mean	SD
V1-Behav: Average unit quiz score	0–100	80.83	25.22
V2-Behav: Midterm exam score	0–100	83.69	15.074
V3-Behav: Facebook engagement rate	0–18	1.96	3.260
V4-Behav: Email activity	0–23	2.51	4.233
V5-Behav: Time spent in course	0–2316	521.73	445.449
V6-Behav: Time spent trend	−22–12	−3.88	5.85
V7-Behav: Quiz score trend in units	−19–6	−1.88	4.29

Table 14.5 Descriptive statistics of readiness variables

Variable	Survey question	Mean	SD	*N*
V1-readiness	I am certain I will be able to master the skills taught in this course	4.08	0.794	387
V2-readiness	I am certain I can figure out how to learn even the most difficult course material	4.12	0.807	383
V3-readiness	I believe I can do almost all the work in this class if I don't give up	4.31	0.769	384
V4-readiness	What was your high school grade point average (Decoded)	2.90	0.901	384
V5-readiness	What grade do you expect to get in the online English proficiency course that you are about to take? (Decoded)	2.35	0.687	393
V6-readiness	When I make a schedule for my coursework, I stick to it	3.82	1.008	387
V7-readiness	I never give up even if the course material is difficult	4.31	0.814	388
V8-readiness	I can ignore distractions around me when I study	3.63	1.092	387
V9-readiness	I keep a record of what my assignments are and when they are due	3.85	1.043	387
V10-readiness	I plan my work in advance so that I can complete all my assignments on time	3.87	0.990	387
V11-readiness	Planning the order of class tasks and following a schedule is easy for me	3.97	0.915	381
V12-readiness	I am quick to get caught up with my coursework if I start falling behind	4.2	0.856	386
V13-readiness	When studying for this course, I plan to set aside time to discuss the course material with a group of students from the class	3.41	1.153	384
V14-readiness	I plan to work hard to do well in this class even if I don't always like what we are doing	3.96	1.142	391
V15-readiness	On average, how many hours per week do you plan to spend on all aspects of this course?	3.06	1.346	392
V16-readiness	I am comfortable asking my instructor and classmates to clarify concepts I don't understand well	3.90	0.943	383
V17-readiness	I believe that participating in a course Facebook page would help me learn	3.89	0.989	348
V18-readiness	I believe that participating in a synchronous online class would help me learn	4.15	0.938	388

Note. Responses were made using a response scale of 1–5

Table 14.6 Results of factor analysis of behavioral variables

	1	2	3	4
V7-Behav: Unit score trend	**.883**	0.050	0.030	−0.147
V1-Behav: Average unit score	**.807**	0.136	0.232	−0.016
V6-Behav: Time spent trend	**.629**	−0.393	−0.410	0.229
V3-Behav: Facebook activity	0.226	**.851**	0.040	−0.051
V4-Behav: Email activity	0.234	**−.562**	0.242	−0.346
V5-Behav: Time spent in course	0.112	−0.077	**.899**	0.086
V2-Behav: Midterm score	−0.034	0.045	0.085	**.929**

of messages sent or received via email and number of messages and likes posted on the class Facebook page. This factor, therefore, was named *social engagement*. The variable that loads highly on Factor 3 (time spent in course) seems to relate to one's ability to allocate time and effort; therefore, we named this factor *time spent learning*. Finally, the midterm score is the only variable that loads highly on Factor 4; therefore, this factor was named *midterm*. These factors explain 76.2% of the total variance in the behavioral variables.

The results of the statements that assess student readiness are presented in Table 14.7. The statements that load highly on Factor 5 (e.g., when I make a schedule for my coursework, I stick to it) seem to all relate to processes that make up activities such as planning, monitoring, and regulating. Therefore, this factor was named *self-regulation*. The statements that load highly on Factor 6 (e.g., I believe I can do almost all the work in this class if I don't give up) seem to relate to one's belief that learning outcomes are contingent on one's own efforts; therefore, this factor was named *learning beliefs*. The statements that load highly on Factor 7 (e.g., I believe that participating in a course Facebook page would help me learn) relate to one's belief that interaction with peers and the virtual instructor via the course communication tools can help the learner clarify course material. Therefore, we named this factor *peer learning*. The two questions that load highly on Factor 8 (what was your high school GPA and what grade do you expect to get in the Online English Proficiency course that you are about to take) seem to relate to two aspects of academic success, past success and performance expectations, and were named *academic success*. Finally, the statements that load highly on Factor 9 relate to effort regulation (e.g., I plan to work hard to do well in this class even if I don't always like what we are doing).

Table 14.7 Results of factor analysis of readiness variables

	5	6	7	8	9
V6-readiness	**.780**	0.111	0.201	0.043	0.066
V9-readiness	**.765**	0.106	0.110	0.142	−0.168
V10-readiness	**.699**	0.198	0.060	−0.098	0.084
V8-readiness	**.681**	0.181	0.151	0.173	0.049
V13-readiness	**.664**	0.224	0.203	−0.040	−0.018
V7-readiness	**.635**	0.264	0.244	0.004	0.340
V12-readiness	**.625**	0.154	0.179	0.162	0.383
V11-readiness	**.619**	0.452	0.071	−0.130	−0.154
V1-readiness	0.181	**.817**	0.215	0.228	−0.002
V2-readiness	0.294	**.809**	0.187	0.252	−0.027
V3-readiness	0.339	**.736**	0.071	0.091	0.173
V17-readiness	0.199	0.106	**.841**	−0.044	0.056
V18-readiness	0.172	0.236	**.790**	−0.011	−0.021
V16-readiness	0.475	0.103	**.523**	0.310	0.008
V4-readiness	−0.063	0.107	0.016	**.771**	0.096
V5-readiness	0.102	0.217	−0.010	**.687**	−0.098
V14-readiness	0.331	−0.001	0.258	0.225	**.654**
V15-readiness	0.228	−0.038	0.290	0.281	**−.611**

This factor, therefore, was named *effort regulation*. These factors explain 64.8% of the total variance in the readiness variables.

The nine factors fit well into the three categories in Deci and Ryan's SDT (see Table 14.8). Three factors fall into the first category—*autonomy*. They include one behavioral-related factor (Factor 3: time spent learning) and two factors related to the student readiness survey (Factor 5, self-regulation, and Factor 9, effort regulation). Four factors fall into the second category—*competence*. These factors include two behavioral-related factors (Factor 1, unit learning outcomes, and Factor 4, midterm) and two factors related to the student readiness survey (Factor 6, learning beliefs, and Factor 8, academic success). Finally, there are two factors that fall into the third category—*relatedness*. They include one behavioral-related factor (Factor 2: social engagement) and one factor related to the student readiness survey (Factor 7: peer learning).

Table 14.9 presents the descriptive statistics for the dependent variables: persistence, achievement, and motivation. As shown, the mean scores for persistence ($M = 85.02$), achievement ($M = 81.53$), and motivation ($M = 4.33$) were all high.

Table 14.8 Fitting the emerged factors into SDT

	Autonomy	Competence	Relatedness
Behavioral data	Factor 3: Time spent learning V5- Behav: Time spent in course	Factor 1: Unit learning outcomes V1-Behav: Average unit score V7-Behav: Unit score trend V6- Behav: Time spent trend Factor 4: Midterm V2-Behav: Midterm score	Factor 2: Social engagement V3-Behav: Facebook activity V4-Behav: Email activity
Readiness survey	Factor 5: Self-regulation V6-readiness V9-readiness V10-readiness V8-readiness V13-readiness V7-readiness V12-readiness V11-readiness Factor 9: Effort regulation V14-readiness V15-readiness	Factor 6: Learning beliefs V1-readiness V2-readiness V3-readiness Factor 8: Academic success V4-readiness V5-readiness	Factor 7: Peer learning V17-readiness V18-readiness V16-readiness

Table 14.9 Descriptive frequency statistics of the dependent variables

Variable	Range	Mean	SD	*N*
Persistence	1–100	85.02	27.530	668
Achievement	13–100	81.53	13.739	574
Motivation	2–5	4.33	0.646	392

Figure 14.1 presents the nine factors that emerged from the factor analysis along with the dependent variables—persistence, achievement, and motivation. These variables were used in this study to quantify student *autonomy* (the degree of learner control over the learning process), *competence* (sense of ability and efficacy), and *relatedness* (the perception of social belonging), as well as student persistence, achievement, and motivation.

Pearson correlation coefficients, which include the nine factors of persistence, achievement, and motivation, are presented in Table 14.10. As shown, unit learning outcomes are significantly and strongly correlated with persistence (r = 0.619, $p < 0.01$); time spent learning is moderately correlated with persistence (r = 0.297,

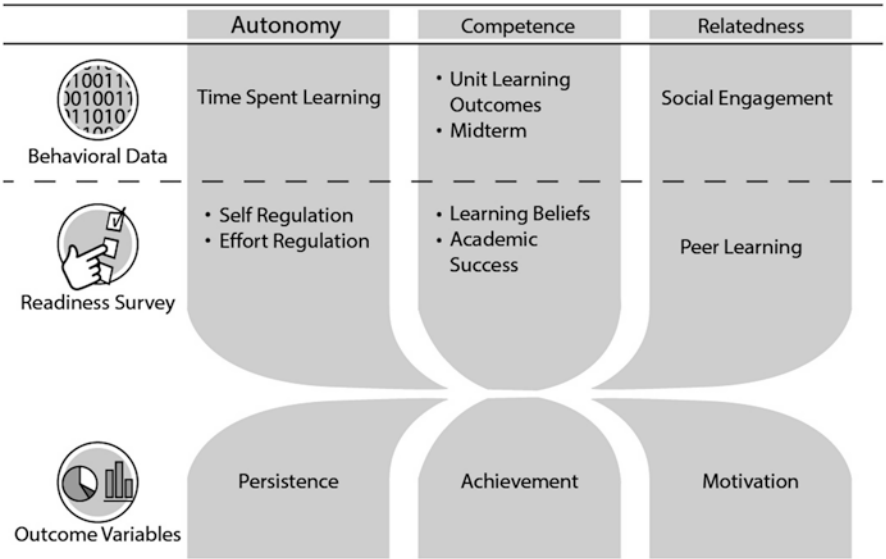

Fig. 14.1 The emerged factors and the outcome variables

Table 14.10 Correlations between predictor factors and the dependent variables

Measure	Persistence	Achievement	Motivation
1. Midterm score	**0.253**[a]	**0.452**[a]	0.008
2. Unit learning outcomes	**0.619**[a]	**0.129**[a]	−0.047
3. Time spent learning	**0.297**[a]	**−0.171**[a]	0.088
4. Social engagement	**0.220**[a]	−0.047	0.075
5. Self-regulation	0.058	0.018	**0.474**[a]
6. Effort regulation	0.100	−0.015	**0.307**[a]
7. Learning beliefs	0.020	−0.054	**0.670**[a]
8. Academic success	−0.024	**0.109**[b]	**0.330**[a]
9. Peer learning	−0.004	**−0.140**[a]	**0.409**[a]

[a]Correlation is significant at the 0.01 level (two tailed).
[b]Correlation is significant at the 0.05 level (two tailed).

$p < 0.01$). In addition, the analysis revealed positive, moderate-to-high significant correlations between motivation and the five readiness factors: learning beliefs ($r = 0.670$, $p < 0.01$), self-regulation ($r = 0.474$, $p < 0.01$), peer learning ($r = 0.409$, $p < 0.01$), academic success ($r = 0.330$, $p < 0.01$), and effort regulation ($r = 0.307$, $p < 0.01$). Additionally, a moderate-to-strong correlation is found between midterm score and student achievement ($r = 0.452$, $p < 0.01$). The results show that three behavioral factors (midterm score, unit learning outcomes, and time spent learning) are significantly correlated with either achievement or persistence. Interestingly, no significant correlation was found between any of the behavioral factors (Factors 1–4) and motivation. On the other hand, the readiness factors (Factors 5–9) were all significantly correlated with motivation.

To test the validity of the emerged factors in predicting student persistence, we ran a stepwise multiple regression model with average completion of course materials (persistence) as the dependent variable. The results can be seen in Table 14.11. Model 3 significantly predicts student persistence ($p < 0.001$). The combination of three factors (unit learning outcomes, time spent learning, and midterm) accounts for 50% of the variance in persistence scores (adjusted $R^2 = 0.50$). These results suggest that average unit score and unit score trend (i.e., unit learning outcomes), time spent learning, and midterm score each uniquely predict how well a student will do in the course.

To test the validity of the emerged factors in predicting student achievement, we ran a stepwise multiple regression model with final exam score as the outcome variable. The results can be seen in Table 14.12. Model 4 significantly predicts student achievement ($p < 0.001$). The combination of four factors (midterm, peer learning, self-regulation, and time spent learning) accounts for 28.2% of the variance in final exam scores (adjusted $R^2 = 0.282$). These results suggest that one's midterm score combined with processes such as planning, monitoring, and regulating (i.e., self-regulation) may predict student score on the final test. Having said that, the proportion of the explained variance is relatively low (28.2%), which suggests that there are other variables which account for 71.8% of the variance.

