Cognitive, Metacognitive and Motivational Perspectives on Learning Analytics

Synthesizing Self-regulated Learning, Assessment, and Feedback with Learning Analytics

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Abstract

Increasingly more students with growing heterogenous background are enrolling in higher education. Due to limited resources individual support is marginal. Furthermore, learning in higher education is evermore facilitated through technology. However, both higher education and digital learning environments are considered to be less structured. Hence, learners need to use strategies to self-regulate their learning processes. Such activities include cognitive, metacognitive, and motivational components, and are considered to take place in three cyclical phases, the forethought, performance, and self-reflection phase. However, learners often do not show such strategies spontaneously. Hence, timely support meeting learners' needs is required. When learners are using digital learning environments they produce trace data. Learning analytics enable to analyze learning behavior and learning environments which can be used for understanding and optimizing learning processes and environments and to support educational decision making.

To receive valid insights and derive appropriate interventions learning analytics need to be grounded in theory on learning, including motivation, assessment and feedback. However, currently learning analytics are lacking this theoretical foundation and empirical evidence. Thus, the overall research question of this thesis is how cognitive, metacognitive and motivational components of learning and theory on assessment inform learning analytics and vice versa. The thesis includes three quantitative studies (studies 2, 3, and 4), and one qualitative study (study 1). To enhance the theoretical foundation of learning analytics the thesis comprises one integrative review (paper 4) focusing on the link of learning analytics to theory on assessment and feedback with regard to self-regulated learning.

As learning analytics should support learning processes and the learners have a central role the first two studies investigate students' expectations towards features of learning analytics. With regard to self-regulated learning potential features of learning analytics were assigned to the three phases forethought, performance and self-reflection.

Learning analytics mostly use dashboards to provide feedback to learners. However, how learners interpret and react to feedback depends besides the quality and level of the feedback also on their individual characteristics such as prior knowledge, attributions or motivational dispositions. Hence, in the third study learners' motivational dispositions such as their goal orientations and their academic self-concept were investigated in relation to their expected support through learning analytics. Furthermore, potential support of learning analytics with focus on enhancing motivation was assigned to the three phases of self-regulated learning.

Many learners have difficulties in self-regulating their learning especially in not particularly structured environments such as higher education or digital learning environments. Hence, instructional means such as prompts are considered to provide additional support. In the fourth study, using a quasi-experimental design, learners were confronted with prompts based on theory of self-regulated learning to investigate how they impact learners' declarative and transfer knowledge and their digital learning behavior plus if trace data can inform learning achievement.

As the collected data need to be interpreted based on theoretical foundation in the fourth paper of the thesis the aim is to synthesize theory on assessment and learning analytics. By integrating current theory on assessment, assessment design, feedback and learning analytics an integrative framework was developed.

Learning analytics might offer additional guidance for increasingly heterogenous learners and support teachers to adjust their instruction to learners' needs and reduce their workload. However, learning analytics are still at an initial level where this thesis adds additional empirical evidence and theoretical contribution to promote learning analytics further. But learning analytics face several limitations and further research especially using an experimental approach is needed which will be discussed further in the concluding section.

Zusammenfassung

Immer mehr Studierende mit zunehmend heterogenen Voraussetzungen immatrikulieren sich in einem Hochschulstudiengang. Aufgrund von begrenzten Ressourcen sind individuelle Unterstützungsleistungen gering. Außerdem wird Lernen in der Hochschulbildung zunehmend durch Technologien unterstützt. Da sowohl die universitäre Bildung als auch digitale Lernumgebungen nur bedingt strukturiert sind, müssen Lernende Strategien anwenden, um ihr Lernen selbst zu regulieren. Diese Strategien beinhalten dabei kognitive, metakognitive und motivationale Komponenten, welche in drei zyklischen Phasen angewandt werden, die Planungs-, Handlungs- und Selbstreflexionsphase. Häufig nutzen Lernende entsprechende Strategien nur unzureichend, so dass zeitnahe Unterstützung entsprechend ihrer Bedürfnisse notwendig ist. Wenn Lernende digitale Lernumgebungen verwenden, produzieren sie digitale Spuren, sogenannte Trace Data. Learning Analytics ermöglichen es, Lernverhalten und Lernumgebungen zu analysieren, um Lernprozesse und -umgebungen zu verstehen und zu optimieren sowie Bildungsentscheidungen zu unterstützen.

Um valide Einblicke in Lernprozesse zu ermöglichen und daraus entsprechende Interventionen ableiten zu können, müssen Learning Analytics theoretisch im Hinblick auf Lernen, Motivation, Assessment und Feedback begründet sein. Derzeit ist diese theoretische Begründung sowie empirische Evidenz von Learning Analytics noch ausstehend. Daher geht diese Arbeit der übergeordnete Forschungsfrage nach, wie kognitive, metakognitive und motivationale Komponenten des Lernens sowie theoretische Annahmen zu Assessments und Learning Analytics sich gegenseitig ergänzen. Diese Arbeit beinhaltet drei quantitative Studien (Studie 2, 3 und 4) und eine qualitative Studie (Studie 1). Um die theoretische Fundierung von Learning Analytics zu ergänzen, beinhaltet diese Arbeit ein integratives Review, welches Learning Analytics mit Theorie zu Assessment und Feedback unter Berücksichtigung selbstregulierten Lernens verbindet.

Da Learning Analytics Lernprozesse unterstützen sollen und Lernende eine zentrale Rolle dabei einnehmen, untersuchen die ersten beiden Studien die Erwartungen von Studierenden im Hinblick auf Funktionen von Learning Analytics. Diese Funktionen werden den drei Phasen des selbstregulierten Lernens zugeordnet.

Learning Analytics verwenden zumeist Dashboards, um Lernenden Feedback zu geben. Aber wie Lernende dieses Feedback interpretieren und darauf reagieren, hängt neben der Qualität und dem Level des Feedbacks auch von ihren individuellen Voraussetzungen ab, wie zum Beispiel Vorwissen, Attributionen oder motivationale Dispositionen. Daher werden in der dritten Studie die motivationalen Dispositionen von Lernenden wie ihre Zielorientierungen und ihr akademisches Selbstkonzept im Hinblick auf die erwartete Unterstützung durch Learning Analytics untersucht. Außerdem wurden die mögliche Unterstützung von Learning Analytics hinsichtlich Lernmotivation beschrieben und den drei Phasen des selbstregulierten Lernens zugeordnet.

Viele Lernende haben Schwierigkeiten ihre Lernprozesse selbst zu regulieren vor allem in weniger strukturierten Umgebungen, wie in der Hochschule oder in digitalen Lernumgebungen. Es wird angenommen, dass Lernhilfen, wie Prompts entsprechende Unterstützung leisten können. In der vierten Studie, die ein quasiexperimentelles Design verwendet, werden Teilnehmende mit Prompts basierend auf Annahmen des selbstregulierten Lernens konfrontiert und es wird untersucht, welchen Einfluss diese auf ihr deklaratives und ihr Transferwissen sowie ihr digitales Lernverhalten haben und ob Trace Data Lernergebnisse erklären können. Da die gesammelten Daten auf Grundlage von theoretischen Annahmen interpretiert werden müssen, hat das vierte Paper das Ziel, Theorie über Assessment und Learning Analytics zu integrieren. Unter Berücksichtigung von theoretischen Annahmen zu Assessment, Assessment Design, Feedback und Learning Analytics wurde ein integratives Rahmenmodell entwickelt.

Learning Analytics könnten zusätzliche Unterstützung für die zunehmend heterogenen Lernenden bieten und Lehrende unterstützen, ihre Lehre den Bedürfnissen der Lernenden anzupassen und ihren Arbeitsumfang zu verringern. Aber Learning Analytics sind noch in einem initialen Stadium, zu dem diese Arbeit sowohl einen empirischen als auch theoretischen Beitrag leisten möchte, um Learning Analytics weiterzuentwickeln. Dabei stehen Learning Analytics einigen Limitationen entgegen und zukünftige Forschung insbesondere experimentelle Zugänge sind notwendig, worauf in der Diskussion näher eingegangen wird.

Not everything that can be counted counts, and
not everything that counts can be counted.

Albert Einstein

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1 Introduction

1.1 Motivation

Enrollment rates in higher education are growing and are related to increasingly heterogenous students with regard to prior knowledge, motivation, learning skills and strategies, or socio-demographic background (Coertjens, Brahm, Trautwein, & Lindblom-Ylänne, 2017; Hommel, Egetenmeier, & Maier, 2019; Tolstrup Holmegaard, Møller Madsen, & Ulriksen, 2017). Not particularly structured learning environments such as in higher education require distinct study skills and are demanding especially for first-year students (Wingate, 2007). High dropout rates in higher education, especially in the first year, are a serious concern with regard to the individuals, the institution and the society (Larsen, Kornbeck, Kristensen, Larsen, & Sommersel, 2013). Hence, providing individual support and feedback to students is necessary. Moreover, early identification of learners who need additional support is crucial to prevent them from dropping out (Cohen, 2017; Colvin et al., 2015; Mah, 2016). However, individual feedback and support are difficult to facilitate in the light of resource constraints and high workload of teaching staff in higher education institutions (Boud & Molloy, 2013; Broadbent, Panadero, & Boud, 2017; Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019).

In addition, digital learning environments are increasingly implemented in higher education institutions (Viberg, Hatakka, Bälter, & Mavroudi, 2018). Not only higher education but also digital learning environments require learners to take over responsibility for their learning processes, and thus demand high self-regulatory skills (Azevedo, Cromley, & Seibert, 2004; Broadbent & Poon, 2015; Cassidy, 2011; Dabbagh & Kitsanas, 2004). Meta-analyses emphasize the impact of learners' study strategies on achievement in higher education (Schneider & Preckel, 2017). Hence, self-regulated learning, comprising cognitive, metacognitive, and motivational components, can be viewed as a relevant theoretical approach for understanding and supporting successful learning processes in not particularly structured learning environments such as in higher education (Cassidy, 2011; Zimmerman, 2001). Self-regulated learners set learning goals, plan, organize, perform, self-regulate, self-monitor and self-evaluate their learning processes to achieve learning goals (Pintrich, 2000; Zimmerman, 2001). As learners often face difficulties to apply suitable self-regulated learning strategies (Azevedo, 2005; Moos & Bonde, 2016; Sonnenberg & Bannert, 2016) interventions are needed such as direct training of relevant strategies or indirectly eliciting known strategies (Bannert, 2009; Boekaerts, 1997; Lehmann, Hähnlein, & Ifenthaler, 2014; Narciss, Proske, & Koerndle, 2007). Such instructional interventions are considered to be more effective when they are aligned with learners' current needs, actions and goals (Molenaar & Roda, 2008; Thillmann, Künsting, Wirth, & Leutner, 2009). However, to gain more detailed insights into learning processes, motivational states or needs as well as learners' reactions to interventions additional and multifaceted data are required.

In addition, digital learning environments are considered to enable the provision of individual support to learners, for example by offering adaptively additional learning resources, scaffolds, self-assessments, and feedback (Azevedo et al., 2004; Bannert & Mengelkamp, 2013; Gašević, Dawson, & Siemens, 2015; Gross, Mokbel, Hammer, & Pinkwart, 2015; Molenaar, Horvers, & Baker, in press). Furthermore, with the advent of digital learning environments possibilities to collect and analyze the data generated through learners using the systems arose (Brown, 2011; Rubel & Jones, 2016; Viberg et al., 2018). When these data are used with focus on understanding and supporting learning processes, this is associated with the term learning analytics (Brown, 2011; Long & Siemens, 2011). Learning analytics use dynamic and static data of learners and learning environments, assessing, eliciting, and analyzing them for real-time modeling, prediction and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). The aim of learning analytics is amongst others to provide adaptive and personalized learning environments offering learners the support they require at the time needed (Aguilar, 2018; Greller & Drachsler, 2012; Ifenthaler & Widanapathirana, 2014; Liu et al., 2017; Maseleno et al., 2018). Simplistically, learning analytics include several iterative process steps (Chatti, Dyckhoff, Schroeder, & Thüs, 2013; Clow, 2012; Colvin, Hardy, Lim, Taddeo, & Trenholm, 2017; Khalil & Ebner, 2015): first data on learners and learning environments from various sources are collected, pre-processed and integrated plus enhanced with other relevant information for the subsequent analyses and visualizations, which are then used to derive interventions and actions to support learning processes or optimize learning environments. Furthermore, the goals pursued with the implementation of learning analytics, the stakeholders involved plus contextual factors need to be considered (Chatti et al., 2013; Greller & Drachsler, 2012; Ifenthaler, 2015; Ifenthaler & Widanapathirana, 2014).

Using constructs related to self-regulated learning seem to be reasonable as theoretical foundation for learning analytics in higher education (Marzouk et al., 2016; Winne, 2017). And vice versa, the various information learning analytics have available about learners and their behavior can serve as a data source for gaining deeper understanding of self-regulated learning processes. Furthermore, self-regulated learning includes the ongoing metacognitive processes of monitoring and generating internal feedback which can be enhanced with external feedback (Butler & Winne, 1995; Winne, 2017). Such monitoring might additionally be supported through the visualizations and recommendations offered through learning analytics (dashboards) (Aljohani et al., 2019; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018). However, generating meaningful results and interventions based on myriads of different data types which need to be integrated from various sources are challenging tasks and need to be guided by learning theory. The integration of diverse snippets of collected evidence on learning performance from different context plus how they can be related to the assessment purposes are discussed in the domain of assessment design. Ongoing assessments over multiple tasks and contexts are preferable for measuring learners' interdisciplinary competencies (DiCerbo, Shute, & Kim, 2016) but also for investigating self-regulated learning. This entails increasing complexity of assessments (Almond, 2010), thus, to validly infer from the assessment data on the assessed concepts, following a principle-based design of assessments is suggested (Mislevy, Almond, & Lukas, 2003). Such approaches might also be capable of supporting the development of valid learning analytics. In addition, the provision of a variety of self-assessments including clear objectives and standards to learners is considered to foster self-regulation (Panadero, Jonsson, & Botella, 2017).

As learning analytics are a relatively new field of research and are at the intersection of different disciplines such as computer science, statistics, and education (Johnson et al., 2013; Romero & Ventura, 2013) a plethora of research gaps demand additional examination. A major issue is that learning analytics are still suffering from lacking empirical evidence of actually supporting learning (Ferguson & Clow, 2017; Viberg et al., 2018), and require theoretical foundation (Colvin et al., 2017; Ferguson, 2012; Marzouk et al., 2016; Wong et al., 2019). Moreover, implementation of learning analytics systems in higher education institutions are predominantly at an initial level (Ferguson et al., 2016; Tsai & Gašević, 2017; West, Heath, & Huijser, 2016) or are focusing on simple analyses such as usage of available resources often without providing direct feedback to the learners (Vieira, Parsons, & Byrd, 2018). Moreover, the identification of valid indicators for understanding learning processes and predicting learning performance is not trivial as they are context-dependent and thus cannot be applied universally similar to the underlying algorithms (Gašević, Dawson, Rogers, & Gasevic, 2016; Greller & Drachsler, 2012; Wilson, Watson, Thompson, Drew, & Doyle, 2017; Winne & Baker, 2013). However, the focus on technical aspects of learning analytics is still predominant whereas pedagogy is not sufficiently considered yet (Macfadyen & Dawson, 2012; Tsai & Gašević, 2017).

Analyzing data without referring to relevant theory does not result in valid interpretations (AERA, APA, & NCME, 2014; Wise & Shaffer, 2015; Wong et al., 2019) and thus cannot guide useful interventions. Hence, within this thesis the focus is on *informative* learning analytics as they are informed through learning theory and vice versa should inform the understanding of learning processes and potentially enhance theory, as well as provide information to the involved stakeholders but are also informed by the stakeholders (e.g., their characteristics, needs, concerns). Thus, the aim of this thesis, using a pedagogical lens, is (a) to promote the theoretical foundation of learning analytics further by integrating theory on self-regulated learning, feedback, and assessment with learning analytics, plus (b) to enhance the empirical evidence of learning analytics. The related overarching research questions plus the specific research questions of this thesis will be described in the subsequent sections.

1.2 Research question of this thesis

As students have a major role in learning analytics as they on the one hand need reveal personal information and on the other hand are recipients of the interventions (Pardo & Siemens, 2014), their perceptions of learning analytics are relevant and need to be investigated already when designing learning analytics systems and interventions (Sclater, 2016). Moreover, pedagogy-based approaches are still lacking in the field of learning analytics (Macfadyen & Dawson, 2012; Marzouk et al., 2016; Tsai & Gašević, 2017; Vieira et al., 2018). However, as the major aim of learning analytics is to support learning by deriving meaningful interventions (Brown, 2011; Clow, 2013; Gašević et al., 2015; Greller & Drachsler, 2012; Long & Siemens, 2011) theory on learning should be an integral part in the field of learning analytics (Ferguson, 2012; Wong et al., 2019).

Furthermore, self-regulated learning is considered to be a relevant theory for learning processes in higher education (Cassidy, 2011) and in digital learning environments (Azevedo, 2005). Hence, the aim of this thesis is to enhance research on learning analytics from a learning theoretical perspective to generate further empirical evidence and promote the theoretical foundation of learning analytics further by investigating:

- Learners' perceptions and expectations towards features of learning analytics with regard to their willingness to use and the perceived learning support through certain features under consideration of self-regulated learning.
- The relevance of learners' motivational dispositions with regard to their perceived learning support through learning analytics.
- How instructional means such as prompts based on self-regulated learning theory support learning and are related to learning behavior, plus if trace data can inform learning performance.
- How learning analytics can be linked to theory on assessment and feedback to increase their theoretical foundation and validity, and to derive meaningful interventions for supporting (self-regulated) learning.

To advance these aims four empirical studies were conducted, three using a quantitative, and one using a qualitative research approach. In addition, a conceptual approach was used to link learning analytics with learning theory.

In sum, the overarching research question of this thesis is how can the cognitive, metacognitive and motivational components of self-regulated learning and theory on assessment inform learning analytics and vice versa. The specific research questions will be described in more detail in the subsequent sections.

1.3 Specific research questions

With regard to the need for further empirical evidence of learning analytics (Ferguson & Clow, 2017; Ifenthaler, Mah, & Yau, 2019), and linking learning analytics with learning theory (Ferguson, 2012; Marzouk et al., 2016), four studies were conducted, learning analytics were related to self-regulated learning, and theory on assessment and feedback in an integrative review. Hence, to be informative, supportive and valid, learning analytics were investigated with focus on

- learners' expectations and perceptions,
- learners' motivational dispositions,
- prompts based on self-regulated learning theory, and
- synthesizing theory on self-regulated learning, assessment and feedback.

Figure 1-1. provides an overview about the research foci and the related studies to advance informative learning analytics including cognitive, metacognitive and motivational perspectives. Furthermore, Table 1-1 gives an overview about the research conducted including the research approach, sample sizes and main foci of interest.

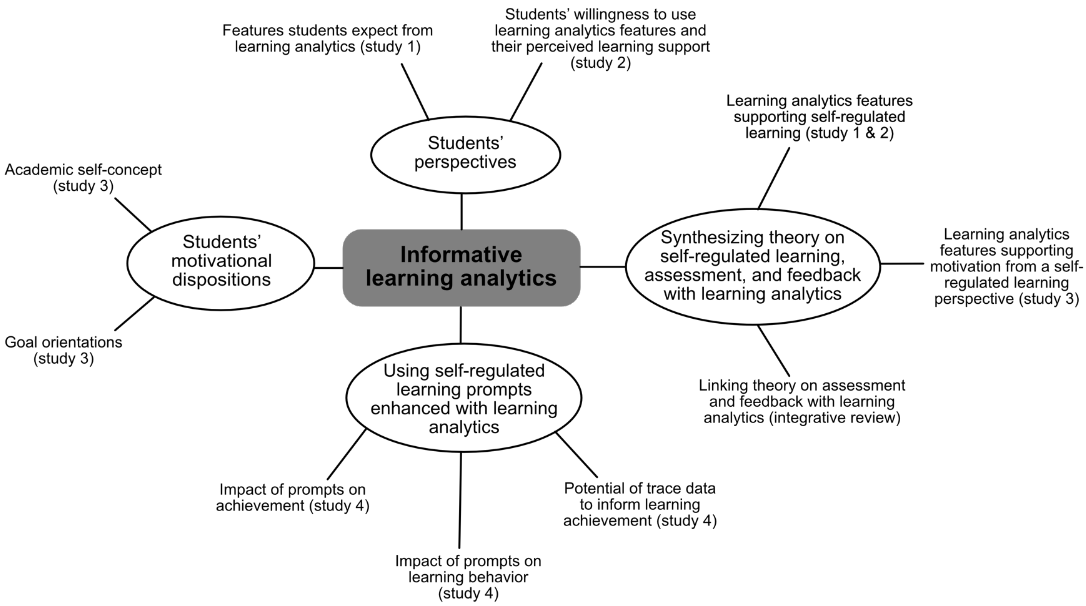

Figure 1-1. Overview of the research foci of the thesis and the related studies

Table 1-1 Overview of papers and research studies included in this thesis

Paper Study	Paper 1 Study 1 Study 2	Paper 2 Study 3	Paper 3 Study 4	Paper 4 -
Reference	Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior, 78,* 397-408.	Schumacher, C., & Ifenthaler, D. (2018). The importance of students' motivational dispositions for designing learning analytics. *Journal of Computing in Higher Education, 30*, 599-619.	Schumacher, C., & Ifenthaler, D. (under review). Designing effective means of supporting students' regulation of learning processes through analytics-based prompts.	Schumacher, C. (2019, accepted). Linking assessment and learning analytics to support learning processes in higher education. In M.J. Spector, B.B. Lockee, & M.D. Childress (Eds.), *Learning, Design, and Technology. An international Compendium of Theory, Research, Practice, and Policy. Cham*: Springer.
Research design	Qualitative and quantitative research approach	Quantitative research approach	Quantitative research approach	Theoretical research
Methods	Exploratory interview study Questionnaire	Questionnaire	Quasi-experimental design	Integrative review
Sample size	$N_{S1} = 20$ $N_{S2} = 216$	$N_{S3} = 802$	$N_{S4} = 110$ $n_{cp} = 30$ $n_{mp} = 31$ $n_{ap} = 28$ $n_{cg} = 21$	-
Main research foci	Investigating students' perceptions of learning analytics features: - Expected features of learning analytics - Willingness to use learning analytics features - Perceived learning support through learning analytics features - Assigning learning analytics features to phases of self-regulated learning	Investigating students' motivational dispositions with regard to perceived learning support through learning analytics: - Relation of goal orientations and perceived learning support through learning analytics - Relation of academic self-concept and perceived learning support through learning analytics - Assigning learning analytics features supporting motivation to three phases of self-regulated learning	Investigating prompts based on self-regulated learning: - Effects of prompts on declarative knowledge - Effects of prompts on transfer knowledge - Effects of prompts over time - Effects of prompts on online learning behavior - Potential of trace data for informing learning analytics to predict learning performance	Synthesizing learning analytics with theory on assessment, and feedback: - Developing an integrative framework based on principle-based assessment design, feedback, and learning analytics - Describing exemplary learning analytics features considering the introduced framework

1.3.1 Students' perceptions of learning analytics features (study 1 and 2)

The first paper (chapter 3) investigates students' perspectives on learning analytics features. To explore which features students in higher education expect from learning analytics an exploratory interview study following a qualitative research design was chosen. The research questions of study 1 were:

- Which features and functions do students in higher education expect from learning analytics?
- How do students think that these features could support their learning processes?

Fifteen of the identified features were used for the subsequent quantitative study investigating students' acceptance to use these features and students' perceived learning support with focus on the following research questions:

- Which learning analytics features are students willing to use?
- Of which learning analytics features do students perceive learning support?
- Do perceptions of learning support, privacy, ease of use and usefulness predict learners' willingness to use a certain learning analytics feature?

In addition, the learning analytics features were assigned to the three phases of self-regulated learning.

1.3.2 Students' motivational dispositions in relation to perceived learning support through learning analytics (study 3)

As motivation is an important driver for initiating and sustaining learning processes the second paper (chapter 4) focuses on motivational dispositions of students with regard to self-regulated learning and digital learning environments, especially learning analytics. In particular, students' goal orientations and academic self-concept were investigated with regard to their perceived support through learning analytics. The quantitative survey study was guided by the following research questions:

- How are learner characteristics such as demographic information and academic characteristics related to perceived learning support through learning analytics?
- How are students' goal orientations related to their perceived learning support through learning analytics?

- How is the academic self-concept related to learners' anticipated support through learning analytics?

Furthermore, the potential support of learning analytics with regard to motivation was described and related to the three phases of self-regulated learning.

1.3.3 Supporting self-regulated learning using prompts enhanced with learning analytics (study 4)

A major aim in literature and research on self-regulated learning is to foster learners' self-regulated learning skills. Thus, in a quasi-experimental study (paper 3, chapter 5) students learning in a digital learning environment were confronted with prompts based on the components of self-regulated learning: cognitive, metacognitive, motivational and resource-related. The following research questions were investigated:

- How do the different prompts support learning performance in a declarative knowledge test and over time?
- How do the different prompts support learners' transfer knowledge and over time?
- Do the different prompts impact students' digital learning behavior in a learning unit as indicated by trace data?
- Can students' academic characteristics and their digital learning behavior in a learning unit inform learning analytics by predicting their learning performance in a transfer test?