Table 14.11 Multiple regression model for student persistence by emerged factors

Model		Unstandardized coefficients		Standardized coefficients		
		B	SE	Beta	*t*	*P*
1	(constant)	89.218	0.732		121.809	0.000
	Unit learning outcomes	17.505	0.971	0.687	18.026	0.000
2	(constant)	88.936	0.727		122.370	0.000
	Unit learning outcomes	17.149	0.963	0.673	17.808	0.000
	Time spent learning	2.473	0.728	0.128	3.398	0.001
3	(constant)	88.937	0.717		124.047	0.000
	Unit learning outcomes	16.481	0.971	0.647	16.972	0.000
	Time spentlearning	2.635	0.719	0.137	3.663	0.000
	Midterm	2.534	0.764	0.126	3.315	0.001

[a]Dependent variable: persistency

Table 14.12 Multiple regression model for student achievement by emerged factors

Model		Unstandardized coefficients		Standardized coefficients		
		B	SE	Beta	*t*	*P*
1	(constant)	81.041	0.610		132.903	0.000
	Midterm	7.661	0.708	0.508	10.813	0.000
2	(constant)	88.341	3.204		27.571	0.000
	Midterm	7.553	0.705	0.500	10.707	0.000
	Peer learning	−1.835	0.791	−0.108	−2.320	0.021
3	(constant)	84.116	3.637		23.125	0.000
	Midterm	7.464	0.701	0.494	10.640	0.000
	Peer learning	−3.168	0.962	−0.187	−3.292	0.001
	Self-regulation	2.448	1.021	0.136	2.397	0.017
4	(constant)	84.619	3.628		23.324	0.000
	Midterm	7.277	0.704	0.482	10.337	0.000
	Peer learning	−3.160	0.958	−0.187	−3.300	0.001
	Self-regulation	2.364	1.017	0.131	2.324	0.021
	Time spent learning	−1.289	0.625	−0.096	−2.062	0.040

[a]Dependent variable: achievement

5 Discussion

Online language learning has been recognized as a promising approach to increase students' English language proficiency in developing countries where high-quality language learning resources are limited (Bai et al., 2016; Glick et al., 2016). Identifying factors that predict students' performance in online courses can inform institutions and instructors of interventions to improve learning experiences and success in online courses (Ai & Laffey, 2007; Romero & Ventura, 2007). Based on the SDT and on data from a pre-course readiness survey, LMS log files, and Facebook activity reports, this study identifies several important predictors of persistence and achievement in online language courses in a low-income developing country.

We first used factor analysis to identify latent factors from behavioral variables and readiness variables and classified these latent factors into three categories of measures based on the SDT. Nine factors emerged from the factor analysis. Specifically, four latent factors (i.e., learning beliefs, academic success, unit learning outcomes, and midterm score) captured students' competence and were indicative of the degree to which students were confident about their performance in the course. It is worth noting though that this may not be an exhaustive list, and additional factors may influence students' sense of competence, such as prior knowledge and students' perceived value (Eccles & Wigfield, 2002). Two factors – peer learning and social engagement – measured students' relatedness and reflected how much students valued social interaction at the beginning of the course and the level of social interaction each student actually engaged in the course. The other three latent factors – time spent learning, self-regulation, and effort regulation – focused on the extent to which students could control their own learning and were classified as measures of autonomy.

In exploring the relationship between each of the three categories and course performance, we found that factors under the categories of competence and autonomy were predictive of students' course persistence and achievement, which aligns with the SDT (Ryan & Deci, 2000). In particular, the factors of midterm score and self-regulation were strong and positive predictors of students' final test score. We also found that time spent on the course was a significantly negative predictor of the final test score, suggesting that students who spend more time in a course may have difficulties understanding the course content or completing the assignments. Interestingly, we also identified a negative relationship between the extent to which a student valued peer learning at the beginning of the course and their course achievement, suggesting that students who value peer-to-peer interactions may encounter particular difficulties in online learning environments, which typically include limited human interactions, compared to in traditional face-to-face environments.

These results have several theoretical and practical implications. First, prior studies on the SDT mainly focused on traditional face-to-face classrooms. Our study extends this line of research on SDT to the online learning environment, which differs substantially from face-to-face classrooms in terms of time and space, methods of communication, and the roles of teachers and students (Moore & Kearsley, 2011). The SDT proposes that students' sense of autonomy, relatedness, and competence improves motivation, thereby positively influencing learning outcomes (Ryan & Deci, 2000). Our findings provide suggestive evidence that the SDT also applies to online learning and that measures related to autonomy and competence are predictive of course performance. Moreover, we took advantage of the nuanced behavioral data in online learning to measure students' behaviors and performance during the course, which reduces possible bias and inaccuracy related to self-reported measures used in previous research in face-to-face classrooms (Baker & Inventado, 2014). As proposed by the SDT, we found that most of the behavioral measures were moderately and positively correlated with persistence and achievement, indicating the validity of these measures. Overall, these results provide guidance for future research in using course behavioral data to measure students' autonomy, relatedness, and competence in online classes.

Second, prior research found that students with certain background characteristics, such as lower levels of academic preparation, have more difficulty succeeding in online courses than in face-to-face courses (Xu & Jaggars, 2014). Yet, it is unclear what specific personal attributes make an individual particularly vulnerable in an online learning environment. As a result, it is difficult to identify students who may suffer in online courses and provide preventative interventions, early warnings, or additional support to increase the success rate of these students. With the rich information collected through the pre-course survey, we found that students who lacked self-regulation skills were more likely to suffer and have lower performance in online classes. These findings are in line with the online learning literature that self-regulation ability plays a particularly important role in the virtual learning environment where students are required to take greater responsibility to control and regulate their own learning (Duffy & Kirkley, 2003). To support students with low self-regulation abilities in online courses, institutions could provide academic recourses, such as workshops on online learning or self-regulation skills, to improve students' capacity to learn effectively online. In addition, institutions may also require pre-course assessment to evaluate students' readiness for online learning before allowing them to take an online course, which could help students make better informed decisions about which course delivery format to opt in.

Third, we found behavioral variables such as time spent in course and midterm exam score were significant predictors of student success. Using these real-time measures, institutions can develop an early warning system to identify struggling students early in a course (Dominguez, Bernacki, & Uesbeck, 2016; Macfadyen & Dawson, 2010). Instructors can then provide timely pedagogical interventions to at-risk students and help them to succeed (Jaggers & Xu, 2016). For instance, our study suggests that students who spend more time in a course might experience higher levels of difficulties understanding the course content or completing the assignments. Instructors can help those students through consultancy support or by digging deep into the behavioral data to identify the specific problem that the students had encountered and provide learning materials that better support students.

There are a few caveats to bear in mind when interpreting the results from the current study. First, while midterm score is highly predicative of students' final course grade and can therefore be used for early identification of at-risk students, the extent to which this strategy could indeed help students largely depends on the quality of follow-up support the instructor is able to provide to the student. Thus, the early warning system needs to be accompanied with comprehensive and effective supports and resources for struggling students. In addition, although midterm score proves to be a strong predictor of students' final grade, it is collected at a point when students have already finished a significant amount of the coursework. Therefore, future research is needed to explore factors that can help identifying at-risk learners as early as possible. The pre-course survey measures that are found to be predictive of persistence and achievement in this study, such as learning beliefs and perceptions on peer learning, provide guidance on future investigations along this direction. Another potential candidate unexplored in this study is user behavior that is indicative of high risk of failing the course. The online learning environment provides educators and researchers with an unprecedented opportunity to achieve a timely understanding of student course experiences by automatically recording a large swath of behavioral information from each learner. Future research needs to be conducted to correlate such behavioral information with course outcomes. Finally, several achievement predictors identified in this study are measured based on student self-report before the course, which is the most commonly used method for measuring psychological constructs, such as self-regulation skills and motivational beliefs (Winne & Perry, 2000). However, the usefulness of self-reported information is limited when the response rate is low. Future research may wish to take advantage of the nuanced behavioral data available in the online learning environments and explore possible ways to measure these psychological constructs using the behavior data.

Students' competence, autonomy, and relatedness are important predictors of student persistence, achievement, and motivation in online learning. In this study, we developed measures of students' competence, autonomy, and relatedness, and among these measures, we identified strong predictors of student success in online language courses. Results from this study could therefore assist institutions and instructors in identifying students who are at risk of failure in online learning and providing effective interventions early on during a course to improve students' learning outcomes.

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Chapter 15
Using Learning Analytics to Examine Relationships Between Learners' Usage Data with Their Profiles and Perceptions: A Case Study of a MOOC Designed for Working Professionals

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1 Introduction

MOOCs, as an emerging online instruction format, have attracted thousands of people around the world to learn topics of their interests without time and geographical constraints. MOOC participants interact with course content, instructors, and their peers through a MOOC platform which leaves a large amount of data on how students access various features of a MOOC. Such analytics can provide useful insights into students' learning behaviors and the design of MOOC instruction. The purpose of this study was to investigate how participants in a MOOC designed for working professionals interacted with various key components of the MOOC (e.g., discussion forums, readings, videos, quizzes, optional resources). Examining and understanding such usage patterns can help MOOC instructors and researchers gain insights into students' knowledge building and MOOC course designs.

1.1 Use of Learning Analytics in MOOCs

In recent years, the use of learning analytics is being investigated in MOOC research focusing on different aspects. For example, studies on MOOCs have been conducted about learner behavioral patterns (Khalil & Ebner, 2016, 2017; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Tseng, Tsao, Yu, Chan, & Lai, 2016), students' engagement and motivation (Lu, Huang, Huang, & Yang, 2017; Xing, Chen, Stein,

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& Marcinkowski, 2016), and predicting learning performances and outcomes (de Barba, Kennedy, & Ainley, 2016; Elbadrawy et al., 2016; Formanek, Wenger, Buxner, Impey, & Sonam, 2017; Tseng et al., 2016).

1.2 Learner Behavioral Patterns in MOOCs

To understand learners' behavioral patterns, Tseng et al. (2016) used students' behavioral data from three courses from a university in Taiwan to identify learners' engagement and learning patterns in MOOCs. The results of cluster analyses found that only 1% of students were classified as active learners, while 90% of students were bystanders, and 9% of students were passive learners. Another interesting finding was that students were relatively more active during the first 2 weeks; thus, it was a crucial point of time to keep students motivated and engaged in MOOCs. Similarly, Kizilcec et al. (2017) conducted a study to examine various types of self-regulated learning (SRL) strategies when learners were interacting with MOOCs. They collected data on learner events within a certain period of time (defined as "sessions") to look at their sequential behaviors and the frequency of transitions between different sessions. Additionally, survey data were collected to identify learner characteristics. Results revealed that students with high levels of self-reported SRL were more likely to go back to course materials, especially course assessments, to repeatedly test themselves. In another study, Khalil and Ebner (2016) presented the implementation of a learning analytics prototype in an Austrian MOOC platform to analyze learners' behavioral patterns. Their learning analytics tool kept track of various learner interactions, such as the logging frequency, the total of document downloads, forum posts from each learner, video statistics, and total of quiz attempts. The researchers applied this tool to examine the logs of two different MOOCs. Results showed that students were much more active (as demonstrated in video views, forum posts, forum reads) during the first 2 weeks of the courses. They also analyzed course scores with student activities in the forum and found that students who read more forum posts may not necessarily achieve higher scores, as their performances were also influenced by other factors, such as what specific content they read in the discussion forum.

Several studies have been done to classify learners based on the level and content of their interaction with other learners (Gillani & Eynon, 2014; Goggins, Galyen, Petakovic, & Laffey, 2016; Khalil & Ebner, 2017; Yang, Wen, Howley, Kraut, & Rose, 2015). Khalil and Ebner (2017), for example, used clustering methods to classify students into appropriate categories based on their level of engagement. Their algorithm fetched user behavioral data such as viewed videos, downloaded files, reading in forums, posting in forums, quiz results, and logins. Three groups were identified with distinctive access patterns: "gaming the system group," "perfect student group," and "dropout group." Their study implied that besides motivating learners extrinsically like providing certificates or badges, course designers should also pay attention to improving learners' intrinsic motivation, such as refining the instructional design and course content itself, in order to make students progress positively toward the "perfect student group."

1.3 Students' Engagement and Motivation in MOOCs

Implementing analytics into MOOCs can contribute to improving students' engagement and enhance learning outcomes. Researchers had investigated ways to increase engagement and diagnose issues through the algorithms of learning analytics (Lu et al., 2017; Xing et al., 2016). For example, Lu et al. (2017) investigated the effectiveness to increase students' engagement of MOOCs by involving analytics to a programming course. They adopted a parallelized action-based engagement measurement algorithm (PAbA) which measured students' levels of engagement through calculating their video views and forum posts. The instructor would receive report and provide intervention when a student's level of engagement was lower than a certain threshold. Their results showed that the monthly reports sent to instructors increased their timely interventions, which ultimately led to higher levels of behavioral, cognitive, and emotional engagement in students. This study indicated that it was crucial for instructors to have easy access to students' online behavioral data and gave nudges to those who were falling behind the schedule.

Likewise, Xing et al. (2016) presented a temporal modeling approach for the early and accurate identification of students at risk of dropping out. Students were labeled based on their level of activeness for each week of the course, which were associated with the weekly course feature vectors: the number of discussion post, number of forum views, number of quiz views, number of module views, number of active days, and frequency of interactions in social network. The data for each individual were then input into the machine learning algorithms to predict the dropout label for a specific week for that student. The study proved how prediction models can be adopted effectively to improve the quality of intervention and increase student engagement.

1.4 Predicting Learning Performances and Outcomes

A main reason for applying learning analytics in MOOCs is to predict students' learning performances and outcomes through the data generated through students' learning progress and learning styles (Nunn, Avella, Kanai, & Kebritchi, 2016; U.S. Department of Education, Office of Educational Technology, 2012). Researchers had implemented series of learning analytics models and techniques to gain more insights on students' success in MOOCs (de Barba et al., 2016; Elbadrawy et al., 2016; Formanek et al., 2017; Pursel, Zhang, Jablokow, Choi, & Velegol, 2016; Qu & Chen, 2015; Tseng et al., 2016). For instance, Pursel et al. (2016) conducted a study on MOOC to find out what variables were indicative of student completion. They used regression analysis to examine the correlations among completion rate, video views per week, posts per week, and comments per week in the discussion forums. Results showed that prior online learning experience in MOOCs had no impact on student completion. Video views were found to be a strong predictor of MOOC completion. Although the forums were not graded, forum posts and comments were significant predictors of completion.

Tseng et al. (2016) performed an agglomerative hierarchical clustering analysis and combined the results from chi-square and one-way ANOVA tests to measure learning performances among different types of learners. The research found positive correlation between students' video and assignments completing frequencies and their passing rate. Similarly, the study of Qu and Chen (2015) showed that students with various types of learning behaviors in MOOCs revealed different levels of learning outcome. Active learners who completed homework assignments and watched videos frequently showed significantly higher rates of passing the courses than the others. It indicated the connection between students' learning motivation and learning outcomes, which corresponded with a research by de Barba et al. (2016). In their study, they measured students' video hits and quiz attempts during learning as an indicator of students' participation and then used Spearman correlations to find out the correlations between the factors that indicated types of motivation and the students' behaviors. The results showed that students' intrinsic motivation and participation were the significant predictors of final learning performances, and both of them relate to students' MOOC learning outcomes directly and indirectly.