1.3.4 Integrating theory on assessment and feedback for designing informative learning analytics (integrative review)

The major aim of the fourth paper (chapter 6) is to analyze how theory on assessment can be integrated with learning analytics to validly infer from trace data on learning processes and use this evidence for supporting learning and instruction, optimizing learning environments as well as educational decision making. Therefore, current perspectives on assessment, feedback and learning analytics were described guided by the following research questions:

- What are current foci and practices of assessment in higher education?
- What are the functions of assessments?
- How should valid assessments be designed?

- How should feedback in assessment processes be provided?
- What are current perspectives on learning analytics in higher education?
- How can learning analytics be integrated with theory on assessment, and feedback for valid analyses, deriving meaningful interventions, and to support self-regulated learning?
- What are the implications, limitations and further research needs with regard to the proposed framework and learning analytics?

Based on these theoretical perspectives an integrative assessment analytics framework was developed and exemplary learning analytics features were described.

1.4 Structure of the thesis

This thesis includes seven chapters and integrates four separate research papers. The first chapter describes the motivation for linking learning analytics with theory on learning and assessment and for investigating them from cognitive, metacognitive and motivational perspectives. Furthermore, the research questions and structure of the thesis are described. The second chapter focuses on the theoretical foundations of the thesis. The concepts include self-regulated learning, with a particular emphasize on motivational concepts. Then, learning analytics and how they are related to self-regulated learning are introduced. As learning analytics collect and analyze data to provide feedback to learners and teachers, theory on assessment is considered as suitable guidance. Thus, use and design of assessments in higher education are described further.

The subsequent four chapters focus on the four research studies and the integrative review. Chapter three includes learners' perceptions and expectations towards learning analytics features (study 1 and 2). Chapter four focuses on learners' motivational dispositions with regard to their perceived learning support through learning analytics (study 3). Chapter five introduces the application of self-regulated learning prompts enhanced with methods of learning analytics (study 4). Furthermore, chapter six presents the conceptual link of learning analytics with theory on assessment and feedback (integrative review). Chapter seven discusses the findings, the implications as well as their limitations and further research needs, and completes with a conclusion of the thesis.

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2 Conceptual foundation of the thesis

2.1 Self-regulated learning in higher education digital learning environments

Learning in general and especially in not particularly structured environments such as higher education digital learning environments demands learners to self-regulate for being successful (Azevedo, Cromley, & Seibert, 2004; Broadbent & Poon, 2015; Cassidy, 2011). At large, theory on self-regulated learning considers learners to be active agents in their learning influenced by external and internal factors but with possibilities of control (Boekaerts & Corno, 2005; Pintrich, 2000b, 2004; Winne, 2001; Zimmerman, 2008). Learners who are self-regulating their learning "set better learning goals, implement more effective learning strategies, monitor and assess their goal progress better, establish a more productive environment for learning, seek assistance more often when it is needed, expend effort and persist better, adjust strategies better, and set more effective new goals when present ones are completed" (Zimmerman & Schunk, 2008, p. 1). Hence, self-regulated learning is considered to include cognitive, metacognitive, motivational, resource-related and behavioral components (Boekaerts, 1992, 1999; Pintrich, 1999, 2000b; Zimmerman & Schunk, 2008). The *cognitive component* includes strategies focusing directly on the learning process such as rehearsal, elaboration and organization (Boekaerts, 1992; Pintrich, 1999; Weinstein & Mayer, 1986), to control cognition *metacognitive* strategies such as planning, goal setting, monitoring, reflection and regulation are used to direct the learning process (Boekaerts, 1992). Metacognition is considered to include knowledge of cognition and regulation of cognition (Flavell, 1979; Schraw & Dennison, 1994; Schraw & Moshman, 1995). The *resource-related component* involves time and effort management, help seeking, seeking for information and structuring the learning environment (Pintrich, 1999; Zimmerman & Martinez Pons, 1986). With regard to the *motivational component* several theoretical concepts are considered to be relevant such as goal orientations, self-efficacy or interest. Strategies for regulating motivation during learning are for example increasing the perceived relevance, interest or value of the task, engaging in cognitive strategies, regulating emotional reactions to task, rewarding oneself or reminding oneself of desired goals (Corno, 1993; Wolters, 1998). The *behavioral component* entails the control of behavioral activities during the self-regulated learning process and includes control of cognition, affect and emotions, the pursuance of intentions or management of the social environment (Boekaerts, 1992; Pintrich, 2000a, 2004). Thus, the behavioral component seems to have some overlappings with the other components but with an emphasize on *setting things into action* and *controlling this behavior*.

Furthermore, it is assumed that learners apply self-regulated learning strategies related to these components within at least three cyclical and recursive but not necessarily subsequent phases: the *forethought phase* (e.g., task analysis, goal setting and planning), the *performance phase* (e.g., learning strategies, monitoring, time management, volition), and the *reflection phase* (e.g., evaluate learning performance against effort and standards, adjust strategies for upcoming learning processes) (see Figure 3-1, p. 47) (Boekaerts, 1992; Panadero, 2017; Pintrich, 2000b; Puustinen & Pulkkinen, 2001; Schmitz, 2001; Winne & Hadwin, 1998; Zimmerman, 2000). However, further research is needed to gain insights into how the different components of self-regulated learning are intertwined and related to learning success (Efklides, 2011).

In more detail, the model of Winne and Hadwin (1998) implies four phases of self-regulated learning which are recursive in any order: (1) *task definition* as learners create their understanding of the task, (2) *goal-setting and planning* for successful task completion, (3) *enacting study tactics and strategies* suitable to the task to reach the designated goals (4) *metacognitively adapting studying* by using metacognitive strategies to adjust current and upcoming learning processes. With focus on the detailed cognitive processes within each of the four phases five relevant components are described using the acronym COPES: (a) *Conditions* which can be internal or external and affecting the task engagement (e.g., cognition, motivation, knowledge, interests, time constraints); (b) *Operations* are the cognitive processes and strategies learners use to deal with the task, they might be observable or not; (c) *Products* as the (un-) observable outcomes produced by the operations (e.g., new knowledge, an essay); (d) *Evaluations* include the feedback on the products that learners create themselves internally or receive from external; (e) *Standards* define the criteria the products are evaluated against. This model particularly emphasizes the use of metacognitive strategies and learners' monitoring activities serving as feedback (Panadero, 2017; Puustinen & Pulkkinen, 2001), the presence of information processing in each phase (COPES) (Greene & Azevedo, 2007; Winne, 2001), plus the relevance of goals for directing self-regulated learning (Winne, 2014; Winne & Hadwin, 2008). Furthermore, Butler and Winne (1995) describe the relation of internal and external feedback to self-regulated learning by referring to this model.

No unique definition or model of self-regulated learning exist, and present conceptualizations emphasize different aspects but do share some common assumptions (Boekaerts & Corno, 2005; Pintrich, 2000b). In this work self-regulated learning is defined as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2000b, p. 453). The definition was chosen as it emphasizes the agency of learners within the learning process who are influenced by their individual goals that might be different across contexts (Pintrich, 2004; Winne & Hadwin, 1998; Zimmerman, 2000). Furthermore, relevant components of self-regulation such as cognition, metacognition, motivation and behavior are included plus external contextual factors which are considered to influence or guide self-regulation. However, not explicitly mentioned are resource-related strategies including social resources learners might use; plus individual characteristics of learners which might serve as constraints and can only be limitedly controlled by the learner (Pintrich, 2000b, 2004). In addition, models of self-regulation assume (Boekaerts & Corno, 2005) that "self-regulatory activities are mediators between personal and contextual characteristics and actual achievement or performance" (Pintrich, 2004, p. 388).

However, a relevant question is why learners are pursuing a certain goal and engaging in learning processes instead of doing something else. As higher motivation is related to increased attention, task choice, effort and persistence (Zimmerman, 2011), motivational concepts have become a crucial facet in models of self-regulated learning and are considered to be closely intertwined (Boekaerts, 1999; Boekaerts & Corno, 2005; Pintrich, 2000a; Schunk, Pintrich, & Meece, 2008; Zimmerman, 2008, 2011). Moreover, regulating cognitive and metacognitive strategies might not be sufficient for initiating and persisting in learning and related processes especially when facing difficulties (Zimmerman, 2011; Zimmerman & Schunk, 2008). Hence, to increase their motivation learners might need to actively regulate their motivation (Winne & Hadwin, 2008; Wolters, 2003a). Motivation can be considered as a process in which learners pursue goals by initiating and persisting in relevant activities to reach their goals (Schunk et al., 2008). Motivation regulation thus are "the activities through which individuals purposefully act to initiate, maintain, or supplement their willingness to start, to provide work toward, or to complete a particular activity or goal" (Wolters, 2003a, p. 190) and thus are in contrast to motivation characterized by awareness and purposefulness. Motivational concepts in the context of self-regulated learning are among others academic self-concept, self-efficacy, goal orientation, attributions, interest, and outcome expectancy (Pintrich, 2004; Schunk, 2008; Zimmerman & Schunk, 2008). At that, sources of motivation such as goal orientations, task values or causal attributions can be precursors, mediators, and concomitant or exclusive outcomes of self-regulated learning (Zimmerman & Schunk, 2008). Within this thesis the focus will be particularly on goal orientations and self-efficacy beliefs in the form of learners' academic self-concept as these concepts are prevailing in the focus of research on self-regulated learning (Wolters, 2003b). Furthermore, relevant models of self-regulated learning consider learners' goals as vital as they initiate and direct self-regulatory actions plus serve as standards for evaluating learning outcomes (Boekaerts, 2011; Cook & Artino Jr, 2016; Duffy & Azevedo, 2015; Panadero, 2017; Pintrich, 2000a, 2000b; Schunk et al., 2008; Sitzmann & Ely, 2011). The literature suggests two overarching achievement goal orientations, performance and learning goal orientation, which are further distinguished into approach and avoidance orientations (Elliot, 2005; Elliot & Hulleman, 2017; Pintrich, 2000a; Senko, Hulleman, & Harackiewicz, 2011) (for further details see section 4.2.1 and Table 4-1). Depending on the context, a certain goal orientation might be more effective than others (Harackiewicz, Barron, & Elliot, 1998). However, especially when facing difficulties, learners' selection of learning goals is competing with goals related to well-being (e.g., ego-protection, safety, social belonging), which is further influenced by situational, contextual, and personal factors (Boekaerts, 2011; Boekaerts & Corno, 2005). Furthermore, self-efficacy or the related academic self-concept are important motivational concepts within the field of self-regulated learning (Sitzmann & Ely, 2011). Both concepts represent persons' perceptions of competences, the academic self-concept with regard to an academic domain and self-efficacy with regard to a certain task (Bong & Skaalvik, 2003). Hence, both concepts are considered to influence learners' strategy use, goal setting, or persistence (Ferla & Valcke, 2009). In summary, the consideration of motivational concepts when investigating self-regulated learning is inevitable.

Learners' level of self-regulation is considered to be relevant for successful learning however, measurement of self-regulation is complex and related constructs are not defined and operationalized consistently (Boekaerts & Corno, 2005; Zimmerman, 2000). Early models and related instruments for assessing self-regulated learning considered self-regulation to be a relatively stable concept independent of the context later advanced by assuming contextual and situational factors to be relevant (Boekaerts & Corno, 2005; Pintrich, 2004). Winne and Perry (2000) distinguish measuring self-regulated learning as an aptitude or as an event: In this regard, the aptitude aims at measuring an overarching representation of learners' self-regulation either decontextualized or related to the context, whereas the event-based measurement focuses on learners' actions with regard to self-regulation at a certain point of time or when dealing with a task and at a more fine-grained and process-oriented level plus over time (Winne & Perry, 2000; Zimmerman, 2008).

Predominantly, self-regulation is measured by applying self-report instruments (Dinsmore, Alexander, & Loughlin, 2008) like questionnaires and interviews such as the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991), the Learning and Study Strategies Inventory (LASSI) (Weinstein, Palmer, & Acee, 2016), the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994) or the Self-Regulated Learning Interview Scale (SRLIS) (Zimmerman & Martinez Pons, 1986). However, self-report instruments face several difficulties such as that the learners need to be aware of the strategies they use or that the answers might be influenced through biases such as social desirability or due to the retrospectivity (Boekaerts & Corno, 2005; Winne, 2010; Winne & Jamieson-Noel, 2002; Winne & Perry, 2000). Furthermore, these inventories tend to consider self-regulated learning to be a relatively stable trait or disposition (aptitude) (Boekaerts

& Corno, 2005; McCardle & Hadwin, 2015; Winne & Perry, 2000). Some instruments are de-contextualized (Dinsmore et al., 2008) whereas other inventories are assuming context-specific self-regulatory activities and the items applied are referencing on a specific course or problem (Pintrich, 2004). Thus, the results on learners' self-regulatory behavior are only valid for this particular context but are considered to portray learners' general learning preferences and self-regulation (Dinsmore et al., 2008; Pintrich, 2004). Another approach of measuring self-regulation focuses on events by tracking learners' behaviors when facing a task and analyzing it to infer on learners' usage of self-regulatory strategies, for example using observations, videotaping, think-aloud approaches or collecting trace data in (digital) learning environments (Bannert & Mengelkamp, 2013; Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; McCardle & Hadwin, 2015; Winne, 2017; Winne & Baker, 2013; Winne & Perry, 2000). With this more processual view on self-regulated learning more fine-grained insights into actual learning processes and behavior over time are possible (Winne, 2017). For example, Dinsmore et al. (2008, p. 406) suggest to investigate variations in self-regulation over time or due to other aspects such as "changing knowledge, interests, goals, and experiences". For increasing validity and providing a more holistic picture a combination of several data sources is reasonable, thus, the processual data should be enhanced with self-reported data to gain insights into learners' perceptions on their learning strategies (McCardle & Hadwin, 2015). Moreover, as self-regulated learning is considered to be goal-directed, Winne (2014) proposes to explicitly integrate learners' goals when tracking their self-regulatory behavior to gain a better understanding of their actions. For example, prompts using single items can be used to collect self-report data during learning processes for example on learners' current goals (Schumacher, 2019, accepted).

However, learners often face difficulties to use appropriate learning strategies which can be supported through different means such as scaffolding, prompting or training (Azevedo et al., 2004; Azevedo, Johnson, Chauncey, & Graesser, 2011; Bannert, 2009; Weinstein & Mayer, 1986). For example, van Laer and Elen (2017) using a systematic literature review approach found seven attributes of blended learning environments that foster self-regulated learning: (a) *authenticity* of the environment supporting motivation; (b) *personalization* of the learning content to learners' needs; (c) *learner* *control* as indicated by control over pace, content used or sequences; (d) *scaffolding* by giving learners support to reach learning goals; (e) *interaction* of learners with content, learning environment but also instructors or pees; (f) *reflection* elements supporting learners thinking about their learning as it occurs or afterwards but also as preflection as thinking about how to tackle an upcoming task; and (g) *calibration* of learners' perception of achievement and their actual performance. However, such support is more effective when it is provided adapted to the learners' needs and goals plus at the time needed (Molenaar & Roda, 2008; Thillmann, Künsting, Wirth, & Leutner, 2009). Thus, the traces of learners' behavior within digital learning environments can be used to provide adaptive learning support (Azevedo et al., 2011).

Research on self-regulated learning in higher education or in the context of digital learning environments focuses on identification of strategies learners use (e.g., Azevedo, Taub, & Mudrick, 2018; Bannert & Mengelkamp, 2013; Broadbent & Poon, 2015; McCardle & Hadwin, 2015), the relation of self-regulated learning and achievement (e.g., Broadbent, 2017; Dörrenbacher & Perels, 2016; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017), the interrelatedness among the concepts of self-regulated learning (Ben-Eliyahu & Bernacki, 2015; Winne & Hadwin, 2008) or on how to foster self-regulated learning (e.g., Kramarski & Kohen, 2017; Müller & Seufert, 2018; Prieger & Bannert, 2018).

Within this thesis, the underlying assumptions of self-regulated learning serve as the theoretical foundation as they encompass a plethora of processes and constructs related to learning by considering cognitive, metacognitive, motivational, emotional and affective, volitional, resource-related, and behavioral processes (Panadero, 2017). In addition, self-regulated learning is considered as a major theory for explaining differences in learning performance especially in higher education (Broadbent & Poon, 2015; Cassidy, 2011; Mega, Ronconi, & De Beni, 2014) and digital learning environments (Broadbent & Poon, 2015; Kizilcec et al., 2017; Lehmann, Hähnlein, & Ifenthaler, 2014). In addition, learners who are capable to self-regulate are considered to be better prepared for adapting to fast changing demands and the associated need for lifelong learning (Ifenthaler, 2012; Kurbanoglu, 2003; Sitzmann

& Ely, 2011). Thus, self-regulated learning is both, key for successful learning and goal of higher education.

2.2 Learning analytics in higher education

Learning analytics are considered to be an important approach for supporting learning and teaching (Johnson et al., 2013). Currently, learning analytics are applied in different contexts (Ferguson, Brasher, et al., 2016) such as higher education (Colvin et al., 2015; Schumacher, Klasen, & Ifenthaler, 2019; Sclater, Peasgood, & Mullan, 2016; Sønderlund, Hughes, & Smith, 2019; Viberg, Hatakka, Bälter, & Mavroudi, 2018), massive open online courses (Kizilcec et al., 2017; Leitner, Khalil, & Ebner, 2017; Romero & Ventura, 2017; Wong, Khalil, Baars, de Koning, & Paas, 2019) in schools (Bienkowski, Feng, & Means, 2012; Ebner & Schön, 2013), and workplace learning (Dawson, Mirriahi, & Gašević, 2015; de Laat & Schreurs, 2013; Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017; Schumacher, 2018; Siadaty, Gašević, & Hatala, 2016; van der Schaaf et al., 2017). Recent research on learning analytics focusses on predicting learning performance and retention by using and comparing a variety of algorithms (Costa, Fonseca, Santana, de Araújo, & Rego, 2017; Howard, Meehan, & Parnell, 2018), the application of learning analytics dashboards and provision of feedback (Aljohani et al., 2019; Howell, Roberts, & Mancini, 2018; Kim, Jo, & Park, 2016; Lim et al., in press; Roberts, Howell, & Seaman, 2017; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018), analyzing and understanding learning behavior by applying paths and cluster analyses plus visualizations of interactions (Chen, Breslow, & DeBoer, 2018; Hsu, Wang, & Zhang, 2017; Liu et al., 2017), the integration of multimodal data for learning analytics (Azevedo et al., 2018; Di Mitri, Schneider, Specht, & Drachsler, 2018; Noroozi et al., 2019; Worsley & Bilkstein, 2015), and the institutional readiness for implementing learning analytics plus data literacy of the stakeholders (Gibson & Ifenthaler, 2017; Ifenthaler, 2017). However, learning analytics are still at an initial level of implementation, and empirical evidence on the effectiveness of learning analytics to support learning and studying is lacking (Colvin et al., 2015; Ferguson, Brasher, et al., 2016; Ferguson & Clow, 2017; Ifenthaler, Mah, & Yau, 2019; Sønderlund et al., 2019; Tsai & Gašević, 2017).

Implementing learning analytics in higher education institutions are accompanied with several challenges, such as limitations of the IT-infrastructure and resources, organizational preparedness and change, preparedness of the educational staff, plus privacy requirements and ethical concerns (Leitner, Ebner, & Ebner, 2019; Macfadyen, Dawson, Pardo, & Gašević, 2014; Schumacher et al., 2019; Tsai & Gašević, 2017). Even though the data required for learning analytics are considered to be a “by-product” (Leitner et al., 2017) they are spread over various sources, stored in different data formats, and are using different identifiers thus making it challenging to aggregate data on individual learners (Bienkowski et al., 2012; Chatti, Dyckhoff, Schroeder, & Thüs, 2013; Leitner et al., 2019; Ocheja, Flanagan, & Ogata, 2018; Siemens, 2013). In the context of higher education, the data might be collected through the learning management system, the student information system and other digital services such as the library or campus network (Ifenthaler & Widanapathirana, 2014; Prinsloo, Slade, & Khalil, 2018; Rubel & Jones, 2016). This might be further enhanced with data from research systems to include survey data on learners within the analyses (Ellis, Han, & Pardo, 2017; Flanagan & Ogata, 2017; Gašević, Jovanovic, Pardo, & Dawson, 2017). However, especially if relying on commercial systems the (real-time) access of data might be limited (Leitner et al., 2019), plus they pose additional privacy risks and ethical concerns (Drachsler & Greller, 2016; Greller & Drachsler, 2012). Furthermore, interdisciplinary cooperation across the different departments is inevitable as educators, the owners of the different technical systems contributing to learning analytics, data scientists, researchers, administrative staff and management level need to collaborate to integrate their competences (Sclater, 2016; West, Heath, & Huijser, 2016). In addition, students and their perceptions as major affected stakeholders of learning analytics need to be included (Sclater, 2016; Tsai & Gašević, 2017). Currently, technical and pedagogical expertise with regard to implementation and use of data-driven approaches such as learning analytics still needs to be developed (Gibson & Ifenthaler, 2017; Ifenthaler, 2017). To facilitate interdisciplinary cooperation among the responsible actors for implementing learning analytics in higher education institutions frameworks and guides, could serve as a useful support (Sclater & Bailey, 2015; West, Heath, et al., 2016). These frameworks emphasize the need to consider different factors such as the institutional context, definition of strategies and purposes for implementing learning analytics, the goals and responsibilities of the different stakeholders, the institution's culture with regard to data-driven interventions and commitment, data management with regard to ethics and privacy, technical preparedness and available resources, provision of resources for staff and students (e.g., training, time) (Sclater, 2016; West, Heath, et al., 2016). Hence, for successful implementation of new technologies and processes, all relevant stakeholders including their demands and concerns need to be involved and management of the organizational change is crucial (Macfadyen & Dawson, 2012; Schumacher et al., 2019; West, Heath, et al., 2016). In summary, institution wide adoption of learning analytics as well as preparedness and collaboration of different stakeholders plus related technologies are still emerging.

However, after being implemented learning analytics provide additional data for understanding and analyzing learning and teaching processes by enabling summative, real-time plus even predictive insights (Daniel, 2015; Ifenthaler & Widanapathirana, 2014). Thus, learning analytics offer a variety of benefits for higher education institutions such as quality assurance and improvement of teaching, identification of at risk or low performing students or even predicting learning performance to initiate timely interventions such as suggesting relevant learning resources, increasing reflection and awareness to enhance retention, plus detecting (undesirable) learning behavior and learners' affects (Sclater et al., 2016; Verbert, Manouselis, Drachsler, & Duval, 2012). Ifenthaler (2015) assigned the benefits of learning analytics to the four different stakeholder levels in educational contexts: at the *micro-level* the learners profit from learning analytics by receiving adaptive materials, support and recommendations; at the *meso-level* learning analytics provide insights for instructional designers and course facilitators to adjust learning design and course materials to learners' needs but also with regard to curriculum design; at the *macro-level* institutions benefit from comparisons across courses and faculties facilitating resource allocation and retention; and at the *mega-level* (governance) comparisons of institutions and programs as well as policy making are facilitated.

Learning analytics are related to educational data mining and academic analytics which have besides overlaps some distinguishing characteristics (Bienkowski et al., 2012; Ifenthaler, 2015; Romero & Ventura, 2013; Viberg et al., 2018): *Educational data mining* is dealing more with automatic extraction of information in large datasets using supervised and unsupervised methods, whereas *learning analytics* are more related to human judgements, guided through assumptions with the aim of increasing understanding of learning processes to support learning and teaching plus providing additional feedback to learners and educators. *Academic analytics* in particular focus on providing insights into aggregated educational data to supporting decision-making on the institutional level (e.g., modeling retention rates, resource allocation)(Campbell, DeBlois, & Oblinger, 2007). Within this thesis the focus is on learning analytics and in particular on the micro-level as the major emphasize is on understanding and supporting (self-regulated) learning processes. Self-regulated learners are considered to continuously generate internal feedback by monitoring their learning which can be further enhanced and supported with external feedback (Butler & Winne, 1995; Hattie & Timperley, 2007). Learning analytics can increase learners' awareness of their learning activities (Marzouk et al., 2016), such monitoring might initially be supported through simple representations or analyses of their (learning) behavior and progress (Winne, 2014). However, this information needs to be presented in a way that the stakeholders understand, informative, and ideally contain additional recommendations on how to improve (Park & Jo, 2015; Sedrakyan et al., 2018; Winne, 2017). Learning analytics and the underlying algorithms, in particular, are difficult to understand without additional visualizations or additional explanations plus mediation through educators (Aguilar, 2018; Greller & Drachsler, 2012; Leitner et al., 2019). Furthermore, the interpretation and use of feedback are constrained by learners' prerequisites and thus feedback is not necessarily leading to the hoped changes (Narciss, 2008; Winne, 2017). In this regard, learning analytics could be a meaningful enhancement as they have available a myriad of data on learners' preferences but also on their level of knowledge enabling to provide feedback and recommendations at the time needed and that might not be overwhelming. However, research on learners' interpretation of and reaction to feedback provided through learning analytics is still limited (Corrin & de Barba, 2014; Howell et al., 2018) as is the provision of feedback to learners through learning analytics (Vieira, Parsons, & Byrd, 2018), and on how to improve (Sedrakyan et al., 2018). Thus, additional research is required to develop meaningful feedback interventions using learning analytics to close the feedback loop and investigate its impact on supporting all components of self-regulated learning. The synthesis of learning analytics and self-regulated is described in more detail in sections 5.1.1 and 5.1.3.