Moreover, several researches had focused specifically on learning analytics model itself as to develop its ability in identifying key performance indicators (Maté, De Gregorio, Cámara, Trujillo, & Luján-Mora, 2016; Peral, Maté, & Marco, 2017). Peral et al. (2017) proposed a five-step data processing model which involved support vector machines (SVM) and decision trees (DT) to refine existing key performance indicator model so as to better predict students' learning performances and outcomes.

2 Purpose of the Study and Research Questions

Given the potential benefits of using analytics, more research is needed to investigate the relationships between behavioral patterns and learner engagement and to understand how learners' usage connected to their profiles and perceptions. Little research is available on this topic for MOOCs designed for working professionals. In this study, we asked the following research questions:

1. How do MOOC participants access various key MOOC components (e.g., discussion forums, readings, videos, quizzes, optional resources)?
2. Is there a connection between participants' usage patterns and learner profiles (i.e., gender and prior MOOC experience) and their perceptions?

3 Method

3.1 Participants and Research Context

Participants were the students enrolled in a 6-week MOOC offered through the Knight Center for Specialized Journalism in the Americas at the University of Texas at Austin in spring 2017. This MOOC was designed primarily for journalism professionals but also were open to everyone interested and had a total of 6675 individuals registered, representing 148 countries, and 2 instructors taught this MOOC.

3.2 Data Sources and Analysis

Two types of data sources were included in this study: (a) the survey responses regarding participants' perceptions of the usefulness of various course components and (b) the usage data.

Survey Data A post-survey was administered by the end of the course. The survey was designed to help capture participants' demographics and their perceptions related to the research questions of this study. Eight questions were asked, and the responses were categorized into two or more groups for each question:

1. What is your gender (male or female)?
2. Have you taken MOOC courses before (first time or non-first time)?
3. Of the various reasons you mentioned, which was *the most* important reason you enrolled?
4. Approximately, how many hours per week did you spend on this MOOC (1 h less or more than 1 h)?
5. How many course-related exercises and assignments have you completed (some/all or none)?
6. Indicate your MOOC completion status and whether you plan to apply for certificate (have applied/will apply or will not apply).
7. Compared to face-to-face instruction, is this MOOC instruction better, worse, or about the same?
8. To what extent did you find discussion forums of this MOOC course to be helpful (helpful, neutral, or not helpful)?

Usage Data Usage data came from user-generated logs from the MOOC course platform—Moodle. A challenge we had when collecting the log data was Moodle's incapability to handle large-quantity data download requests. There were 615,328 rows of log data for this course, and a crash would happen if we used the administer tool provided by Moodle to download the data. Alternatively, we implemented a web scraping script with a Python package, called Scrapy, to collect the data. During the data collecting process, we were cautious of data loss caused by network request failures. Failed network requests would be retried for ten times. If network requests still failed after ten times, an error would return to prompt us, so we could decide what to do next. Fortunately, the scraping process was performed smoothly, and we were able to get all the available data.

Data Cleaning and Transformation First, irrelevant raw log data to our research questions were removed. The final dataset consisted of 301,010 rows. However, the raw log data did not offer us the granularity we needed for this study such as module information on various key course components (discussion forums, quizzes, videos, readings, and optional resources); or the format was in such a way it was hard to tell which log was about videos, readings, or optional resources. For example, all log events were categorized with a general label of "url component." After browsing the MOOC course web page, we found that each page has a unique ID associated with each page. Using the unique IDs, we manually collected these page IDs and constructed a dictionary with page ID as the key and module number as the value using a Python script. This dictionary allowed us to trace the module information that was obviously displayed from the raw data. We constructed another dictionary for various course components (e.g., videos, readings, and optional resources) that helped transform log data with the details we needed for this study.

Matching User's Log Data with Their Survey Data A total of 578 participants completed the survey. The survey was anonymous. We were interested in understanding the connection between participants' survey responses and their usage data (RQ2). Using IP addresses, we matched respondents' survey data with their data logs. As a result, a total of 200 unique IP addresses were found during the 6-week course with a total of 26,327 rows of data for further analysis. A row of log data consisted of the participant's IP address, the date and time, and a series of course events.

Given our research questions, nine events related to the course components were extracted and analyzed (see Table 15.1 for each event name and its definition). These events included can be categorized into active and passive learning behaviors. Active learning behaviors indicate students' active participation in the course, such as discussion created and quiz started. Passive learning behaviors, on the other hand, represent students' passive receiving of course materials, such as video viewed and reading materials viewed.

Data Analysis We first plotted graphs to examine the data descriptively. There were eight survey questions and five course components (discussion forums, quizzes, videos, readings, and optional resources) in the log data. Each component contained

Table 15.1 Definitions of events in user log file

Event name	Definition
Discussion created	The number of times students created a new thread under a discussion question
Discussion subscription created	The number of times students created an email subscription to a discussion thread
Discussion viewed	The number of times students accessed a discussion thread
Discussion replied	The number of times students replied to other students' post
Reading materials viewed	The number of times students accessed reading materials provided by the instructor
Video viewed	The number of times students accessed instructional videos in the course
Optional resources viewed	The number of times students accessed optional materials provided by the instructor, including videos and readings
Quiz started	The number of times students started a quiz
Quiz submitted	The number of times students finished and submitted a quiz

different events. For example, discussion forums included events such as discussion viewed and discussion replied. Drawing graphs for each of these components were labor intensive. To make the process more efficient, a Python script was written using packages of Seaborn and Matplotlib to automatically plot the graphs. Seaborn and Matplotlib are graphing packages in Python, which allow users to plug in in variables to plot different graphs easily. In our case, we wrote a script with Seaborn and Matplotlib to generate bar charts of events' frequency in each component. We first tested several auto-generated graphs and checked if they matched the manually plotted graphs and found the automatically drawn graphs matched manually drawn ones 100%. The research team examined each graph for its accuracy before including them in the analysis. When missing data or data ranges were incorrectly displayed, we reexamined the input data for the graphs and redrew the graphs. These graphs along with their data points were then used to analyze the overall usage patterns, and descriptive statistics were used. We also used the graphs to help us decide which grouping variable(s) that might show differences to further investigate using statistics.

Because the data did not meet all assumptions of parametric hypothesis testing, such as normality, the Mann-Whitney U and Kruskal-Wallis H tests were used to compare differences between the groups of similar sizes. In two cases, the sizes of the groups were very different from each other, and descriptive statistics were used instead. For all cases, data visualizations, using Tableau, were used to create graphs to illustrate the findings, which allowed us to plot multiple data points in one graph (see Fig. 15.3 below).

4 Findings

4.1 Overall Usage Patterns

4.1.1 Passive Learning Behaviors

Figure 15.1 showed the overall video viewed, reading materials viewed, and optional resources viewed across 6 weeks from all participants (n = 6675). In general, the frequency of views of these three course components was gradually declining. Particularly, for optional resources viewed and reading materials viewed, the most precipitous drop occurred in Week 2 (a drop around 6800 from Week 1 for each). By contrast, for video viewed, there was a slight increase from Week 1 to Week 2, followed by a sharp drop of 6248 in Week 3. Since Week 3, video viewed decreased steadily (a weekly drop around 3000) until it went down to 4074 by Week 6. For optional resources viewed, the number continued to drop until Week 5 (a slight increase of 522 from Week 4). By Week 6, the number went up slightly to 1313. For reading materials viewed, despite of its continuous declining trend, the decrease was much less dramatic in Week 5 (a mild drop of 363).

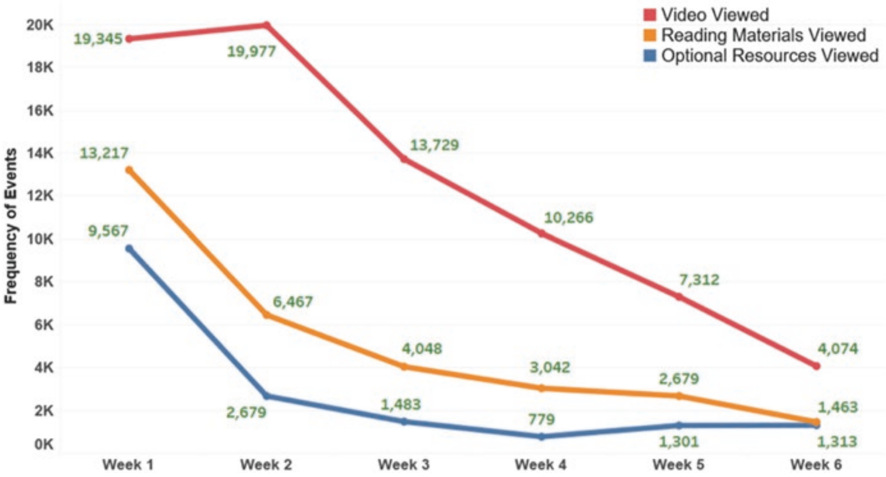

Fig. 15.1 Overall videos, readings, and optional resources viewed across 6 weeks

4.1.2 Active Learning Behaviors

Similarly, the events in quizzes experienced the same downward trend (Fig. 15.2). In particular, the trend of quiz submitted closely followed that of quiz started. It is worth noting that the number of quiz submitted was consistently fewer than quiz started since participants may not finish every quiz they had started. Again, Fig. 15.2 showed that the most significant decrease for both events happened in Week 2 (an average drop around 650 from Week 1), followed by more steady drops in Week 3 and Week 4. There was a noticeable uplift in Week 5 (an average increase around 90 for both events). Nevertheless, they quickly resumed their declining trend by Week 6.

For events in discussion forums (Fig. 15.3), the decline of discussion viewed (from 10,313 in Week 1 to 1337 in Week 6) was much more conspicuous than the rest of the three events: discussion created, discussion subscription created, and discussion replied. The most dramatic drop for discussion viewed occurred in Week 2 and Week 3, with a plummet of 4867 and 2200, respectively, from their previous weeks, followed by a slower decreasing trend for the rest of the course. For discussion created, discussion subscription created, and discussion replied, the most noticeable drop happened in Week 3 (discussion created, −197; discussion subscription created, −359; discussion replied, −202). During the following weeks, the frequency for these three events continued to fall but in a much lower speed.

Could the decline of usage be due to variations of the course materials provided? Table 15.2 presented the number of course materials provided in the MOOC for each week. For videos, the number of videos provided almost doubled after Week 1, yet the frequency of video viewed steadily declined from Week 2, as shown in Fig. 15.1. Similarly, reading materials viewed were observed in a downward trend although a similar number of reading materials were provided. For optional resources, the drop the frequency of views may partly be due to that fact that less optional resources were provided after Week 1. However, the optional resources in

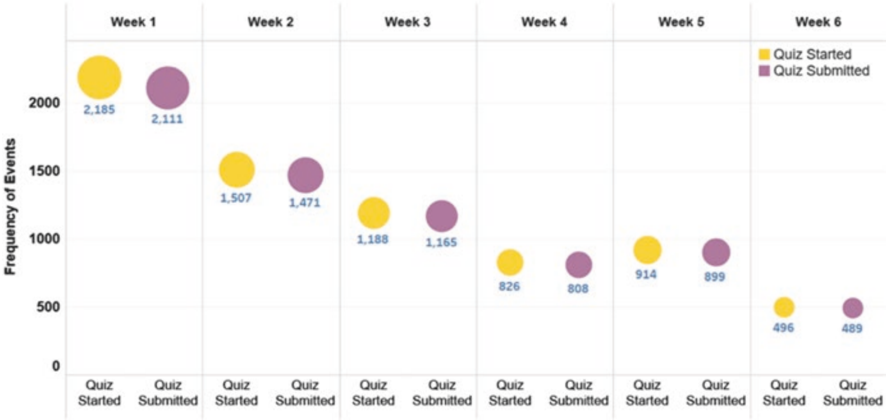

Fig. 15.2 Overall usage of quizzes across 6 weeks

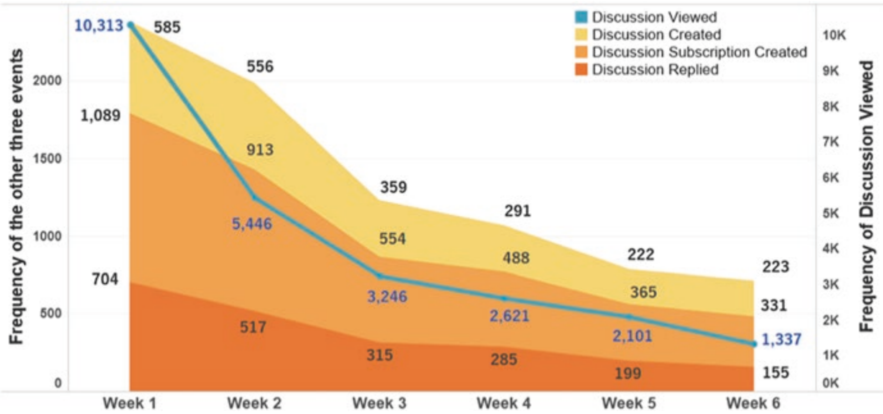

Fig. 15.3 Overall usage of discussion forums across 6 weeks

Table 15.2 Number of course materials provided in the MOOC for each week

	Videos provided	Reading materials provided	Optional resources provided
Week 1	5	5	8
Week 2	9	8	4
Week 3	11	4	3
Week 4	10	4	2
Week 5	10	6	3
Week 6	7	4	6

Week 2 was half of that in Week 1 in quantity, for example, yet the number of views in Week 2 shrunk to only 30% of the views observed in Week 1. That is, that the declines of video viewed, reading materials viewed, and optional resources viewed appeared to be attributed to reduced usage rather than less course content provided in subsequent weeks.

4.2 Connection Between Usage Patterns and Participants' Survey Responses

Given participants' responses for each question, we categorized them into different groups to find out how participants from different groups accessed the MOOC. The means and standard deviations of frequency of events for each group were presented in Table 15.3.