To validly infer on learning processes and learners' needs, and to provide meaningful support, a variety of data is needed such as behavioral data (e.g., navigation, use of resources, social interaction), learner characteristics and socio-demographic data, learning artefacts and performance, plus self-reported survey data (Ferguson & Buckingham Shum, 2012; Ifenthaler & Widanapathirana, 2014; Sclater et al., 2016). Access and aggregation of data across systems are still difficult and even if the data are accessible valid indicators or measures are not defined yet, difficult to measure (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Greller & Drachsler, 2012; Winne & Baker, 2013; You, 2016), and are further dependent on contextual or situational factors (e.g., the design of the learning environment, available tasks) (Macfadyen & Dawson, 2012; West, Heath, et al., 2016). Furthermore, collection and especially integration of data from different contexts plus relating them to individual learners raise privacy and ethical concerns constraining learning analytics (Ferguson, Hoel, Scheffel, & Drachsler, 2016; Heath, 2014; Kay, Korn, & Oppenheim, 2012; Pardo & Siemens, 2014; Prinsloo & Slade, 2017; Rubel & Jones, 2016; Sclater, 2014; Slade & Prinsloo, 2013; West, Huijser, & Heath, 2016). In this regard, it is assumed that willingness to disclose certain data is depended of the context (Nissenbaum, 2011) which might be in contrast to the aim of generating a holistic picture about learners' competencies, skills, and knowledge across different contexts (DiCerbo, Shute, & Kim, 2016; Shute & Becker, 2010). Hence, policies and institutional standards considering privacy with regard to data-driven approaches such as learning analytics need to be developed and already considered when designing and implementing learning analytics (Drachsler & Greller, 2016; Hoel & Chen, 2016; West, Huijser, et al., 2016; Willis & Strunk, 2015). For example, Drachsler and Greller (2016) developed the DELICATE checklist for trusted learning analytics including eight action points with regard to privacy and ethics that should be considered when implementing learning analytics. The checklist includes the definition of the different goals pursued with learning analytics, the integration of all stakeholders and seeking their consent, plus technical aspects. As ethical and legal issues are constraining adoption of learning analytics, Sclater and Bailey (2015) developed a code of practice for learning analytics including eight areas such as the responsibilities of the stakeholders, considering privacy and ensuring validity. They further emphasized that the purpose of learning analytics is to benefit learners and particularly stressed the need for transparency. Furthermore, Ferguson, Hoel, et al. (2016) identified 21 challenges associated with ethical dimensions related to learning analytics and derived nine ethical goals such as focusing on student success or equal access to education. Comparable, West, Huijser, et al. (2016) developed a four-step guideline for ethical decision making to increase the awareness of stakeholders and to emphasize the need to consider ethical questions when implementing learning analytics but also to reiterate after implementation. Furthermore, learners as stakeholders have a dual role in the context of learning analytics as they have to reveal personal data and are recipients of the analyses (Pardo & Siemens, 2014), and thus need to be willing to share their information. Following the assumptions of a privacy calculus model (Dinev & Hart, 2006) students' concerns over privacy related to learning analytics are an interplay of an analysis of the data that need to be provided and the perceived or expected benefits, further influenced by risk-minimizing factors such as trust in the system or the institution, the control over data, possibility to opt-out, and the perceived transparency as well as risk-maximizing factors (non-transparency, negative perceptions about the system). By evaluating their concerns over privacy against their expected benefits learners might decide whether to disclose personal information or not (Ifenthaler & Schumacher, 2016). Hence, high transparency with regard to the purpose and methods of data collection and analyses, the duration and place of storage including information who has access to which data and analyses, who has control over data, the possibility to opt-in or out, plus level of de-identification are crucial (Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Furthermore, the staff dealing with student data needs to be trained with regard to privacy, ethics, functionalities of the algorithms plus their limitations to guarantee proper handling, transparency, and more important meaningful interventions (Leitner et al., 2019; Sclater, 2014).

Closely related to the discussion of privacy with regard to learning analytics are ethical concerns (Drachsler & Greller, 2016; Ferguson, Hoel, et al., 2016; Prinsloo & Slade, 2017; Sclater, 2016; Slade & Prinsloo, 2013; West, Huijser, et al., 2016): such as unequal support due to the intended individual learning support, that analyses and predictions might promote teachers' biases, not taking appropriately into account contextuality and temporality of the data or analyses, simplifying multifaceted constructs related to study success, the imbalanced power and contradictory interests of the institution and the learners, not considering agency and autonomy of learners, undermining possibilities of opting-out plus the related potential disadvantages. Furthermore, teachers might not use the additional information as intended or feedback provided through learning analytics not considering theory on feedback might cause harm to learners (Kruse & Pongsajapan, 2012; Lawson, Beer, Rossi, Moore, & Fleming, 2016). In addition, the algorithms applied are not free from biases and might provide invalid analyses due to the incompleteness of the data available (Dringus, 2012; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016).

Hence, also from an ethical and privacy perspective on learning analytics the predominant focus of such interventions should be on supporting learners, their learning processes and success plus their literacy for understanding learning analytics. Consequently, learning analytics need to be strongly linked to theory on learning including motivation, and feedback. Furthermore, theory on assessment might pose a fruitful enhancement to develop valid learning analytics systems and meaningful interventions, which would in turn increase transparency, reduce ethical and privacy concerns, and increase stakeholders' willingness of adoption.

2.3 Use and design of assessments in higher education

Assessments are considered to shape students' learning processes with regard to strategies, activities, time and effort allocated in order to achieve good grades (Gibbs, 2019). Joughin (2009, pp. 1-2, emphasis in original) lists three prevailing functions of assessments: *"supporting the process of learning*; *judging students' achievement* in relation to course requirements; and *maintaining the standards of the profession or discipline* for which students are being prepared." Summative assessments focusing on judgments of achievements and maintaining standards are predominant in formal education as in higher education (Boud, 2007; Yorke, 2003). In this regard, summative assessment is considered to be a summary of a student's achievement at the end of a course or a degree (Brown & Knight, 1994) evaluated against prior set standards and with the purpose of grading (Shute & Becker, 2010). However, due to several reasons such as increased study cohorts with diverse backgrounds (Bosse, 2015; Yorke, 2001), changes in pedagogical knowledge, or the need for supporting first-year students' understanding of assessment practices (Smith, Worsfold, Davies, Fisher, & McPhail, 2013) formative assessments are more and more implemented in higher education. Formative assessment is "assessment that is specifically intended to provide feedback on performance to improve and accelerate learning" (Sadler, 1998, p. 77). Taras (2005) argues that every assessment starts with the summative function of judgement and formative assessment enhances summative assessment with the provision of feedback which is used to improve learning. Hence, these two functions are considered to be not fully distinct and located on a continuum plus can be assessed with the same tools (e.g., essays, tests) (Black & Wiliam, 2018). Depending on the stakeholder receiving the results of an assessment different information is demanded, such as feedback on improvement, a summative overview of knowledge, skills and competencies of a particular student, or information about grades in a course or graduation rates (Brown & Knight, 1994). As Pereira, Assunção Flores, and Niklasson (2016) identified in a literature review assessments in higher education are realized using written and oral examinations, portfolio assessments, group assessments and diaries, including modes of self- and peer assessments plus formative, continuous and summative assessments. With regard to support self-regulated learning, self-assessments and related feedback are considered to be relevant (Panadero, Jonsson, & Botella, 2017). This formative feedback serves as an external support for learners' internal monitoring processes (Butler & Winne, 1995). However, with evermore complexity of knowledge, interdisciplinary work and cross-contextual competences designing assessments which are capable of measuring and relating the collected evidence to the assessment purposes gets increasingly difficult (DiCerbo et al., 2016; Shute, Leighton, Jang, & Chu, 2016). Hence, assessments should be designed following design principles to validly infer from data of observable learning behavior and products from different tasks and contexts on learners' knowledge, skills and competencies (Mislevy, Almond, & Lukas, 2003). Several frameworks guiding principle-based assessment design exist. Such frameworks are transparently guiding assessment design through clearly defined constructs that should be assessed and the stimuli for eliciting the related behavior. Furthermore, they focus on collecting evidence, its evaluation and accumulation plus using probabilistic models for inferring on the assessment constructs (Nichols, Kobrin, Lai, & Koepfler, 2017). Within the context of technology-enhanced assessments the Evidence-centered Assessment Design framework is prevailing (Webb & Ifenthaler, 2018). This framework focuses on integrating and aggregating assessment data from different contexts considering the increasing complexity of assessments and the data (Almond, 2010; Mislevy et al., 2003). Particularly, beneficial of the framework is that it considers contextual and domain specific factors plus provides detailed information on how to conceptualize assessments with regard to what needs to be measured, which tasks enable measuring the relevant data, how scores are assigned to the learning products or behavior and how the scores can be aggregated and related to the assessed constructs. Hence, within this thesis the Evidence-centered Assessment Design framework is considered to represent the best fit for guiding the conceptualization of learning analytics as constituted in the holistic framework developed by Ifenthaler (2015) (see section 6.4.2).

Both, assessments and assessment design are considered to be vital for developing valid learning analytics systems supporting learning (Schumacher, 2019, accepted). Because, formative (self-)assessments are on the one hand a relevant means for supporting learning, and on the other hand previous performance is a valid indicator for future performance (Richardson, Abraham, & Bond, 2012; Tempelaar, Rienties, & Giesbers, 2015). Furthermore, principle-based assessment design can serve as a basis for theory-driven integration of the data collected through learning analytics (e.g., information on the weighting of the data plus which data are related to which assessed construct) and enables adaptive self-assessments and feedback.

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3 Features students really expect from learning analytics

3.1 Introduction

Due to the need for lifelong learning, one major aim of higher education is to engender self-regulated learners (Nicol & Macfarlane-Dick, 2006). Self-regulated learning is conceptualized as “an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment” (Pintrich, 2000a, p. 453). Differences in learning success are predominantly attributed to students’ self-regulation capabilities that are relevant for initiating and sustaining learning processes (Zimmerman, 2002).

The advance of technology-enhanced learning environments is opening up new opportunities for reconstructing and analyzing students' learning behavior. Consequently, higher education institutions are developing and implementing learning analytics systems to better support and understand student learning. It is thus relevant to consider students’ expectations of such systems in terms of learning. Learners directly interact with the user interface or dashboard of the learning analytics system, which offers different features such as visualizations, learning recommendations, prompts, rating possibilities, and self-assessments. Furthermore, learning analytics systems aim to offer highly adaptable and personalized learning environments (Ifenthaler & Widanapathirana, 2014). Personalized learning environments can help to foster students’ skills in managing, monitoring, and reflecting their own learning (McLoughlin & Lee, 2010).

The ability to design, develop, and implement personalized learning analytics systems involves investigating what learners expect from these systems and which learning analytics features support students in self-regulating their learning. The implementation of learning analytics systems as a means of supporting learning could otherwise fail, as it might even hinder self-regulated learning: Students might fear losing autonomy in managing their learning activities, which is a key component for motivation (Deci, Ryan, & Williams, 1996), or they might feel demotivated due to their performance in comparison to their peers. Conole, Creanor, Irving, and Paluch

(2007) showed in their study on e-learning that it is necessary to recognize a full range of student perceptions, as otherwise institutions might fail to meet learners' needs. Nonetheless, only little empirical research to date has treated student expectations of learning analytics to facilitate learning (Marzouk et al., 2016).

Endeavors to self-regulate learning are crucial to succeed in higher education and online learning environments and build the learning theoretical approach (section 3.1.1). Learning analytics (section 3.1.2) attempt to use student data to understand and support learning processes while the learner interacts with the dashboard showing several learning analytics features (section 3.1.3). The qualitative exploratory study in section 3.2 investigates the expectations of students towards learning analytics features. These findings were assigned to the phases of self-regulated learning in paragraph 3.2.2. Based upon the qualitative results, 15 potential learning analytics features were selected and in study 2 (section 3.3) presented to 216 students to investigate their acceptance and perceived learning support. Moreover, students were asked to evaluate potential benefits of learning analytics features and their willingness to disclose personal data for learning analytics. The findings of both studies, their practical implications (3.4.1) as well as the limitations and future research (3.4.2) were discussed in section 3.4 and finalized in the conclusion section (3.5).

Accordingly, this research paper aims to investigate students' expectations on learning analytics features and how students rate learning analytics features in terms of their willingness to use a certain feature and the potential support of their learning activities. This allows an empirical validated implementation of learning analytics features considering students' needs and thus makes possible further empirical research on learnability of certain learning analytics features extending beyond simply focusing on technical possibilities.

3.1.1 Self-regulated learning

The concept of self-regulated learning is accepted as a vital factor for learning success and it is still relevant for research on learning in higher education, especially with the advent of educational technology and online learning environments (Lehmann, Hähnlein, & Ifenthaler, 2014; Nussbaumer, Dahn, Kroop, Mikroyannidis, & Albert, 2015; Zimmerman & Schunk, 2008). On the one hand, students are particularly autonomous in the way they select material to meet their needs and proceed at their own pace in online learning environments. However, on the other hand, the complexity of such learning environments, the variety of information sources, and the lack of guidance demand high self-regulation of the students (Azevedo, Cromley, & Seibert, 2004).

Self-regulation can be seen as a cyclical process in which learners try to control their learning by regulating themselves on cognitive, metacognitive, and behavioral dimensions (Boekaerts, 1999; Zimmerman, 2002). However, learners are also influenced to self-regulate their learning by individual characteristics and other external factors, for example task characteristics and learning situations (Lehmann et al., 2014).

Most authors assume that a cyclical self-regulated learning process comprises three phases (Boekaerts, 1992; Pintrich, 2000b; Schmitz, 2001; Zimmerman, 2000): 1) In the forethought phase, learners analyze the task, plan their activities to reach their goals, influenced by (academic) self-concepts, motivation, (meta-) cognitive knowledge about themselves, the task, and the context. 2) The performance phase is where the actual learning process occurs. Here learners use the strategies they selected beforehand, monitor their learning activities and adjust them if necessary. Relevant factors for perpetuating the learning engagement even against setbacks include volitional components and the application of appropriate resources. Achieving a successful learning outcome involves applying suitable learning strategies and spending sufficient time on learning. 3) In the final self-reflection phase, learners reflect on and evaluate the learning outcomes in terms of effort and success. This internal or external feedback influences attributions, motivation, and self-efficacy beliefs of learners and might thus lead to modifications. Additionally, this affects upcoming preparatory phases for closing the loop of the cyclical self-regulated learning process (see Figure 3-1).

In addition to the assumed cyclical phases of self-regulated learning, three components are vital for self-regulated learning: the cognitive, metacognitive, and motivational component (Boekaerts, 1992; Pintrich, 2000b). Component models focus more on learner characteristics, influencing self-regulated learning and on how self-regulation can be fostered (Boekaerts, 1999; Pintrich, 2000b; Weinstein & Mayer, 1986).

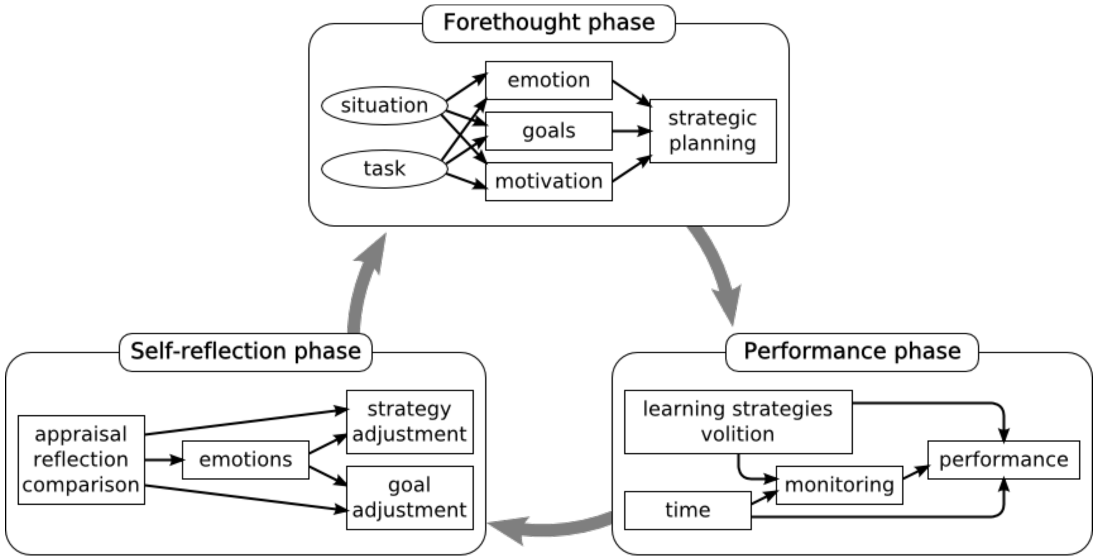

Figure 3-1. Self-regulated learning process (adopted from Schmitz, 2001)

Monitoring helps learners to obtain information about their current progress towards learning goals and plan further learning steps. It may be seen as internal feedback and is strongly relevant for self-regulated learners (Butler & Winne, 1995). Self-regulated learners need to receive (external) support as encouragement, as learners often lack appropriate learning strategies or knowledge about how to use them (Azevedo et al., 2004). Students in higher education generally receive summative feedback about their performance at the end of a course. Fostering students' monitoring activities or adding external feedback to them necessarily involves formative and learner-centered or adaptive feedback (Ifenthaler & Widanapathirana, 2014). In this regard, the application of learning analytics in higher education can facilitate to provide informative and adaptive feedback to learners during the learning process, as learning analytics take into account various data, such as learner characteristics, curricular information or trace data.

3.1.2 Learning analytics

Higher education institutions have always collected various data about students, but the advent of big data analysis, online learning environments, and thus vast amounts of available data have led to increased interest in the collection and analysis of student data to support and obtain insight into students' learning activities (Ferguson, 2012; Greller & Drachsler, 2012; Long & Siemens, 2011).

Learning analytics use static and dynamic information about learners and learning environments, assessing, eliciting, and analyzing them for real-time modeling, prediction, and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015).

Learning analytics provide benefits for all levels of stakeholders in the educational arena: mega-level (governance), macro-level (institution), meso-level (curriculum, teacher/tutor), and micro-level (learner) (Ifenthaler & Widanapathirana, 2014). As this study focuses on the micro-level of learning analytics, namely supporting the learning activities of students, the benefits include but are not limited to the following (Ifenthaler & Widanapathirana, 2014):

- Summative: understand learning habits, compare learning paths, analyze learning outcomes, track progress towards goals
- Real-time: receive automated interventions and scaffolds, take assessments including just-in-time feedback
- Predictive: optimize learning paths, adapt to recommendations, increase engagement, increase success rates

Perceived autonomy, responsibility for and control over learning processes are vital for supporting learning motivation (Deci et al., 1996; Fazey & Fazey, 2001). However, learning in formal educational settings still occurs often in pre-structured and primarily teacher-centered learning environments (Watt & Richardson, 2007). The implementation of learning analytics allows offering personalized and adaptive learning environments based upon analyses of various data about the students and their individual learning progress. Learning environments are personalized and adaptive when they tailor education to learners' current situation, characteristics, and needs to help them achieve the best possible learning progress and outcomes. These learning environments enable individual learning paths, personalized assessments and feedback, and learning recommendations that better meet the students' individual needs and foster their capability to manage their own learning in terms of self-regulation (Corrin & de Barba, 2014; McLoughlin & Lee, 2010).

However, the alignment of learning analytics with learning theories such as self-regulated learning, is still at an early stage and needs to go beyond focusing on technical possibilities to enable developing learning analytics systems that support learning processes and thus help to unveil how (self-regulated) learning in higher education occurs (Marzouk et al., 2016).

3.1.3 Learning analytics feature

In software engineering, a feature is defined as a distinguishing characteristic of a software item (IEEE, 2008). Feature-rich software includes many options and functional capabilities for the user. A learning analytics feature is a distinguishing element which supports the learning analytics process. Learning analytics features are implemented on web-based dashboards (Few, 2013). Learning analytics dashboards are customizable control panels displaying personalized learning analytics features which adapt to the learning process in real time (Park & Jo, 2015). Learning analytics features may focus on learning opportunities, self-assessments, recommendations, comparison to peers, social interactions or additional links (see Table 3-1).

Learning analytics features are based upon the analyses of various data (Ifenthaler & Widanapathirana, 2014): Learner characteristics including prior knowledge, psychometric tests about learning strategies and competencies, socio-demographic data or prior academic performance; external data such as searches in the library catalog, geo-data or information from social media could be included; traces generated by the learning management system (e.g., frequency and time online, activities in discussions and other online interaction, results of self-assessments, etc.); and curricular information about study paths and learning objectives need to be integrated into the analyses of formal learning environments (Ifenthaler, 2015).

Many learning analytics systems focus on visualizations and outline descriptive information, such as time spent online, access of resources, progress towards the completion of a course, and comparisons with other students (Kim, Jo, & Park, 2016; Verbert et al., 2014), which already helps learners monitor some of their (learning) activities. However, planning upcoming learning activities or adapting current strategies also involves further recommendations based upon dispositions of learning, previous behavior, self-assessment results, and learning goals. Dashboards designed to offer beneficial learning analytics features need to be aligned with theory on (self-regulated) learning, feedback and instruction to avoid unfavorable educational consequences (Gašević, Dawson, & Siemens, 2015). The findings from a comparative study of three learning analytics systems have shown that students prefer more detailed learning analytics systems with elaborated analyses and personalized recommendations for their learning (Ifenthaler & Schumacher, 2016).

Table 3-1 Description of learning analytics features in this study

Feature	Function
F1: time spent online	Overview about time spent in the online learning management system offering different visualizations and comparisons (time spent online today, the day before, this week, last week, last month, term), analysis about activity in the system
F2: suggestion of learning partners	The learning analytics system suggests learning partners on the basis of learning material worked on, competencies of the learners, current knowledge, learning goals, self-assessment results, etc., to create synergies for both learners
F3: learning recommendations for successful course completion	Recommendations which subjects need to be learned for successful course completion based on self-assessment results, content the learner has already worked on, and curricular information
F4: rating scales for learning material	Learners can rate learning material (e.g., texts, videos, presentations, self-assessments) on a 5-point scale regarding the overall evaluation, difficulty, fit of the material to subject, helpfulness, etc. Furthermore, they can see other students' ratings
F5: timeline showing current status and goal	Progress toward (self-set) goals is illustrated (e.g., as a bar chart); learners can get information about remaining learning subjects, texts they need to read, pending assignments, etc., to be able to reach the goal by the set point of time
F6: time expected to complete a task or read a text	Next to learning material (e.g., texts, videos, presentations, self-assessments) learners can click an icon symbolizing a watch, to be informed about their expected reading or working time on the basis of their average processing time in relation to the average working time of the other participants
F7: prompts for self-assessment	With distance of time after learning, students are offered matching self-assessments
F8: further learning recommendations	When learners have recurrent problems with subject areas, the system takes the results of self-assessments or forum discussion to offer additional learning material or explanations to the learner
F9: comparison with fellow students	Allows comparisons with the course average regarding tasks processed or texts read, time spent on learning, learning outcomes, etc.
F10: considering the student's personal calendar for appropriate learning recommendations	Learning analytics consider personal schedule and preferences of the student as well as the term schedule to offer appropriate learning possibilities for the remaining time
F11: newsfeed	Shows relevant news related to the learning content

F12: revision of previous learning content	In courses which build upon content from previous courses, the system makes cross-references to previous learning material, self-made learning material (mind maps, summaries, etc.) to refresh students' knowledge and facilitate assimilation
F13: feedback for assignments	Seminar papers can be created in the learning management system for semantic analysis, to receive feedback on structure, content, plagiarism, and improvement
F14: reminder for deadlines	Provides reminders for examination dates, submission, enrollment, and re-registration deadlines and announces upcoming events. Students can set preferences regarding time and content of the alerts
F15: term scheduler	Recommends relevant courses that fit the learners' prior knowledge, curricular requirements, individual scheduling, and preferences and shows alternative courses and study paths

3.2 Study 1

Learning analytics dashboards with features for students are still on an initial level and thus the research on learning analytics features and students' expectations (Sclater, Peasgood, & Mullan, 2016). Learning analytics dashboards and features are currently being investigated in terms of visualizations and dashboard elements that the system is capable of providing (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Verbert et al., 2014) or in terms of their technical possibilities (Park & Jo, 2015). Most studies on learning analytics dashboards have been conducted in controlled settings. This qualitative approach provides additional detailed insights for understanding students' needs regarding learning analytics features (Park & Jo, 2015; Verbert et al., 2014). Since one of the main purposes of learning analytics is to support students' learning activities and their motivation to learn, it is reasonable to go beyond technical possibilities while considering students' expectations of learning analytics features (Ferguson, 2012). Thus, the purpose of the first study was to investigate which features and functions students expect from learning analytics systems to gain insights into their perceptions about how learning analytics could support their learning processes. Additionally, due to the uninvestigated area the findings are a basis for the second quantitative study (see section 3.3).