4.2.1 Gender and Prior MOOC Experience

In order to examine whether there was a difference in MOOC usage between genders, Mann-Whitney U tests were conducted between male (n = 77) and female (n = 108) groups. The analysis revealed significant differences in quiz started ($z = -2.361$, $p < 0.05$) and quiz submitted ($z = -2.128$, $p < 0.05$). There were no other significant differences for other events (Fig. 15.3).

Regarding participants' familiarity with the form of MOOC learning, we categorized them into two groups based on their responses: (a) first-time MOOC users ($n = 81$) and (b) non-first-time MOOC users ($n = 104$) who have taken other MOOC courses before. Mann-Whitney U tests were conducted to determine whether there were significant differences in the frequency of events between these two groups. Results of analysis found significant difference only in discussion viewed ($z = -2.005$, $p < 0.05$).

4.2.2 Time Spent and Assignment/Exercise Completion

In looking at usage patterns of the participants who spent more time or completed more exercises/assignments, we examined descriptively the mean frequency of the nine events performed by each group of participants, given the quite uneven sample size between groups. The analysis showed more usage of different course components by those who spent more time or completed more exercises/assignments than those who contributed less efforts (see Table 15.3).

4.2.3 Most Important Reason to Enroll and Certificate Applying Plan

We asked the participants to indicate the most important reason for them to enroll in this MOOC. The results showed varied responses regarding their use of discussion forums (see Table 15.4). Participants who were motivated by earning a certificate/statement of accomplishment were most active across four different types of events in discussion forums compared to those who chose other reasons to enroll. Those who chose general interest in the topic and relevant to academic research exhibited low participation in discussion forums. Additionally, we further categorized the participants into two groups based on the reasons they indicated: (a) intrinsically motivated group ($n = 82$) that contained participants who chose general interest in topic,

Table 15.3 Usage patterns for each group

		Discussion				Quizzes		Optional resources	Readings	Videos
	Groupings	Discussion created	Discussion subscription created	Discussion viewed	Discussion replied	Quiz started	Quiz submitted	Optional resources viewed	Reading materials viewed	Video viewed
Categories		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Gender	Male $n = 77$	1.77 (3.09)	3.16 (5.28)	16.87 (24.73)	1.96 (3.37)	5.04[a] (3.9)	4.81[a] (3.94)	5.47 (6.17)	13.88 (12.37)	34.87 (25.92)
	Female $n = 108$	1.54 (2.71)	2.39 (4.15)	16.83 (29.01)	1.82 (4.99)	3.88[a] (4.97)	3.77[a] (4.98)	5.43 (7.22)	12.50 (13.17)	30.30 (30.41)
Previous MOOC experiences	First time $n = 81$	1.72 (3.02)	3.10 (4.54)	19.17[a] (27.04)	1.94 (3.79)	4.94 (5.42)	4.81 (5.44)	5.09 (6.72)	14.74 (14.12)	37.79 (32.48)
	Non-first time $n = 104$	1.59 (2.77)	2.43 (4.76)	15.20[a] (27.5)	1.85 (4.83)	3.95 (3.77)	3.76 (3.77)	5.76 (6.88)	11.89 (11.65)	28.13 (24.58)
Most important reason to enroll in MOOC	Intrinsically motivated $n = 82$	1.00[a] (2.32)	1.59[a] (2.85)	11.62[a] (17.12)	0.93 (1.56)	3.74 (3.73)	3.55 (3.80)	8.39 (10.24)	14.34 (13.78)	33.89 (31.97)
	Extrinsically motivated $n = 99$	1.92[a] (2.95)	3.35[a] (5.28)	22.99[a] (35.08)	2.20 (4.25)	4.94 (5.21)	4.87 (5.23)	8.71 (10.57)	17.55 (16.42)	40.65 (34.20)
Hours per week spent on MOOC	1 h or less $n = 35$	0.14 (0.55)	0.54 (1.75)	2.06 (5.46)	0.49 (1.56)	1.20 (2.11)	1.11 (2.07)	2.77 (4.95)	5.06 (6.62)	14.94 (21.59)
	More than 1 h $n = 150$	1.99 (3.08)	3.23 (4.98)	20.41 (29.14)	2.21 (4.77)	5.13 (4.69)	4.95 (4.72)	6.09 (7.03)	15.03 (13.21)	36.43 (28.6)
Exercise and assignment completion status	None $n = 13$	0.08 (0.28)	0.15 (0.38)	1.31 (2.46)	0.08 (0.28)	0.54 (1.45)	0.46 (1.39)	2.46 (4.45)	5.77 (7.97)	13.62 (14.64)
	Some or all $n = 172$	1.76 (2.95)	2.92 (4.78)	18.12 (27.95)	2.02 (4.53)	4.67 (4.61)	4.51 (4.63)	5.69 (6.9)	13.7 (12.97)	33.78 (28.96)

(continued)

Table 15.3 (continued)

Categories	Groupings	Discussion				Quizzes		Optional resources	Readings	Videos
		Discussion created	Discussion subscription created	Discussion viewed	Discussion replied	Quiz started	Quiz submitted	Optional resources viewed	Reading materials viewed	Video viewed
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Certificate application plan	Completed MOOC, going to apply or received the certificate $n = 72$	2.82[a] (3.64)	4.71[a] (5.56)	24.74[a] (28.29)	2.65[a] (3.65)	5.53 (4.05)	5.43 (4.04)	5.86 (6.99)	15.72 (13.64)	38.93 (28.49)
	Completed MOOC but do not plan to apply for the certificate $n = 57$	1.28[a] (2.25)	2.18[a] (4.44)	16.21[a] (29.78)	2.21[a] (6.37)	5.46 (5.62)	5.33 (5.62)	5.93 (6.41)	15.02 (13.59)	39.89 (31.14)
Perception toward MOOC compared to face-to-face instruction	MOOC is much better or somewhat better $n = 45$	1.78 (3.69)	3.02 (5.74)	18.42 (29.59)	1.64 (3.11)	3.82 (4.29)	3.78 (4.26)	6.40 (7.66)	13.96 (13.81)	29.71 (26.9)
Perception toward MOOC compared to face-to-face instruction	MOOC is about the same $n = 56$	2.07 (2.95)	3.38 (4.96)	17.39 (25.29)	2.14 (3.89)	5.77 (5.61)	5.66 (5.59)	5.09 (6.04)	13.57 (12.91)	36.73 (31.5)
	MOOC is somewhat worse or much worse $n = 41$	1.66 (2.73)	2.34 (4.13)	16.85 (31.5)	2.37 (6.73)	3.59 (3.54)	3.27 (3.54)	4.83 (6.19)	11.66 (11.39)	31.41 (28.49)
Perception toward discussion forums	Helpful $n = 57$	1.65 (3.69)	3.47 (7.34)	14.06 (31.85)	1.88 (3.85)	4.12 (3.9)	4.18 (3.89)	4.00 (4.46)	11.24 (12.44)	30.29 (22.61)
	Neutral $n = 52$	1.78 (2.88)	2.83 (4.16)	16.47 (20.81)	1.88 (2.5)	4.52 (3.96)	4.45 (3.91)	5.03 (6.06)	13.65 (12.79)	34.47 (26.24)
	Not helpful $n = 17$	2.11 (3.25)	3.44 (5.08)	22.14 (33.48)	2.60 (6.29)	4.78 (5.66)	4.43 (5.74)	5.86 (7.3)	14.16 (13.41)	33.67 (32.95)

[a]Significantly different from the other(s), $p < 0.05$

Table 15.4 Events in discussion forums in relation to participants' reasons to enroll in the MOOC

	Intrinsic motivation			Extrinsic motivation				
	General interest in the topic	For personal growth and enrichment	For fun and challenge	Earn a certificate	For career change	Relevant to academic research	Relevant to job	Relevant to school or degree program
Avg. discussion created	0	1	1	5	1	1	2	2
Avg. discussion subscription created	1	2	2	4	3	0	4	3
Avg. discussion viewed	8	14	16	38	28	6	23	17
Avg. discussion replied	0	1	1	5	2	0	3	1

for personal growth and enrichment or for fun and challenge. We considered this group to enroll in MOOC purely out of their own will and interest without expected external rewards; and (b) extrinsically motivated group (n = 99) that included participants who stated one of the following reasons: relevant to school or degree program, for career change, relevant to job, relevant to academic research, or to earn a certificate/statement of accomplishment. We considered this group to enroll in MOOC due to some external factors. Mann-Whitney U tests revealed significant differences between the intrinsic motivation and extrinsic motivation groups for three types of events: discussion created ($z = -2.300$, $p < 0.05$), discussion subscription created ($z = -2.373$, $p < 0.05$), and discussion viewed ($z = -1.962$, $p < 0.05$). However, there was no significant difference in discussion replied between these two groups or other events.

Mann-Whitney U tests were conducted to determine whether there were significant differences in the usage of discussion forums between the group who had completed MOOC and planned to apply for certificate (n = 72) and the group who completed the MOOC but did not plan to apply for certificate (n = 57). Results of analysis found significant differences in all four events of discussion forums: discussion created ($z = -3.014$, $p < 0.05$), discussion subscription created ($z = -4.008$, $p < 0.05$), discussion viewed ($z = -2.520$, $p < 0.05$), and discussion replied ($z = -2.677$, $p < 0.05$).

4.2.4 Perceptions

To examine how participants' perceptions toward MOOC affected their usage of the MOOC, a Kruskal-Wallis H test was performed to see whether there were differences among three groups: (a) the group that thought MOOC was much better or somewhat better than face-to-face instruction (n = 45), (b) the group that thought MOOC was about the same with face-to-face instruction (n = 56), and (c) the group that thought MOOC was somewhat worse or much worse (n = 41). The results showed that there was no statistically significant difference in any events among those three groups.

The participants were also asked about their perceptions of helpfulness of the discussion forums for learning. Their responses were categorized into three groups: (a) the group who found discussion forums to be helpful (n = 57), (b) the group whose perception was neutral (n = 52), and (c) the group who found discussion forums to be unhelpful (n = 17). A Kruskal-Wallis H test was conducted in an effort to find statistically significant differences among these three groups in the events of discussion forums. No significant difference was found.

Apart from the overall usage patterns as presented above, we then further examined the daily usage of discussion forums by the three groups. The participants' daily usage data showed that among the four events, postings to the discussion forums had a lower frequency compared to participants' viewing and subscription of the discussion forums. Overall, the participants who rated discussion forums as helpful showed more usage than those in the other two groups (see Fig. 15.4). This

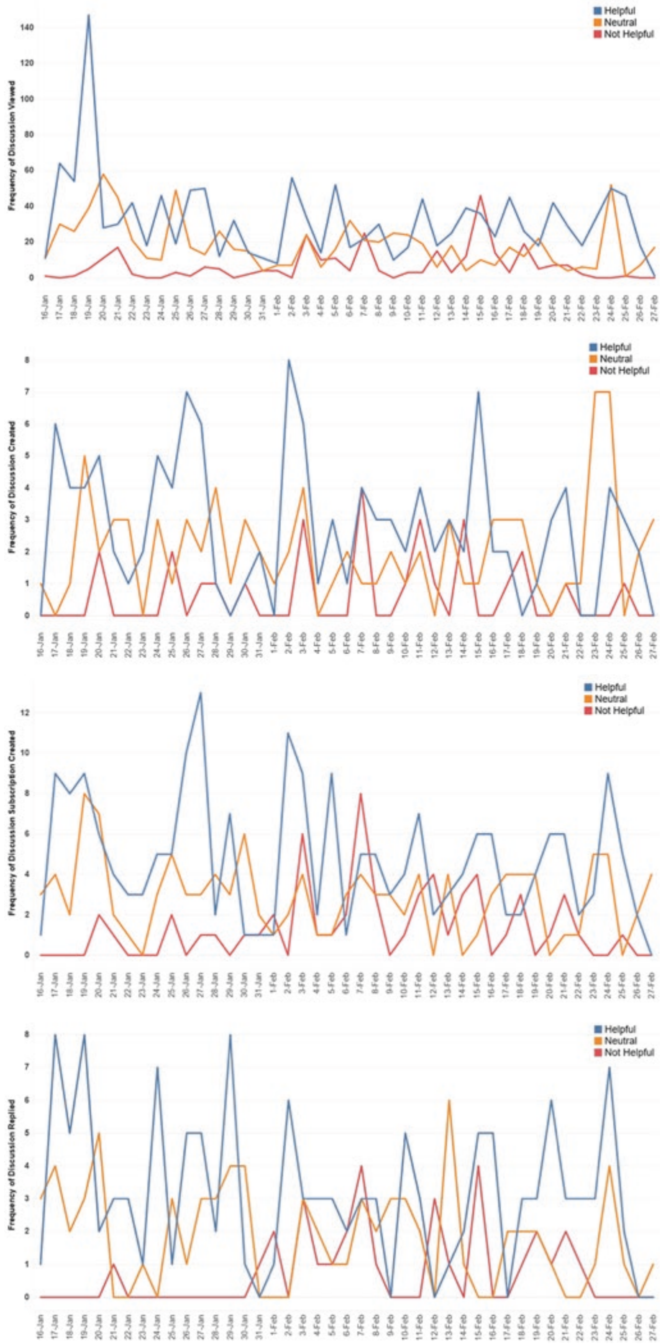

Fig. 15.4 Events in discussion forums in relation to participants' perceptions toward discussion forums

active usage seemed to continue throughout the course. The total number of participants in the group that found forums unhelpful was much smaller. It is worth noticing that although the number of people in group that considered discussion forums neutral was slightly more than three times of that of the group finding forums unhelpful, and the usage pattern of discussion forums of these two groups was similar. However, during the first 2 weeks the group considering discussion forums neutral appeared more active than the group finding forum unhelpful across all four events in discussion forums (see Fig. 15.4). But again, this could be caused by the difference on the number of people between the two groups.

5 Discussion and Conclusion

In this study, we examined how MOOC participants used various course components and whether and how their usage patterns connected to their perceptions. The course components we were interested in were the use of discussion forums, readings, videos, quizzes, and optional resources, which were the key components this MOOC platform offered, and the eight grouping categories are (a) gender, (b) previous MOOC experience, (c) most important reason to enroll in MOOC, (d) hours per week spent on MOOC, (e) exercise and assignment completion status, (f) certificate application plan (whether they plan to apply for certificate), (g) perceptions toward MOOC compared to face-to-face instruction, and (h) perceptions toward discussion forums (whether they consider it useful).