3.2.1 Method study 1

Participants and design

The study was designed as a qualitative exploratory study with oral individual interviews, which were conducted in May 2016. After removing one incomplete response, we considered the responses of 20 graduate students (14 female, 6 male) for further analyses. The participants were enrolled in economic and business education at a European university. The average age of the participants was 24.55 years (*SD* = 2.21). Concerning the level of awareness of learning analytics, three participants have never heard about learning analytics before, seven have heard about it without having a concrete idea what it is about, eight participants reported having a more detailed knowledge about learning analytics due to lectures or reading texts and two stated to have used learning analytics during a semester abroad or in an internship. Participants received one credit hour for participating voluntarily in the study.

Materials and instruments

Introduction to learning analytics

A short lecture (approx. 5 min) including presentation slides introduced the basic concepts of learning analytics and provided an overview of various types of data used for learning analytics such as learner characteristics, curricular information, and trace data from the online learning environment. The session concluded with a possibility to clarify comprehension questions.

Learning analytics features

Students were confronted with three guiding questions regarding learning analytics features, which they were asked to answer in oral form or illustrate with a whiteboard or on paper. (1) Please reflect on possible features or dashboard elements you would like to have as an application in a learning analytics system. (2) Please explain which functions these elements should have. (3) Please indicate how you think these features or dashboard elements can support learning.

Background information

With an additional questionnaire, we surveyed students' usage and attitude towards technology for learning purposes and asked them to state demographic information such as age, grade point average, course load.

Procedure

We invited students to participate in a three-part qualitative interview study over a period of two weeks in May 2016. In the first part, the participants received a general introduction to learning analytics (approx. 5 min). Second, they reported on the features they expected from learning analytics systems and how they thought these features could support learning (8-80 min; *Mdn* = 13.5 min). In the third part, participants completed a questionnaire for background information focusing on their technology usage for learning and their demographic information (12 min).

Analysis

The audio recordings of all interviews were transcribed in single text documents. Using f4anaylsis (www.audiotranskription.de) – a software for qualitative data analysis – we analyzed the transcribed interviews in terms of learning analytics features and critical statements the students mentioned. Following a content sensitive qualitative research approach, we took into account both learning analytics features that tended to be more relevant to the students and individual statements. Based upon self-regulated learning theory (Zimmerman, 2000) three main categories (three phases) were established and complemented with students' general expectations and attitude towards learning analytics. The statements of the participants were analyzed in an iterative process and assigned to the three categories according to their characteristics related to the corresponding components of each phase of self-regulated learning.

3.2.2 Results of study 1

Since self-regulated learning skills are especially relevant in higher education and technology-enhanced learning, the findings will be assigned to the three phases of self-regulated learning.

Forethought phase

The students demanded that learning analytics systems include several features to help them analyze and plan their learning be-forehand such as basic reminders for deadlines up to automated to-do lists and agendas or even a feature accessing their personal calendar to provide learning recommendations matching their schedule (interviewee 4, 21).

> *"That the system considers my personal schedule. I wouldn't mind if the system knows 'watching soccer with friends at 9 p.m.' and advices me to work for another hour." (interviewee 4)*

Some students asked for motivational prompts and precise learning objectives to initiate learning activities or they wanted information about the learning progress of their fellow students.

> *"... connected to my smartphone for receiving prompts 'you haven't done anything the last three days, how about starting now?' Might be problematic for persons who are not able to learn under pressure, for me it would be great." (interviewee 6)*

Performance phase

In terms of being supported during the actual learning period, the students wanted analyses about their current state of knowledge and their progress towards the learning goals. Enabling them to revise or extend beyond the learning content, they asked for further material that matched their individual needs and preferences recommended by the system. The students also stressed that they wanted the system to offer sufficient exercises to allow them to examine their status quo. In terms of easier learning, they demanded keywords that are highlighted and linked to further resources (e.g., further learning content or definition of the keyword). It appeared that social learning was strongly relevant to the respondents, as they demanded discussion forums, chat, video conferencing, and online-teamwork functions to realize interaction with fellow students or lecturers. Several of them even wanted the system to suggest learning partners (interviewee 1, 11, 20).

> *"If the system would recognize other students dealing with the same content and suggests connecting to each other for exchanging ideas and for testing or even meeting in person." (interviewee 20)*

The additional questionnaire (see *Background information* in section 3.2.1) and student responses revealed that they prefer printed texts to reading a screen, and they thus considered it necessary that learning activities occurring offline can be integrated into the learning analytics system.

Self-reflection phase

As already mentioned in the second phase, the students strongly demanded self-assessment opportunities aligned with the learning objectives.

> *"... that exercises are offered for self-monitoring so that I am learning during the semester instead of delaying it to the end of the semester." (interviewee 14)*

Furthermore, the students emphasized that they wanted to receive subsequently valid, detailed, and just-in-time feedback that allowed them to assess their need for improvement.

> *"… that the system shows an analysis, which subject area I am struggling with, instead of only showing which question I answered wrong …" (interviewee 1)*

Analyses such as time spent on one learning area or progress towards learning goals provided by the system could support in terms of self-evaluation. However, the students were divided over whether they preferred to receive analyses comparing their own performance or analyses comparing their learning activities with those of their peers as this could influence their motivation. If we acknowledge the assumption that self-regulated learning can be illustrated as a cyclical process, learning recommendations from the learning analytics system may give students hints on how to adjust their future learning activities.

Expectations on the system

Besides the aforementioned recommendations, the students noted that the system should offer a high degree of customization concerning the possibility to choose the features displayed as well as the layout of the learning environment to meet their individual needs.

> *"… that the dashboard contains all programs available and everyone can arrange his own dashboard functions and structure … and that I can choose a wallpaper." (interviewee 6)*

In addition, the respondents expected a highly evolved and holistic system including several programs for text processing, management of literature synchronized with the library, annotation of PDF files, etc.

Attitude towards learning analytics

The interviewees predominantly had a positive attitude regarding the application of learning analytics systems and would like to use such systems. Only two respondents indicated in the questionnaire that they do not want to use learning analytics systems due to privacy concerns, the risk of too much surveillance of learning activities, and the loss of autonomous learning, or due to not being willing to change established learning habits. However, even the students with a positive attitude towards learning analytics raised concerns about demotivating consequences of some analyses or the risk that the use of technology might distract them from learning.

> *"… showing the probability to pass the exam with current learning progress … if I am to 80% likely to pass the exam it's great, but if the system says, most likely you will fail the exam, it would be demotivating." (interviewee 2)*

In summary, the students considered learning analytics to be an additional resource for learning but not a substitute for traditional learning processes or interpersonal communication. Thus, the use of learning analytics needs to be voluntary and should respect privacy.

3.3 Discussion of study 1 and introduction to study 2

As learning analytics are of growing interest for higher education institutions (Ifenthaler, 2017), it is important to understand students' expectations of learning analytics features to align them with learning theory and technical possibilities before implementing them (Marzouk et al., 2016).

The findings of this exploratory study highlight that students generally have a positive attitude towards learning analytics, but they also raised concerns regarding privacy issues (Ifenthaler & Schumacher, 2016), too much surveillance, potential demotivation (Marzouk et al., 2016), and the need to consider offline learning activities for valid analyses (Ifenthaler, 2015). The findings showed that the students prefer learning with printed materials, and they discussed a function to document learning activities occurring offline. This suggests that it is necessary to investigate how learning offline or conscious informal learning could ideally be entered into a learning analytics system, whereby invalid analyses due to incomplete data could be reduced and students will not be demotivated only because the system did not consider all their learning efforts. As long as most learning takes place outside the online learning environment, learning analytics systems can only be considered as an additional service. Likewise, the study of Verbert et al. (2014) revealed that learners rated the usefulness of learning analytics dashboards low, when many relevant activities happened outside the tracked learning environment.

Students' expectations of a learning analytics system, combining several programs and functions would allow tracking their learning behavior in an easier way. Using a PDF annotation program, highlighted content and their added thoughts would become more obvious to analyses as well as their paths through different programs. By tracking text processing, the emergence of artifacts could be analyzed by the system in terms of which further resources might help the student to proceed. As real-time feedback was mentioned from almost all students in the qualitative study, it has presumably strong relevance for learning, as already postulated by Hattie (2009). Concerning this, learning analytics could offer an appropriate approach as the system can provide personalized and adaptive real-time feedback to each individual learner in much more detail than one single teacher could.

Because learners interact with the features the learning analytics system offers, 15 potential learning analytics features were derived from the qualitative data of the first study (see Table 3-1). The selection of the 15 potential features was based upon the frequency the students mentioned a certain feature and their theoretical assumed value to support self-regulated learning. Furthermore, we selected common as well as innovative features out of the interviews for further analysis. Thus, the purpose of the second study is to examine students' acceptance to use a certain feature and how students rate a certain feature in terms of supporting their learning activities.

Due to the findings of study 1 the first assumption was that the learning analytics features presented to the students were rated differently in terms of students' willingness to use the feature for their learning (Hypothesis 1). Second, based upon the qualitative exploratory study it was assumed that students' evaluation of the presented features in terms of learning differed significantly (Hypothesis 2). Students evaluate their concerns over privacy against the expected benefits the learning analytics system offers, students are more willing to share data for learning analytics systems providing them with meaningful information (Ifenthaler & Schumacher, 2016). Furthermore, theories on acceptance and use of technology assume, that among others the perceived usefulness of a technology and the perceived difficulty to use a new technology influence the willingness to adopt it (Venkatesh, Morris, Davis, & Davis, 2003). Thus, it was expected that students are more willing to use a certain learning analytics feature for their studies when rating the feature high in terms of learning (Hypothesis 3a), do not perceive that the feature is invasive

(Hypothesis 3b), and do not think that the feature is complicated to use (Hypothesis 3c) or not useful for them (Hypothesis 3d).

3.3.1 Method study 2

Participants and design

The second study was designed as a quantitative online study conducted in May and June 2016. The average age of the participants was 23.83 years (*SD* = 2.99). The dataset included *N* = 216 responses (142 female (66% valid) and 73 males (34% valid) [1 missing]), with 17 participants who already took part in study 1. More than half of the participants were enrolled in the Bachelor's program (54.6%) and 45.4% students studied in the Master's program of economic and business education at a European university. The average course load in the current semester was 5.42 courses (*SD* = 1.91). Almost half of the students (46%) indicated that they prefer reading texts for university on a display, whereas 54% preferred reading printed texts. Eighty-eight percent of the interviewed students want to use learning analytics for their studies, whereas 12% did not want to use learning analytics. Participants received one credit hour for participating voluntarily in the study.

Materials and instruments

Learning analytics features

The participants were confronted with 15 different learning analytics features, deduced from the qualitative exploratory study: (1) time spent online; (2) suggestion of learning partners; (3) learning recommendations for successful course completion; (4) rating scales for learning material; (5) timeline showing current status and goal; (6) time expected to complete a task or read a text; (7) prompts for self-assessment; (8) further learning recommendations; (9) comparison with fellow students; (10) considering the students' personal calendar for appropriate learning recommendations; (11) newsfeed with relevant news matching the learning content; (12) revision of previous learning content; (13) feedback for assignments; (14) reminder for deadlines; (15) term scheduler, recommending relevant courses. The students were asked to rate each of the 15 features in terms of learning, acceptance, and privacy aspects (LAF; 20 items; Cronbach's α = .93). All items were answered on a 5-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree).

Learning analytics benefits

The learning analytics benefits scale (LAB) focuses on benefits, learning analytics could offer, such as understanding one's learning habits, track the progress towards goals, optimize one's learning paths or adapt to recommendations (Ifenthaler & Widanapathirana, 2014). The students were asked to rate the 36 items on a 5-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree) (LAB; 36 items; Cronbach's α = .94). Sample items of LAB are: "The use of learning analytics would help to compare my learning progress to that of my fellow students" (item 1) or "The use of learning analytics would help to easier define my learning goals" (item 13).

Learning analytics privacy

In the privacy for learning analytics questionnaire (LAP) the students were asked to state their willingness to share personal data for learning analytics systems; for example, tracking of their online paths, educational history, course of studies, etc. All items were answered on a Thurstone scale (1 = Agree; 2 = Do not agree; LAP; 23 items, Cronbach's α = .84).

Demographic information

Students stated demographic information such as age, gender, course load, Internet use, current academic performance (20 items).

Procedure

In May and June 2016 over a period of three weeks, students could participate in an online study, implemented on the university's server and consisting of four parts. In the first part, students received a general introduction into learning analytics (approx. 5 min). The second part focused on learning analytics: The students rated the 15 learning analytics features, each by answering 20 items (LAF; 30 min). Subsequently, they completed the learning analytics benefits scale (LAB; 36 items, 15 min). Finally, they participated in the privacy for learning analytics questionnaire (LAP, 23 items, 10 min). In the third part, the students reported their demographic information (20 items, 7 min).