5.1 Overall Usage Patterns

The results of the overall behavioral patterns showed there was an overall decline from the first week to the last week in accessing the various course components, and the biggest drop occurred in Week 2. This declining trend was consistent with other research (Khalil & Ebner, 2016; Qu & Chen, 2015; Tseng et al., 2016) showing students were more active during the first 2 weeks, an important point for MOOC instructors to keep in mind. This result suggests the critical point of time to retain students in MOOCs is during the first 2 weeks. This finding is especially important in light of the high dropout rates found in the MOOC literature. Of all course components provided, it is understandable that optional resources were used the least. Interestingly, the overall usage of videos provided was much higher than the use of readings provided. This could mean that of the three course components (readings, videos, and optional resources), the participants found the videos more useful or engaging, which is probably because of the presence of instructors in the videos to present teaching in a more interactive way.

5.2 Usage Patterns by Grouping Categories

In examining the usage patterns by eight grouping categories based upon participants' survey responses, the results revealed some interesting findings. Although there was an overall decline trend from week to week, male participants consistently accessed significantly more course components than female participants. Specifically, male participants accessed quizzes significantly more than female participants, in both events quiz started and quiz submitted. First-time MOOC users had significantly higher frequency of discussion viewed. It is worth noting that there were no significant differences in discussion created and discussion replied, two more active actions between first-time MOOC users and non-first-time MOOC users. This finding corresponds with a previous study (Pursel et al., 2016) in which users' prior MOOC experience had no significant impact on posts and comments created in discussion forums.

Looking at the usage patterns by the time the participants spent per week, the findings showed those who spent more time per week accessed more course components than those who spent only 1 h or less. Those who completed some or all exercises and assignments accessed more course components than those who did not complete exercises and assignments. Such findings are expected, as if one spent more time in the MOOC, it was most likely they were using the MOOC components as indicated by the analytics. These findings are aligned with previous research, which found self-regulation ability to be closely related to students' level of engagement in MOOCs (Lu et al., 2017).

We examined the most important reason to enroll in the MOOC by the participants. The findings showed that students who wanted to earn a certificate were more active in the events in discussion forums, especially discussion created and discussion replied, which make sense since certificate requirement of the course included participation in discussion forums. Students who took the course because it was relevant to their current jobs or degree programs or for career change also showed more frequent usage of the discussion forums. We further investigated the usage patterns by participants in two categories: those who enrolled for reasons showing intrinsically motivated (e.g., general interest in topic, for personal growth and enrichment, and for fun and challenge) and those who enrolled for reasons related to external factors or extrinsically motivated (e.g., relevant to school or degree program, for career change, relevant to job, relevant to academic research, and earning a certificate/statement of accomplishment). The results showed that while there were no significant findings in usage patterns for most of the course components, there was one noticeable and significant finding between those enrolled in MOOC for intrinsic reasons and those enrolled for extrinsic reasons: the use of the discussion forums. The participants extrinsically motivated had significantly higher frequency in discussion created, discussion subscription created, and discussion viewed. The discussion forums is the most interactive component of this MOOC; a higher frequency is an indication of higher engagement. This finding supports other research that showed motivation were significant predictors of student engagement in the course (Xiong et al., 2015). However, there was no significant difference between the two groups in discussion replied. This finding is further supported by the analysis of usage patterns on MOOC certificate status: those who indicated they completed MOOC and were going to apply or already received the certificate used discussion forums significantly more than those who completed the MOOC but did not plan to apply for the certificate. This suggests providing more extrinsically motivating factors may help some participants complete a MOOC and use course components more often (Xiong et al., 2015). By contrast, previous research showed that providing a free completion certificate had no impact on students' completion rate (Impey, Wenger, & Austin, 2015).

While there were no significant differences in usage patterns between the groups considering discussion forums helpful, neutral, or not helpful in the survey, the "helpful" group showed a higher frequency of overall usage in discussion forums, although this difference was not statistically significant. A surprising finding was there were no significant differences in usage patterns between the groups considering if the MOOC was better, same, or worse when compared to face-to-face instruction. Those who considered that the MOOC was about the same as face-to-face instruction consistently accessed more course components than the other two groups. This seems to suggest the delivery platform, face to face or online, did not affect how participants accessed the course. More research is needed.

This MOOC was designed for working professionals, and assessments such as exercises, assignments, and quizzes were offered to help participants learn and practice what they learned, not to give grades. The analysis of participants' behaviors offered a snapshot of how these working professionals accessed the course components in this setting and what components were important to these participants given their motivation to enroll in the MOOC. Research has indicated participation in a MOOC could be a strong predictor of performance (de Barba et al., 2016; Xiong et al., 2015). Findings of this study revealed factors connected or not connected to their participation as reflected in the analytics. De Barba et al. (2016) also indicated that students' intrinsic motivation was a significant predictor of final learning performances. The finding of this study suggests that students' extrinsic motivation is also very important for MOOCs such as this one where participants enrolled to gain new knowledge and skills related to their jobs or careers. Some significant differences were found between several group categories as discussed. However, these differences occurred were in passive learning behaviors (e.g., discussion viewed), not active learning behaviors (e.g., discussion created). The frequencies of passive actions were higher in most cases. This finding is in line with research showing that 90% of students were passive learners and bystanders (Qu & Chen, 2015).

6 Limitations of the Study

This study is limited in that the survey was given out anonymously, and due to voluntary nature of the survey, not all participants took the survey. Therefore, the data for this study was limited to those who completed the survey. Additionally, given the anonymous nature of the surveys, in order to match participants' usage data and their survey responses, we used participants' IP addresses which were traced to a computer but not a person. This reflects the challenges of analyzing log file data. On the one hand, log data provides a more truthful picture of how users access various components of a computer system. At the same time, matching user characteristic data with their behavioral patterns anonymously remains to be a challenge for researchers who are interested in making sense of log data. Finally, the findings of this study are confined to the MOOC under study. Readers should not assume generalizability to other MOOCs.

7 Conclusion

There have been increasing interests in recent years by researchers and practitioners in examining and using analytics to support teaching and learning. In this study, we investigated the analytics of the participants in a MOOC designed for working professionals. While the results of this study provided additional evidence to support previous research, a few findings are shown to merit additional attention. Most importantly, extrinsic motivation factors are important for MOOC participants, especially working professionals, who seek to learn new knowledge and skills from MOOCs on contemporary topics. Given high dropout rate typically happens during the first 2 weeks, MOOC instructors should consider providing some interventions or incentives to motivate participants to continue. Future research should further examine the usage patterns by those extrinsically and intrinsically motivated. We hope this study offers useful insights for MOOC instructors and designers as they create and offer MOOC courses.

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Chapter 16
Learning Analytics Leading to Remote Invigilation for eTests: A Case Study

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1 Introduction

Online education is growing in popularity; platforms such as EdX are testament to this (Vioreanu, 2018; Woldeab, Lindsay, & Brothen, 2017; Yu & Hu, 2016). Students often perceive that the workload of an online course will be less rigorous than in a classroom setting, a perception that is not supported in the literature (Brocato, Bonanno, & Ulbig, 2015). The perception in academia is that traditional face-to-face courses can be put online with little to no modification, but this is also incorrect (Harris & Parrish, 2006; Porter, Pitterle, & Hayney, 2014). Courses must be altered to accommodate the affordances and limitations of the online environment, especially in regard to assessment. In the hurried transition to the online environment, only certain assessment types or selected aspects of assessment have migrated, while others have been largely ignored. Consequently, eAssessment is dominated by the multiple-choice question (MCQ) format which can be 'marked' automatically within the learning management system (LMS), while open-ended response questions are generally unused. Some may consider electronic submission of text-based assessments (e.g. via text-matching software) to be a form of eAssessment. However, both of these approaches to assessment have inherent risk to academic integrity or jeopardise the assurance of student learning. In the rush to capitalise on flexibility for learners and thus to attract new students, higher education providers have willingly accepted compromises. Increasingly, these compromises have begun to erode the credentialing of student learning, which arguably is the key function of the modern university in the information age where knowledge is readily accessible.

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eAssessment, in its current dominant form of largely MCQs presented via a LMS test/quiz tool, certainly has its place within the learning landscape. When used appropriately, the tool, which is easily understood by the majority of students and academics, offers good opportunity for students to milestone their learning progress. Thus it is most suited to formative or low stakes summative assessments. However, when the function of the assessment is medium to high stakes, the inability to control the test taking environment and the student's behaviour during a non-invigilated online test creates unacceptable risk to the integrity of the assessment and assurance of diligent study and genuine study success.

During the early 2000s, the webcam has been commandeered as a window into the test taker's environment. This combined with the ability of computer systems to record different input sources, such as what is displayed on screen, ambient sound via built-in microphones, and keyboard or mouse interactions, a number of 'surveillance' type approaches have emerged. These approaches, however, have significant technical and practical limitations (James, 2016). A key limitation is cost. Some approaches have attempted to overcome technical limitations of the built-in web cameras by requiring students to use specialised camera devices with 360° panoramic views; however, access to and cost of these devices is prohibitive in most circumstances. The cost to institutions to license, integrate, and support remote invigilation software is significant and must increasingly be evaluated in terms of the cost/benefit ratio. This cost has largely been passed on to the student in North America, whereas within Australia institutions are responsible for this cost. A hidden institutional cost that must also be considered is that of staff time to monitor the recordings and data collected and to investigate and process suspected breaches of academic integrity. Given the limitations imposed by the acceptance of built-in cameras to reduce overall user costs, the ratio of false-positive identifications of suspect behaviour is high and may result in significant staff workload.

One of the biggest barriers to this technology has been staff and student resistance. Student resistance may be something of a white elephant, as the use of this technology can be written into the course requirements such that non-invigilated assessments will not be accepted. However, this requires institutions to ensure that students have the facilities and resources available to use the technology. Staff resistance is another matter, as in a university environment where the pressure on academics is constantly increasing (Papadopoulos, 2017), adding the review of videos to ensure academic integrity for online students is difficult (Garrison, Anderson, & Archer, 1999; Gregory & Lodge, 2015).

Remote invigilation is becoming an increasingly popular educational approach. One company, Software Secure Inc., has licence agreements with over 200 institutions (Davis, Rand, & Seay, 2016). The authors of this study however found third-party services to be cost prohibitive and therefore decided to develop a solution in-house. Compared to other identity-verifying alternatives, e.g. optic retinal scan, fingerprint scans and keystroke pattern analysis (Jortberg, 2010), webcams coupled with a browser-based plug-in are less costly and complex. Moreover, unlike other techniques, webcams can place a virtual teacher in the presence of the student, creating a greater sense of being part of a learning community.

1.1 Case Structure

Research has shown that ensuring online students are adequately invigilated when completing eTest in their own time is problematic (Karim, Kaminsky, & Behrend, 2014). It is also difficult to ensure academic integrity for student cohorts located in different regions and time zones without some form of remote invigilation. Recent developments in remote invigilation technology may help to better ensure assessment integrity for online students, which has not previously been available (Davis et al., 2016; Karim et al., 2014; Phillips & Lowe, 2003; Schaffhauser, 2017). Hence, this research provides an account of a proof-of-concept study examining the use of a browser-based plug-in to remotely invigilate students' online tests.

This case begins with an overview of the course, Business Capstone, and first use of eTest learning analytics amongst an internal study mode cohort (Table 16.2). This prompted the examination of internal compared to external results (Table 16.3). Learning analytics data gathered successively was used to build a body of evidence suggesting that online students were potentially engaging in academic misconduct. This data included average weekly eTest scores, overall average eTest scores, a benchmark assessment score and study mode comparisons. The case shows how learning analytics data evidence raised suspicions to the point where action had to be taken and a remote eTest invigilation trial commenced, wherein year on year eTest scores (with/without remote invigilation) are compared to the internal on-campus cohort.

Detail is provided on the problem of academic misconduct and the use of learning analytics to help resolve the issue. The case study highlights some of the challenges faced, explains the technological development process and shares details of the trial-and-error process. Furthermore, it examines the staff perspectives in terms of time, effort and organisational requirements and provides information about the student perspectives in terms of their usage and comfort with the technology, with the aim of highlighting the staff and student perspectives for using this sort of technology for online assessments, now and into the future.

2 The Vehicle

Business Capstone is Curtin University's Bachelor of Commerce capstone unit. The unit is owned and run by the School of Marketing and is a common core unit, meaning all commerce students must complete the unit, regardless of major (Accounting, Business Law, Economics and Finance, Information Systems, Management, Marketing). The unit is in all commerce major study plans in the final study period (semester/trimester); however, it can be taken in the second last study period. The unit has two prerequisites: (1) completed 400 credit points (equivalent to 2 full years of study) and (2) completed Communication in Business, a first year common core unit. The unit has three study modes: internal on-campus (Perth, Australia; Singapore; Miri, Malaysia; Mauritius), fully online, and Open Universities Australia (OUA).

Table 16.1 Business Capstone course overview

Seminar	Content
1	Introduction and overview
2	Personal and team dynamics
3	Governance and strategy
4	Accounting, finance and economics
5	Marketing, production, Research and Development
6	Human resource management
7	Labour negotiations and ethics
8	Management
9	Business information systems, supply chain and logistics
10	International business
11	Business sustainability and resilience
12	Company presentations and conclusion

The unit runs in the flipped teaching mode; students have a 2-h weekly seminar (instead of 3 h for non-flipped units) which they must attend regardless of study mode. Students are expected to come to class fully prepared to participate in the unit, having viewed/read the iLecture, pre-readings and associated videos for that week.

The aim of Business Capstone is to give all commerce students an understanding of the different disciplines of business and of how they interact. With this, the lecture content is broken into different business disciplines each seminar, with the exceptions of seminars 1 and 12, across the 12 seminar teaching period. Table 16.1 shows the breakdown of Business Capstone's content coverage.

2.1 *eTests*

The eTest assessments are a series of ten weekly individual multiple-choice electronic tests. Business Capstone uses a 'choose your own eTest' system where, for each week's eTest, students have the option to complete one out of a choice of two eTests, assessing slightly different material from the course. Each eTest consists of ten randomly selected questions (from a bank of 50+ questions per eTest) and is worth 2% of the unit (ten eTests × 2% = 20% total). The eTests are an effective tool to ensure students learn the required pre-seminar material as required by the flipped teaching mode, such as reading of journal articles and watching of specific videos.

Students have 10 min allocated for each eTest (ten questions = 10 min). Students are permitted one attempt for each eTest, and each eTest must be completed in one session. Students are permitted to refer to paper copies of specific material for each eTest and handwritten notes.

2.2 History of the eTest Assessment

The eTests were developed to ensure students attended class fully prepared. Prior to the implementation of the eTests, when the flipped teaching mode was first initiated, students would not do any preparation work (pre-reading/watching) before coming to class, and since the in-class time was reduced from 3 contact h to 2, students would understandably struggle.

This prompted the initial application of a series of ten formative weekly eQuizzes, which were not assessed, and a final summative eTest at the end of the study period. The summative eTest (worth 20% of the unit) would assess the entire study periods material, with questions being drawn from the formative eQuiz data banks. Students were given 30 min to complete 20 questions in the final, summative eTest.

Unfortunately, it was found that since the eQuizzes were formative, the majority of students would not complete them and feedback showed that students did not like having a 30-min assessment with material covering the entire study period. Therefore, a proposal was submitted to change this to be a series of ten weekly eTests, worth 2% each. The university has a policy of every unit containing no more than four assessment items. As a single eTest worth 20% (one assessment) was being transformed into ten eTests worth 2% each (ten assessments), special permission had to be granted for this to occur.

The first study period of weekly eTests was closed book, 15 min eTests with no option to choose. They were also done outside of class. Over subsequent study periods, due to student feedback and review to improve the assessment, the time was reduced to 10 min, eTests were done in class time, they became partial open book, and the 'choose your own eTest' system was implemented.

Another assessment within the course is the written case study report. The case changes every study period; however, the assessment criteria remain the same, so the results are stable. Unlike the eTests, students know the report is submitted to text-matching software. From the students' perspective, to engage in academic misconduct while writing the report poses a higher risk comparted to the eTests. Therefore, the report average is included as a benchmark of how the students genuinely perform. See Table 16.2 which highlights this across a 20-month period in a single campus location.

Of the assessment iterations, the change from the eTests being done outside of class to in class time in 2015 was the most pressing, because it was found that students were getting abnormally high results on eTests yet performing noticeably weaker on all other assessments in the unit, particularly the written report (Table 16.2).

Prior to trimester 3A, 2015 for all study modes, no cases of alleged academic misconduct were reported for the eTest assessment within the Business Capstone unit, as the eTests were done without invigilation, and this was recognised as a serious risk to the integrity of the assessment. From trimester 3A, 2015, to trimester 3A, 2016, all *internal* study modes completed the eTest in class, and a total of 18 cases of alleged academic misconduct (cheating during a test or exam) were reported. In all of these cases, students brought into class cheat notes; printouts of questions and

Table 16.2 Internal study mode eTest with benchmark comparison

Study period	eTest done	Invigilation	Report average (out of 20)[a]	eTest average (out of 20)	Difference
Trimester 1A, 2015	Before class	No	10.65	13.32	13.4% better on eTests than report
Trimester 2A, 2015	Before class	No	11.61	14.25	13.2% better on eTests than report
Trimester 3A, 2015	In class	Yes—In class	11.46	10.16	6.5% worse on eTests than report
Trimester 1A, 2016[b]	In class	Yes—In class	11.16	7.98	15.9% worse on eTests than report
Trimester 2A, 2016	In class	Yes—In class	11.62	9.50	10.6% worse on eTests than report

[a]The report average does not include late submissions
[b]A proportion of eTest material (all Video Business Interviews) were revised prior to this study period, with old videos and questions being deleted in place of a new series of videos and associated question banks

answers of former or current questions of eTests that students who did the eTest without invigilation (prior to trimester 3A, 2015) had taken screenshots and posted the material up on websites, such as www.coursehero.com.

The learning analytics collected to date had proved very useful. Monitoring eTest results by location with/without in-class invigilation and benchmarking against another assessment (where academic misconduct is arguably less likely) led to a suspected academic integrity issue amongst internal students in trimester 1A and trimester 2A, 2015. Since recognising that this was almost certainly occurring at regular intervals (every 4–6 months) the Unit Coordinator of the Business Capstone unit performed online searches for these question and answer pages of the eTest material and requests the website(s) to remove them (if they are US based and abide by the Digital Millennium Copyright Act [DMCA]). To date, this has resulted in six takedown requests with between 30 and 78 (per request) different web addresses of content (eTest questions and answers, Unit Outlines, course notes) owned by the Business Capstone unit. In each of these requests, the website has complied and removed the offending material within 24 h.

When given the opportunity (trimester 1A and trimester 2A, 2015), internal students cheated. That much is clear. The solution was to hold all eTests during class time with an invigilator. But what of online students? With no invigilator, were they behaving like their internal counterparts? The authors' attention now turned to the online study mode.

For the online study modes (both fully online [hereto referred to as online] and OUA), Business Capstone requires attendance at a 2-h synchronous online seminar every week of the study period. Thus, completing the unit in the online mode had parity with completing it internally, with the exception of attending a virtual classroom on a computer as opposed to a physical classroom. However, one major differ-

Table 16.3 Comparisons for internal verses online[a]

Study period	Study mode[b]	Invigilation	Report average (out of 20)[c]	eTest average (out of 20)	Difference
Semester 1, 2016	Internal	Yes—In class	11.91	11.48	Online performed 3.5% better on eTests than internal
	Online	No	11.64	12.18	
Semester 2, 2016	Internal	Yes—In class	12.48	11.65	Online performed 0.8% worse on eTests than internal
	Online	No	12.11	11.49	

[a]Tables 16.2 and 16.3 pertain to two different student cohorts in different locations within Australia
[b]All comparisons between study modes have been analysed via t-test and are significantly different at 0.000
[c]The report average does not include late submissions

ence was that online students completed their eTests before the online seminar and were not invigilated since the instructor did not have the technology available to invigilate the assessment virtually for all online students synchronously. Therefore, prior to the remote invigilation trial taking place (semester 1, 2017), online study modes were at greater risk of assessment integrity breaches compared to face-to-face modes of study due to a lack of invigilation. This discrepancy and risk to the integrity of the online assessment caused concern, since a student that is actively looking to cheat on the eTest assessment can do so without fear of retribution in the online study mode.

In semester 1, 2016, online students performed 3.5% better on eTests compared to their internal study mode counterparts (as seen in Table 16.3). This result was counter to the report average, and indeed the norm, as it has been found that online study mode students generally perform worse on all assessments for a number or different reasons such as parenting duties and full-time work schedules (many students choose online study due to their full-time job or parental responsibilities) and the lack of physical interaction. The analysis of this data led to the theory that online study mode students scored better on their eTests through cheating due to a lack of assessment invigilation (Carstairs & Myors, 2009). The trend was investigated further in semester 2, 2016 but was not shown to continue. Still, given the trimester results (Table 16.2), the possibility of academic misconduct amongst online students was still very strong.

In early 2017, an opportunity was presented to trial a remote invigilation system, which had the possibility of creating equity between online and internal study modes. The use of the remote invigilation system for the eTest assessment allows invigilation for online students, regardless of their location. The online students of Business Capstone already required a webcam and microphone for the unit to effectively complete the other assessments, so there was little that had to change initially to include invigilation in the unit. The fact that the unit already had ten separate, weekly eTests of just 10 min duration also made it a perfect choice for testing and improving the invigilation system.

3 The Technology

A chance meeting at a conference by some of the co-authors led to Curtin University and the Engineering Institute of Technology (EIT) collaborating on a remote invigilation system proof-of-concept study. EIT had been developing and using the software within their courses for a few years and were eager to share and collaborate. Curtin University had never used the software before and, with assistance from EIT, are implementing it in a large-scale environment, bringing with it rigorous market testing and potential commercialisation possibilities.

The Business Capstone unit was chosen to test the system implementation. The team was assembled for the first time in February 2017 where the requirements were discussed. The first challenge to overcome was integration into the LMS: EIT uses the Moodle platform, whereas Curtin uses Blackboard. EIT proposed that the software remain browser-based, as the Google Chrome internet browser has features to facilitate this, making the software lightweight, and easy to activate on restricted corporate networks (Engineering Institute of Technology, 2017). This is unlike most competitor offerings whereby a software package must be downloaded and installed by the student onto their personal machine. Browser-based extensions require a small plug-in file to be downloaded into the browser itself.

3.1 Functionality Overview

The remote invigilation software was designed to monitor the audio, video and screen of students' work environment during online tests and automatically flag behaviour that may show academic dishonesty. The application needed to be relatively nonintrusive, easy to use for students and easy for academic staff to assess and manage afterwards.

EIT upgraded their existing invigilation module (Engineering Institute of Technology, 2016) to an Angular 2 (at the time of writing) single-page application that is incorporated into Google Chrome as a stand-alone plug-in/extension. This stand-alone plug-in is able to record for several hours and, upon completion of the test, upload the recorded data to the server.

The plug-in's user interface includes four steps asking students for their names, IDs, microphone and webcam access. Furthermore, a screenshot of student IDs are taken, and the student's computer screen is captured. These fields are mandatory to progress to the test.

The stand-alone remote invigilation module integrates into LMS platforms by means of Uniform Resource Locator (URL) detection. When the predetermined assessment is in the browser URL, the extension pops up and starts the invigilation process. The final submission of the test prompts the extension to stop recording and upload the recorded files. This same methodology is used for Blackboard LMS and can be used for other LMS integrations in the future.

Facial presence recognition was implemented to search for instances when a face is not identifiable on the student facing camera. Initially, facial recognition was analysed after the recorded file was uploaded to the server, at which time the system flagged suspicious sections of the recording. Recently, a client side detection library was introduced to indicate to the student their facial recognition status in real time, which is analysed on their own machine rather than on the server.

Finally, the recorded sessions are accessed via a cloud-based password-protected administration and lecturer platform, with review features such as recording and flagged frame summary playback, filtering and session search.

3.2 Implementation

The first major task was to ensure that the remote invigilation system extension was supported in the Blackboard LMS used by Curtin. By using a Chrome extension, as opposed to an embedded Blackboard or Moodle plug-in, the Chrome extension remains LMS agnostic and was found to work successfully in both institutions' LMS.

Fortunately, there was little that had to change within the course itself, as the eTests were already set up for the students, and they required little modification. The main element that required implementation was the instructions for students, as it had to be made clear that this was a requirement of students taking the course and that the Google Chrome browser must be used, and the Curtin University plug-in downloaded into the browser. With this, information was placed in the Unit Outline (the course's legally binding contract) and in the Blackboard LMS.

Perhaps the biggest alteration to the remote invigilation process between the different cohorts of students came in the form of passwords. In the study periods in the first half of 2017 there were no passwords for the eTests for the online and OUA students. This was standard, as mentioned previously, since the students could complete the eTest in their own time before attending their virtual classroom; hence, there was no need to restrict any usage of the eTests.

Consequently, there were no measures in place to force students to use the remote invigilation plug-in in the Google Chrome browser. This offered the opportunity for students to exploit the system. If a student were to use Internet Explorer or Firefox, they could still complete the eTest without remote invigilation. If a student used Chrome and did not install the plug-in, they also could still complete the eTest. This resulted in no recordings being present for some students. While follow-up could be and often was made with students, ultimately this increased the academics workload as the responsibility was currently upon the student themselves to ensure they had the invigilation operational.

This issue was resolved by implementing Blackboard passwords for each eTest in the study periods in the second half of 2017. The remote invigilation software was updated so it could automatically populate the password field in the eTest, after the invigilation started, thereby eliminating the need for staff or students to exchange passwords and ensuring the remote invigilation software is active and in use. Thus, without activating and running the invigilation software, a student would be unable to complete the eTest each week. Each password was a random generation of letters and numbers of varying length, so although students could not see the characters, they could witness the different numbers of characters each week.

This had increased the number of eTest remote invigilation recordings captured but also uncovered another issue that needed to be resolved—students shutting down the software before the recording could finalise and upload to the server. Depending on internet speed (bandwidth), the upload process would take up to 30 s after completion of the eTest. If students closed the invigilation window before the file had completely uploaded, the file would be deleted and would not be recoverable. This meant that while students were being remotely invigilated, staff could not check the recording as the system had nothing uploaded. The solution to this issue was twofold: first to further clarify the instructions, headings and prompts within the software were implemented to make students aware that they must wait for the recording upload to finish (at which time the invigilation window would automatically close) and second to save recording files to a student's computer and allow the software to recommence the upload upon opening the software for the next eTest, thereby saving the recording regardless of when the software is closed. If the recording of the final eTest was not available in the server, the student would be advised to reopen the software and press a button that uploads any stored recordings to the server.

3.3 Outcomes

The technology proved very effective for the course in the proof-of-concept that took place. Table 16.4 shows eTest comparisons for both online and OUA students across a 1-year period without remote invigilation and a 1-year period with remote invigilation. While it is difficult to say definitively the result remote invigilation had on the eTest average, it can be concluded that the numbers are very consistent throughout the periods analysed (with the possible exception of the Semester 1, 2016 standard deviation, but this had the lowest student number cohort).

From this, it could be surmised that the use of remote invigilation, at least for a unit with medium to large student numbers per study period, has no beneficial nor detrimental effect on student grades yet helps ensure academic integrity. This is in agreement with the findings of Karim et al. (2014) and Amanullah, Zaman, Patel, and Mohanna (2013). In Table 16.4, it is of interest to note that the highest eTest average was achieved when they were completed in class time, the 'choose your own eTest' option had no noticeable effect on the eTest average (or if it did it was moderated by the remote invigilation), and the 'choose your own eTest' option resulted in students completing an average of 12.4 eTests per semester, compared to an average of 9.7 eTests per semester without it. The difference between the eTest average and the Report average was never more than one grade point, or 5%.

Table 16.4 eTest comparisons

Study period	eTest done	Type of invigilation used	Number of students[a]	eTests completed	eTest average (out of 20)	eTest standard deviation	Report average (out of 20)[b]
Semester 1, 2016	In class	In class	75	740	12.26	0.112	11.55
Semester 2, 2016	Before class	None	125	1184	11.70	0.085	11.82
Semester 1, 2017[c]	Before class	Remote	94	1186	11.67	0.088	12.67
Semester 2, 2017	Before class	Remote	98	1192	12.19	0.084	12.94

[a]The number of students includes online (semester) and OUA (study period)

[b]The report average does not include late submissions

[c]This study period saw the introduction of the Choose your own eTest option, allowing students to choose the material they are assessed upon, as well as allow them the option to complete both eTests in which case the higher score will be recorded

The use of the remote invigilation software did result in the capture of the first case of academic misconduct in the units' online teaching formats. This occurred in semester 2, 2017 where a student was attempting both of the seminars eTests in a single sitting. The student would (1) complete eTest A, (2) screenshot their eTest page, (3) go and check the answers and mark a tick or a cross upon the screenshot image and (4) complete eTest B with these images as unauthorised help. In this case, the screenshots did not help the student perform any better on their second eTest, as questions were randomly selected from a bank of 50+ questions per eTest, meaning the student did not see any of the same questions twice. Nonetheless, as this was discovered, it was put through the university's process for academic misconduct. Needless to say, this was an excellent result in less than 1 year of usage and shows the importance of the technology for ensuring academic integrity going forward.

The analysis of learning analytics has been crucial in getting the project to its current state and will be necessary going forward. Learning analytics provide important data points for making the technology effective, efficient and user-friendly, as well as providing important justification for the project (Amigud, Arnedo-Moreno, Daradoumis, & Guerrero-Roldan, 2017). Without the initial learning analytics data, it would have been more difficult to justify the project, as it was through the analysis of this data that it was found there was a problem. The analysis of the proof-of-concepts' first year of data also helped highlight issues, such as the lower than expected recording uploads, which has resulted in solutions developed to fix these issues for the future.

The learning analytics of the technology will need to be closely monitored as the project continues and expands, especially as the proof-of-concept is turned into a trial phase whereby more units are approached to use the remote invigilation. With more units comes additional assessment types, thereby allowing for a greater scope of data which could be used for analysis. The learning analytics within remote invigilation has huge potential to uncover more than just academic integrity issues.

4 Student Perspective

With the introduction of anything new, there will always be some form of student resistance until the practice becomes commonplace. In regard to the eTests, it was also important to ensure students felt no more or less stressed while completing the assessment. So it did surprise the authors that throughout 2017, there were no issues or complaints coming from students about the use of remote invigilation at the start of the study periods; students simply accepted the fact ($n = 192$). However, feedback was received at the end of the course. It came through two channels: (1) a research-based questionnaire created specifically for this purpose and (2) the university's general unit feedback questionnaire. Both channels were anonymous and optional for students to complete but had chances to win prizes as motivation.

The research-based questionnaire included the following questions:

- Before you participated in the project, please describe how you felt about the idea of being remotely invigilated.
- After you participated in the project, please describe your level of comfort in relation to being remotely invigilated.
- How has your attitude towards remote invigilation changed over the course of the unit?
- How effective do you think remote invigilation is for discouraging cheating?

While the general unit feedback questionnaire included:

- The learning experiences in this unit help me to achieve the learning outcomes.
- The assessment tasks in this unit evaluate my achievement of the learning outcomes.
- I make best use of the learning experiences in this unit.
- Overall, I am satisfied with this unit.

Some issues arose at the end of the course when students were given the opportunity to provide feedback. The instructions for students were one of the biggest causes for concern; feedback after the first cohort of students that used the remote invigilation system (semester 1, 2017) indicated that the instructions document was not clear enough. While the instructions were clear on getting the remote invigilation operational, they were not clear on issues such as who would be viewing the recordings, where would they be kept and for how long will they be kept. This is in line with the findings of Lilley, Meere, and Barker (2016). In the age of information technology we live in, this detail is expected by students to ensure that their confidential information is not being compromised. This was revised and improved by adding additional information into the instructions document for the second study periods in 2017. A set of frequently asked questions (FAQs) were also created readdressing some of the information in the instructions document (in case it was missed) and adding additional questions and/or concerns that were raised. Surprisingly, further feedback from the second cohort of students showed they still wanted improvement in this area, although more focused on information security. This was developed and clarified for the next study period in 2018 after seeking clarity around the university's IT and data retention policies.

Students generally understood the purpose and need for remote invigilation, as was addressed by some comments from students. This is a good sign, as it shows that students recognise the importance of this technology to ensure that everyone is on the same playing field. However, the fact that they had come through at least 2 years of their degree and then in a final year unit to be told they must be remote invigilated was concerning for some students, but this is something that, for the most part, is unavoidable. As the proof-of-concept expands to a trial, and then onto a university-wide rollout, it is anticipated that these concerns will dissipate.

Students were generally comfortable using the remote invigilation. Students were being recorded in their workplace, kitchen, lounge room, lecture theatres, in bed and even in a car. It became clear that during a 10 min eTest, the students focus needed to be maintained on the test, not anything else around the student. As mentioned previously, the concerns were primarily around the security and privacy of the data, as opposed to concerns getting the plug-in working or why it was being used.

5 Staff Perspective

The staff perspective may well be the most important consideration in using this technology, as without staff believing in and supporting the process it will never work as it is designed. The pressure and workload on academic staff is constantly increasing (Papadopoulos, 2017), so the addition of another step in the assessment grading process may be met with some resistance. There will always be some staff members that are very eager to use this technology to ensure the academic integrity of their assessments within their unit for online students. However there will also be staff at the other end of the spectrum, who are hesitant and resistant to change and ignore any potential breaches of academic misconduct rather than using a potential solution that may increase their workload. In this way, institutional readiness plays an important role (West, Luzeckyj, Searle, Toohey, & Price, 2018).

The good news is that the technology is easy to use, and once adequate processes are in place, the workload becomes quite minimal. The initial setup of integrating the remote invigilation into a course will take an hour or two; this includes putting links to the remote invigilation plug-in into the LMS, linking/creating instruction sheets on downloading and/or using the plug-in, and creating a demonstration eTest (if not already available) so students can verify the plug-in works on their computer as expected before any real eTest takes place. The setup of integrating the eTest back into the remote invigilation plug-in is very quick, as all that is required is an eTest name, web address of the eTest from the LMS, time of the eTest and LMS password of the eTest.

The review time required for staff will vary according to the time of each eTest and the number of eTests in a given study period. To focus on the example within the case study given, 10 min eTests were used; each eTest required the staff approximately 1 min per student to review their submission. If it was found that students were not following the specified rules, for example, had headphones on or the camera was not adequately showing their face, additional time was required for follow up with the student.

The time required for student queries or concerns was lower than anticipated in our trial. As mentioned earlier, students accepted the fact that they had to use the remote invigilation as it had been written into the course documentation. In semester 2, 2017, when the plug-in was refined and did not require updates during the study period, there were only a handful of emails relating to the remote invigilation, and these primarily occurred due to students not attending the online class or reading the documents. The emails that were received could be answered with a standardised email, asking questions such as ‘are you using the Google Chrome browser?’, ‘have you downloaded the remote invigilation plugin?’, and ‘have you completed the demonstration eTest?' The time required for responses to student queries would be less than 1 h per study period.

Overall the effort required for a staff member is fairly marginal, as once the documentation has been created, the rest of the setup is very minimal. The review of the recording for each eTest actually allows a wonderful insight into students' behaviour during eTests and can allow staff to improve their teaching and/or assessments to help ensure study success. For example, the remote invigilation actually allows a window into the students' life when conducting an eTest; students quite quickly get used to being recorded, and assessing students' reactions to certain questions within an eTest was insightful. A quick meta-analysis of this data could prove to be very interesting and would draw back to the advantages of using learning analytics to support study success. These types of learning analytics provided by remote invigilation allow a shift from broad, numbers based, quantitative type data analysis to a more real-life, personal, qualitative type analysis to be done.

6 Discussion

Through the data gathered and analysed over numerous study periods and campus locations, it highlights that learning analytics has played an important role in the assessment and review process. Remote invigilation as a field of research is still in its infancy, so there is much more work to be done to gain a complete understanding of the benefits and drawbacks of the technology. However, it is something that will be gaining momentum and popularity as institutions look for ways to better assure academic integrity during this transition to the digital educational economy.

From a student perspective, online education allows them to study at their convenience, fitting around their work and other obligations which may not be otherwise possible (Woldeab et al., 2017). Jefferies et al. (2017) state that online invigilation 'can be no more stressful for assessments when taken in their chosen personal environment' (p. 221). That is not to say any form of test or exam is not stressful. Rather the point is that remote invigilation should not make them any more stressed than in a physical environment (classroom or exam hall). It should be noted that the majority of concerns students have had with the software in this case have been addressed to date, and continual monitoring of learning analytics will ensure this going forward. The aim here is to improve genuine study success specifically for students who choose to study online.

From a staff perspective, there are two schools of thought regarding the uptake of this technology: (1) implement it now while there is time to modify assessments and analyse the learning analytics or (2) wait until it becomes an institution requirement (which in some cases may never occur). Jefferies et al. (2017) note the practical issues with the software technology are still substantial and 'must receive ample attention because the procedures and technologies currently result in too many flaws and failures and backup procedures are not clarified' (p. 227). The authors believe their remote invigilation software to be very effective in the context of this case but recognise that further testing and analysis of data is required before their institutions, let alone any others, have a mass rollout of the technology.

It has to be acknowledged that other forms of remote invigilation exist in the market. One such form different from the method in this case study is the use of live remote invigilators. Other studies have examined these in detail (e.g. Jefferies et al., 2017; Woldeab et al., 2017) and found live invigilators (in an online context) to be distracting to students. The authors' remote proctoring software seems much more capable and user-friendly for the purpose it was used for in this case study than some other providers in the market, such as that researched by Woldeab et al. (2017).

6.1 Limitations and Future Research

It is worth noting some limitations within this case study. This case has only discussed one assessment type (MCQ eTests) in one course type (business unit); hence, the authors do not consider the results generalisable. It is hoped, however, that this example of using a variety of learning analytics to uncover a problem will stimulate others to do the same, in any context. The result in this example, being remote invigilation, is no silver bullet; ongoing analysis of the learning analytics must be done to provide a stronger case for genuine study success.

A further limitation is that the unit of analysis is the student, specifically how they behave in a test environment. The remote invigilation solution to the problem does not provide the ability to know what the student is actually learning or what they are doing while they learn. The style of the study is behaviourism, (in this case the very end of the learning process), which clearly has its place, but is not without its critics (e.g. Siemens, 2005).

The possibilities for future research in this field are enormous, as the authors are only just scratching the surface of what remote invigilation can do. Further development of countermeasures, intelligent flagging and alternative test types (non-MCQ) will be investigated as the proof-of-concept progresses to pilot and commercial implementation.

In regard to learning analytics, student behaviour during an online test can be examined (calm-anxious, relaxed-confused), as well as time taken for online tests (and how much this varies depending upon test type) or even time to complete specific questions. The location of where students choose to complete the online tests would make an interesting analysis, as well as the time of day/night.

A trial could also compare results with an expensive third-party invigilation service on the same eTest assessment to see what happens to the eTest results. That would permit three data points to compare; no invigilation, invigilation via the Chrome plug-in and invigilation via more complex methods (e.g. biometrics, eye/fingerprint scans, key stoke analysis). Analysis of this dataset could analyse if students are more or less content with the third-party service. Further answers could be gained to the questions of whether third-party services create even greater internal/online parity, and whether third-party service catch more cases of academic misconduct.

7 Conclusion

The use of learning analytics helped justify the creation of a browser-based plug-in to remotely invigilate online students while completing an eTest. The analysis of the learning analytics data acted as a warning system which leads to some real concerns that would not be unique to this University. Hence the case study explaining the year of rapid development between EIT and Curtin provides a simple, cost-effective and reliable tool. This tool helps ensure academic integrity by remotely invigilating students while they take an eTest thereby providing equity between the internal and online study modes of the unit and promoting study success.

Work on the project will continue into the future, with a list of further improvements for students and for staff constantly being developed. The proof-of-concept will be expanded into a trial in the second half of 2018, with the potential for commercialisation after this. One way or another, universities are going to have to address the issue of increasing online student numbers/assessments and the inherent difficulties they bring with regard to academic integrity and the greater potential for academic misconduct.

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Chapter 17
Epilogue: Future Directions on Learning Analytics to Enhance Study Success

Dana-Kristin Mah, Jane Yin-Kim Yau, and Dirk Ifenthaler

1 Introduction

Enhancing student success in higher education has been a crucial issue for many years. Learning analytics as an emerging educational field show promise to improve learning and teaching in higher education and thus increase student retention. Students' data is captured when they interact with digital learning environments, such as learning management systems, mobile devices, and social media. Accordingly, the expectations towards learning analytics to predict student success, identify students at risk, and provide personalised feedback and academic support services are very high (Ifenthaler, 2015; Long & Siemens, 2011).

This edited volume presents a broad collection of work and findings on how educational data contribute towards successful learning and teaching scenarios. Overall, this edited volume features chapters focusing on theoretical foundations, technological frameworks and innovations, issues and challenges for implementing learning analytics systems, as well as case studies, empirical research findings, and examples of higher education institutions, which adopted learning analytics.

This epilogue provides an analysis of the previous chapters with major themes that have emerged. Moreover, this chapter presents ideas for future directions on learning analytics and shall serve as a platform for further discussion and dialogues about enhancing student retention in higher education.

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Firstly, we provide an overview of learning analytics in higher education. Then, we discuss four key themes: the first theme is acceptance and competence for the implementation of learning analytics, the second theme is personalised learning and early interventions, the third theme is data privacy and ethics, and the fourth and last theme is technical considerations. We conclude with a discussion of implications and future directions on using learning analytics for supporting study success.

2 Learning Analytics to Enhance Study Success

One objective of learning analytics is to construct predictive and prescriptive models in order to identify students at risk of failing a course and who are thus more likely to leave the institution prior to degree completion (Ifenthaler, 2015). In this regard, learning analytics are used as an early warning system, which provides students with personalised feedback and information about academic support services to help them to improve their skills and therefore enhance student success (Mah & Ifenthaler, 2017). Prominent examples for learning analytics systems include course signals by Purdue University in the USA, predictive analytics at Nottingham Trent University in the UK, or personalised adaptive study success (PASS) by Open Universities Australia (Ifenthaler & Schumacher, 2016). Providing students with meaningful real-time feedback and academic support is crucial for successful studies (Tinto, 2005). This may be particularly relevant for the first year in higher education, as students often decide to leave the institution within this period (Mah & Ifenthaler, 2018). Thus, many studies and conferences such as the 'European First Year Experience Conference' address this relevant period, showing its importance for higher education institutions.

Study success includes the successful completion of a first degree in higher education to the largest extent and the successful completion of individual learning tasks to the smallest extent (Sarrico, 2018). The essence here is to capture any positive learning satisfaction, improvement, or experience during learning. As some of the more common and broader definitions of study success include terms such as retention, persistence, and graduation rate, the opposing terms include withdrawal, dropout, non-completion, attrition, and failure (Mah, 2016). Learning analytics show promise to enhance study success in higher education (Pistilli & Arnold, 2010). For example, students often enter higher education academically unprepared and with unrealistic perceptions and expectations of academic competencies for their studies. Both the inability to cope with academic requirements and unrealistic perceptions and expectations of university life, in particular with regard to academic competencies, are important factors for leaving the institution prior to degree completion (Mah, 2016).

However, rigorous empirical research focusing on the impact of learning analytics on study success and student retention in higher education is still scarce (Ferguson & Clow, 2017). Sclater, Peasgood, and Mullan (2016) provide a review of learning analytics in higher education which identifies promising case studies and their impact on student success. Further, projects like this edited volume or the project 'STELA – Utilising Learning Analytics for Study Success', supported by the German Ministry of Education and Research, aim to capture empirical evidence regarding learning analytics' contribution to student retention and study success in higher education (Yau, Mah, & Ifenthaler, 2018). The broad collection of chapters presented in this edited volume provides valuable insights into theoretical considerations and practical experience on learning analytics.

3 Key Themes Emerging from Current Research

Various perspectives on learning analytics have emerged from the chapters of this book. We identified four major issues in using learning analytics to enhance study success which shall be highlighted and further analysed: (1) acceptance and competence for the implementation of learning analytics, (2) personalised learning and early interventions, (3) data privacy and ethics, and (4) technical considerations.

3.1 Stakeholders' Acceptance and Competence for the Implementation of Learning Analytics

Stakeholders' acceptance and competence regarding learning analytics are crucial prerequisites for utilising this emerging research field in higher education (Daniel, 2015). Overall, numerous learning analytics frameworks have been proposed considering important aspects for developing learning analytic projects and for successful implementation in institutions such as by Scheffel (2017), Ifenthaler and Widanapathirana (2014), or Greller and Drachsler (2012). For example, Leitner et al. (Chap. 6) describe learning analytics challenges to overcome in higher education institutions. With this regard, they present seven main categories for implementing learning analytics initiatives, which include representation and actions, data, IT infrastructure, development and operation, privacy, ethics, and purpose and gain. The latter addresses the stakeholders' perspective on learning analytics and the relevance and the suggestion to provide the highest possible transparency.

Focusing on students, research such as the LAPS project, described by Hinkelmann and Jordine (Chap. 7), shows that many students appreciate the feedback concerning learning process, risk analysis, and additional support offerings. Furthermore, research shows that transparent communication and aspects such as data privacy are important issues for students' acceptance and a successful implementation of learning analytics in higher education institutions.

Issues while implementing learning analytics into existing digital platforms and database systems add another obstacle. Klasen and Ifenthaler (Chap. 4) describe how a prompting application has been implemented into an existing university environment by adding a plugin to the local digital learning platform which injects user-centric prompts to specific objects within their digital learning environment.

For educators, the competence for interpreting the provided data correctly is necessary. They need to know about the underlying algorithms, which usually include variables such as socio-demographics, grades, and activities in the learning environment, as well as about the many reasons that may influence students' progression such as illness or general risk factors for student dropout. Thus, advisors should participate in mandatory consultation workshops to improve this competency (Hinkelmann and Jordine, Chap. 7).

Overall, multiple benefits can derive from using learning analytics in higher education institutions; however, Ifenthaler (2017) reveals that there is a lack of specialised staff with a strong background in learning and teaching as well as in data science for learning analytic projects.

3.2 Personalised Learning and Early Interventions to Enhance Student Success

Personalised feedback provides students with information about their learning performance, their likelihood of being successful in a course, and guidance for support services, helping them to improve their skills. On the basis of the currently available data, students can receive real-time information about their learning, for instance, as just-in-time feedback after taking a test or summative in order to understand learning habits, analyse learning outcomes, or track their progress towards goals (Ifenthaler, 2015). Personalised feedback on their learning status and their risk status may be particularly valuable for first-year students, who are often unsure of what is expected of them in academic terms. Besides, the emphasis on personalised learning is essential due to increasing student diversity. For instance, Chernobilsky and Hayes (Chap. 12) compared nontraditional to traditional student performance in various online course formats. The results indicate that on average, nontraditional students are not succeeding in online courses at the same rate as traditional undergraduate students. Thus, personalised feedback, personalised support recommendations, and early interventions may be very helpful for students, especially in their first year of higher education, to keep on track and thus be successful in higher education (Mah & Ifenthaler, 2017). In the face of growing student numbers, tuition fee costs, and diversification, Arthars and colleagues (Chap. 13) present the a platform (the Student Relationship Engagement System (SRES)), which directly helps teachers to act on data to provide at-scale personalised support for study success.

Hawlitschek, Krenz, and Zug (Chap. 5) emphasise the need of adaption in order to facilitate individualised learning environments and thus to support efficient and effective learning and reduce high dropout rates. In their study, they used learning analytics to identify learner characteristics, which are relevant for dropout rates in computer science courses. Based on their findings, they can automatically detect learners that got stuck in their learning path and apply interventions suited for the different needs of these learners. Similarly, Derr and colleagues (Chap. 8) highlight heterogeneous student groups with different educational backgrounds, knowledge levels, and needs. Their research provides insight into how web-based preparatory courses can support the highly heterogeneous student body in the transition from school education to higher education studies.

3.3 Data Privacy and Ethics

Due to the essential capture and storage of personal data, which is required to facilitate the implementation of learning analytics models and systems, a number of data privacy and ethical concerns have been raised. Initially, these concerns presented huge obstacles and barriers to possible implementations especially due to the new European General Data Protection Regulation (GDPR) that came into effect on 25 May 2018. The GDPR protects persons with regard to the processing of personal data and on the free movement of such data. Under the new law, prior to their personal data being obtained, individuals must give their consent. Institutions utilizing personal data must make it transparent what data is being stored, the purpose of the data being stored, and the duration of storage. These obstacles and barriers to implementations can be overcome with some knowledge and skills required to build successful and transparent learning analytics systems in higher education institutions as seen in various chapters of this book. It is important to note that some countries (such as the USA and Australia) have less strict regulations concerning personal data and theoretically it is simpler to implement learning analytics systems without considerations to what may breach the law.

Examples of data transparency in European countries include Hinkelmann and Jordine (Chap. 7). Their concept includes voluntariness, self-determination, and self-responsibility, respecting individuality, confidentiality, and anonymity. Students are made known that when they deregister from the course for any reason, their personal data will no longer be visible to any user of the system. It is possible to view their personal data and risk analysis only with explicit consent from enrolled students. Students may decide or change their decision at any time regarding their participation. Students receive information via email to inform them how their data is used, the system is presented to students, as well as an information booth (Q & A) once per semester is available to students. The system adheres fully to the GDPR. In the work of Derr and colleagues (Chap. 8), the university's data privacy official gave ethical approval and that participants of their study were informed on the purpose of the study and gave consent to their data being collected, anonymised, and analysed. Interview participants took part voluntarily and were informed that their data would be kept secured and analysed confidentially.

Another example is described by Klasen and Ifenthaler (Chap. 4) where the students are tracked via a pseudonymous hash. This enables a collection of students' data throughout various systems without the necessity to collect further personal data. It further enables to merge this data with other university-known data like demographic data and grades at the end of the semester into a complete, anonymous dataset for further investigation.

3.4 Technical Considerations

The implementations of learning analytics models and systems in higher education institutions are still relatively new and rare. Technical issues that should be considered include the availability of technical staff with the necessary skills and knowledge for system maintenance and the corresponding technological resources (Ifenthaler, 2017).

As Arthars and colleagues (Chap. 13) learnt two important lessons from their study, technology itself plays a role in influencing and shaping teachers' teaching practices, and the way that teachers use the technology may be mismatched with students' needs or expectations. They highlighted three implications for learning analytics practice—(1) address actual needs, (2) start small but provide for growth, and (3) foster communities. (1) The needs of institutions vary amongst each other as well as the needs of the teachers and students within the institutions. Therefore, it is very important to support a bottom-up implementation/approach of learning analytics, which is to support teachers collect and use meaningful data relevant to their pedagogical needs. The benefits of this can include greater workload efficiency in data entry, analysis, and communication with students. (2) Some of their teachers also acknowledged that they found simple functions (such as collecting attendance) to be useful. Allowing simple as well as complex functions in the system is therefore advised to allow teachers to apply functions of their choice and that they are comfortable with. (3) Having a learning and teaching support unit available could make a large difference in supporting staff in using the system and providing support to the relevant areas such as learning design, educational technology, and/or software development expertise (see also Chap. 4 by Klasen and Ifenthaler).

4 Future Directions on Learning Analytics

On the basis of the previous chapters, many areas for future research and future directions can be identified. Overall, more longitudinal research is needed to provide insight into how learning analytics impact learning and teaching in higher education. With this regard, Wong and colleagues (Chap. 1) emphasise the importance of taking learning theories into account when employing learning analytics in studies to support study success. They conducted a review on whether learning theories were integrated in the utilisation of learning analytics. Their results showed that self-regulated learning, motivation, and social constructivism theories were used in studies utilising learning analytics. However, at present, these studies are mostly correlational and thus lacking experimental and empirical data (see also Chap. 2 by Ifenthaler, Yau, and Mah). Initial work has been conducted on how to facilitate educational research employing learning theories to guide the data collection and analyses of the learning analytics and forms the basis for future work.

Arthars and colleagues (Chap. 13) emphasised the importance of personalising learning support for each individual student and developed a platform utilising learning analytics to fulfil this aim. Precisely, the identified future works include the evolving uses of students' data, the factors that lead to the inclusion and analysis of this data, and enabling teachers to personalise the learning experiences for students. Similarly, in Hawlitschek, Krenz, and Zug (Chap. 5), the identified future research includes improving the detection of error streaks, which are used to analyse the specific attributes of at-risk students. Following this, employment of more sophisticated and individually personalised support, guidance, and assistance can be more successfully utilised, thus forming a good foundation for future directions.

The implementation of learning analytics systems into higher education institutions is not a straightforward process in any domain or country (see Chap. 4 by Klasen and Ifenthaler). Leitner and colleagues (Chap. 6) presented six challenges and possible ways to overcome these forming further research directions in learning analytics. The challenges are as follows: (1) shortage of leadership, (2) shortage of equal engagement, (3) shortage of pedagogy-based approaches, (4) shortage of sufficient training, (5) shortage of studies empirically validating the impact, and (6) shortage of learning analytics-specific policies.

Automated analysis is another important issue for future directions. Due to growing student numbers, personalised face-to-face feedback is challenging to provide. Thus, automated feedback processes derived from learning analytics systems may be helpful to deal with the limited time resources. Bektik (Chap. 9) describes writing analytics that focuses on the measurement and analysis of written texts to improve the teaching and learning of writing. The chapter highlights various challenges and ethical considerations when using automated text analysis based on machines. Machines and human markers should complement each other, with the aim of providing better feedback to students. This perspective is crucial when talking about algorithms, machine learning, and artificial intelligence in general. Online courses become more and more established and thus more data will be available for analyses. Based on the vast amount of student data, advanced learning analytics may identify known but also new student patterns (e.g. through machine learning, deep learning) regarding behaviour, preferences, and study success factors, for instance. Likewise, Hinkelmann and Jordine (Chap. 7) described an automated process (involving three phases – extraction, transformation, and load), which can be utilised in the future to improve the upload of new student and examination data. Additionally, these can be anonymised to protect the students' privacy.

Another future research field may be the use of multimodal analysis (e.g. eye tracking data). For instance, using eye tracking for digital material or online courses, various information can be captured such as view time, preferences, and difficulties. Together with learning analytics data, adaptive and personalised learning content could be generated which may help to provide a personalised learning journey.

5 Conclusion

Learning analytics becomes more and more established in higher education institutions. The expectations in this emerging research field are high, and current research supports its promise to positively impact student retention. The chapters of this edited volume provide in-depth insights and understanding of the current state of utilising learning analytics to enhance study success in higher education. There remain serious challenges and concerns, while more and more higher education institutions embrace learning analytics (Ifenthaler, 2015):

- Not all educational data is relevant and equivalent.
- Learning analytics need to grow as an interdisciplinary field including (but not limited to) learning science, educational psychology, data science, learning design, and computer science.
- Ethical issues and data privacy need to be considered by all stakeholders when building learning analytics strategies for higher education institutions.
- Limited access to educational data and analytics algorithms generates disadvantages for involved stakeholders.
- Continuous professional learning is required for the preparation of stakeholders involved in learning analytics.
- Information from distributed networks and unstructured data cannot be directly linked to educational data; hence, data quality needs to be confirmed before interventions can be provided to stakeholders.
- Technical frameworks and organisational change management need to be in place before learning analytics can be implemented in higher education.
- Learning analytics need to move beyond the collection and analysis of numerical data (e.g. click streams)—A qualitative analysis of semantic-rich data (e.g. content of discussion forums, responses to open-ended assessments) enables a better understanding of learning processes and possible misconceptions.

In sum, learning analytics are moving towards a mature field of research and development. A broader (and system-wide) adoption of learning analytics will provide new testbeds for empirical research. In addition, the growing field of learning analytics also requires experimental and quasi-experimental investigations demonstrating the validity of learning analytics to support learning and teaching as well as study success.

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