3.3.2 Results of study 2

Acceptance of learning analytics features (Hypothesis 1)

The five learning analytics features that students most commonly accepted for their studies were as follows: (1) A reminder function, reminding them of deadlines – for example, for enrollment or assignments – (M = 4.2, SD = 1.07), which can be assigned to the organizing and time management activities of self-regulated learning. (2) Students asked for a feature helping to revise corresponding learning content of former semesters (M = 4.12, SD = .94), which refers to the revision of learning materials of the cognitive component. (3) Receiving prompts with self-assessment questions with just-in-time feedback (M = 4.07, SD = .99) helps learners to obtain information about their current knowledge and plan further learning activities, thus providing external feedback to support learners' monitoring processes. (4) Receiving feedback for assignments they created in the online learning environment (M = 4.07, SD = 1.18). This feature also assists students to align their evaluation with external feedback. (5) Learning recommendations for successful course completion (M = 3.98, SD = 1.01) help students to modify their learning activities to reach learning objectives successfully. This is related to monitoring processes of the performance phase. Computing ANOVA and Games Howell post-hoc comparisons (see Table 3-2) revealed significant differences in students' acceptance of the 15 presented learning analytics features $F(14,3225) = 48.07$, $p < .001$, $\eta^2 = .173$. Thus, hypothesis 1 was accepted.

Table 3-2 Post-hoc comparisons for item “would I like to use for my studies” by learning analytics features

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Time online	-														
2. Learning partner	.1759	-													
3. Learning recommendations for course completion	.8565***	.6806***	-												
4. Rating scales for learning material	.1806	.0046	-.6759***	-											
5. Timeline showing current status and goal	.6528***	.4769***	-.2037	.4722**	-										
6. Time for reading and task completion	-.8009***	-.9769***	-1.6574***	-.9815***	-1.4537***	-									
7. Prompts for self-assessment	.9491***	.7731***	.0926	.7685***	.2963	1.7500***	-								
8. Further learning recommendations	.5602***	.3843*	-.2963	.3796	-.0926	1.3611***	-.3889*	-							
9. Comparisons with fellow students	-.6343***	-.8102***	-1.4907***	-.8148***	-1.287***	.1667	-1.5833***	-1.1944***	-						
10. Integration of personal schedule	.375	.1991	-.4815**	.1944	-.2778	1.1759***	-.5741***	-.1852	1.0093***	-					
11. Newsfeed	.2963	.1204	-.5602***	.1157	-.3565	1.0972***	-.6528***	-.2639	.9306***	-.0787	-				
12. Repetition of learning content	.9954***	.8194***	.1389	.8148***	.3426	1.7963***	.0463	.4352**	1.6296***	.6204***	.6991***	-			
13. Feedback for assignments	.9444***	.7685***	.088	.7639***	.2917	1.7454***	-.0046	.3843*	1.5787***	.5694***	.6481***	-.0509	-		
14. Reminder	1.0741***	.8981***	.2176	.8935***	.4213**	1.875***	.125	.5139***	1.7083***	.6991***	.7778***	.0787	.1296	-	
15. Term scheduler	.5417***	.3657	-.3148	.3611	-.1111	1.3426***	-.4074*	-.0185	1.1759***	.1667	.2454	-.4537**	-.4028	-.5324***	-
M	3.125	3.301	3.981	3.306	3.778	2.324	4.074	3.685	2.491	3.5	3.421	4.12	4.069	4.199	3.667
SD	11.923	11.277	10.114	13.465	11.799	13.594	.9996	11.626	13.189	13.012	13.921	.9272	11.772	10.663	13.399
N	216	216	216	216	216	216	216	216	216	216	216	216	216	216	216

Note: *** $p < .001$; ** $p < .01$; * $p < .05$

Students' evaluation of learning analytics features in terms of learning (Hypothesis 2)

Students rated prompts for self-assessment with immediate feedback high in terms of supporting their learning (M = 3.73, SD = .69). The feature allows learners to evaluate their current state of knowledge and plan further learning steps and thus supports monitoring processes. Second, students indicated that learning recommendations for successful course completion would support their learning (M = 3.7, SD = .67) by helping them to adapt their learning strategies accordingly. This feature is comparable to the timeline showing the current status towards learning objectives (M = 3.63, SD = .76) which also allows the students to verify their own monitoring activities with external feedback and modify their learning activities adequately. In order to repeat learning material from previous courses and connect it to new knowledge, the feature to revise learning content was evaluated high to support learning (M = 3.57, SD = .71). Reviewing and connecting learning content belong to the learning strategies self-regulated learners apply during the performance phase. ANOVA and Games Howell post-hoc comparisons (see Table 3-3) revealed significant differences between the 15 presented learning analytics features in terms of students' evaluation regarding learning $F(14,3225) = 56.49$, $p < .001$, η^2 = .197. According to the results, hypothesis 2 was accepted.

Table 3-3 Post-hoc comparisons for learning scale by learning analytics features

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Time online	-														
2. Learning partner	.13757	-													
3. Learning recommendations for course completion	.70668***	.56911***	-												
4. Rating scales for learning material	-.19841	-.33598**	-.90509***	-											
5. Timeline showing current status and goal	.63856***	.50099***	-.06812	.83697***	-										
6. Time for reading and task completion	-.58929***	-.72685***	-1.29597***	-.39087***	-1.22784***	-									
7. Prompts for self-assessment	.73909***	.60152***	.03241	.93750***	.10053	1.32837***	-								
8. Further learning recommendations	.49504***	.35747**	-.21164	.69345***	-.14352	1.08433***	-.24405	-							
9. Comparisons with fellow students	-.38558***	-.52315***	-1.09226***	-.18717	-1.02414***	.2037	-1.12467***	-.88062***	-						
10. Integration of personal schedule	.23743	.09987	-.46925***	.43585***	-.40112***	.82672***	-.50165***	-.25761	.62302***	-					
11. Newsfeed	-.19246	-.33003**	-.89914***	.00595	-.83102***	.39683***	-.93155***	-.68750***	.19312	-.42989***	-				
12. Repetition of learning content	.58399***	.44643***	-.12269	.78241***	-.05456	1.17328***	-.15509	.08896	.96958***	.34656**	.77646***	-			
13. Feedback for assignments	.40212***	.26455	-.30456*	.60053***	-.23644	.99140***	-.33697**	-.09292	.78770***	.16468	.59458***	-.18188	-		
14. Reminder	.09854	-.03902	-.60813***	.29696*	-.54001***	.68783***	-.64054***	-.39649***	.48413***	-.13889	.29101*	-.48545***	-.30357*	-	
15. Term scheduler	-.20172	-.33929**	-.90840***	-.00331	-.84028***	.38757***	-.94081***	-.69676***	.18386	-.43915***	-.00926	-.78571***	-.60384***	-.30026*	-
M	2.9897	3.1273	3.6964	2.7913	3.6283	2.4005	3.7288	3.4848	2.6042	3.2272	2.7973	3.5737	3.3919	3.0883	2.788
SD	.80049	.75453	.67053	.90699	.75945	.94404	.69613	.7374	.89386	.8465	.90176	.70591	.87541	.88097	.92716
N	216	216	216	216	216	216	216	216	216	216	216	216	216	216	216

Note: *** p < .001; ** p < .01; * p < .05

Relation of features to learning, privacy, difficulty, and usefulness (Hypothesis 3)

A hierarchical regression analysis was conducted to determine whether students' evaluation of the features in terms of learning (3.3.1, LAF), privacy (3.3.1, LAP), difficulty (3.3.1, LAF), and usefulness (3.3.1, LAF) are significant predictors if students would like to use a certain learning analytics feature (3.3.1, LAF). The final regression model (see Table 3-4) explained a statistically significant amount of variance in willingness to use a certain learning analytics feature, $\Delta^2 = .652$, $F(7, 3235) = 1518.77$, $p < .001$. Results of the hierarchical regression analysis show that all four variables positively predict the willingness to use a certain learning analytics feature. Especially students' rating in terms of learning and usefulness of a certain learning analytics feature positively predict students' willingness to use it. Accordingly, Hypotheses 3a, 3b, 3c, and 3d are accepted.

Table 3-4 Regression analysis predicting willingness to use learning analytics features on learning, privacy, difficulty, and usefulness

	R^2	ΔR^2	*B*	*SE B*	*β*
Step 1	.496	.495			
learning			1.011	.018	$.704^{***}$
Step 2	.561	.560			
learning			.942	.017	$.656^{***}$
privacy			.276	.013	$.259^{***}$
Step 3	.577	.577			
learning			.918	.017	$.639^{***}$
privacy			.205	.014	$.193^{***}$
difficulty			.170	.015	$.147^{***}$
Step 4	.653	.652			
learning			.676	.018	$.471^{***}$
privacy			.096	.013	$.091^{***}$
difficulty			.037	.015	$.032^{*}$
usefulness			.392	.015	$.392^{***}$

Note. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$

3.4 General discussion

Learning analytics applications such as dashboards and reporting engines are being developed that use learner-generated data and other relevant information to personalize and continuously adapt the learning environment. Learning analytics are expected to provide the pedagogical and technological background for producing real-time interventions at all times during the learning process (Mah, 2016). However, learning analytics have obvious limitations: The first is that learning analytics lack a sound embeddedness in learning theories (Marzouk et al., 2016). The second is the missing empirical evidence of learning analytics regarding their support, acceptance, and effectiveness for learning and teaching (Marzouk et al., 2016). Third, while the field of learning analytics is receiving a lot of attention for its capacity to provide lead indicators of student failure (e.g., attrition, drop-out) (West, Heath, & Huijser, 2016), to date it has focused on individual courses in isolation rather than the capabilities of higher education institutions in general (Ifenthaler, 2017).

This research project addressed the aforementioned limitations by linking self-regulated learning theory with learning analytics features and providing empirical evidence towards acceptance and benefits of learning analytics from a student perspective.

The findings of the first study emphasize students' positive attitude towards learning analytics. Personalized feedback whenever the student needs it seems to be an essential learning analytics feature (Kinshuk, 2012). However, the implementation of such learning analytics features requires distinct analytics-driven assessments that harness formative data from learners and learning environments to facilitate learning processes (Ifenthaler, Greiff, & Gibson, 2018). In addition, the first study revealed that students had ambivalent voices in terms of comparisons with fellow students. The second study confirmed these findings as this feature was rated significantly lower in terms of willingness to use it (see Table 3-2).

Furthermore, the findings of the regression analysis showed that students' evaluation of a learning analytics feature in terms of learning positively predicts their willingness to use it. This further emphasizes the need to design learning analytics features focusing on supporting (self-regulated) learning. Three of the five features that students are the most willing to use, are strongly related to support learning and are also evaluated to support learning by the students: repetition of learning content, prompts for self-assessments, and further learning recommendations to complete a course.

As learners in learning analytics are both producing and sharing data but also benefiting from data analyses (Pardo & Siemens, 2014) the willingness of students to use learning analytics is a prerequisite. Anticipated use of learning analytics is related to students' willingness to share personal data with learning analytics (Ifenthaler & Schumacher, 2016). However, there remain many open questions how learning analytics can support learning processes, as shown in the qualitative study, students are concerned if too much support from learning analytics might reduce their autonomy of learning.

3.4.1 Implications

Students demand highly elaborated and intertwined learning analytics systems. Meeting students' expectations of learning analytics may also increase their willingness to disclose personal data required for valid analytics results (Scholes, 2016; Slade & Prinsloo, 2013). To support students in self-regulating their learning, learning analytics systems should include features related to each phase of self-regulated learning. As the phases of self-regulated learning have a processual character and influence each other some of the features presented in this study can be assigned to more than one phase (see Table 3-5).

Monitoring is seen as an important factor of self-regulated learning and can be complemented with external feedback (Butler & Winne, 1995). Students evaluated self-assessments with immediate feedback, learning recommendations for successful course completion, and the timeline showing the current status towards learning objectives high in terms of supporting their learning these three features are related to monitoring. Due to the strong relevance of real-time feedback revealed in the present studies, time, content, and instructional character of feedback in learning analytics to support learning need to be further examined (Bannert, 2009; Corrin & de Barba, 2014; Gašević et al., 2015).

3.4.2 Limitations and future work

This research focuses on students' perceptions of learning analytics. However, for implementing and using learning analytics systems in higher education all other stakeholders need to be involved; for example, the institutions need to allocate resources (e.g., specialized staff, online learning environment), and facilitators need to create and implement further learning material to the system as well as professionalizing their knowledge in using and interpreting learning analytics analyses (Ifenthaler, 2017). Hence, in future research the positions and expectations of other stakeholders need to be taken into account. To control order effects, the sequence of the presented learning analytics features should be randomized in future studies. To consider the dependency of the students' rating on each feature a larger sample size from multiple institutions and countries would be necessary.

Furthermore, self-reporting inventories for assessing students' self-regulated learning skills are limited as they can only gather strategies after learning happened and of which the learners are aware (Veenman, 2013). Using other methodological approaches to investigate self-regulated learning during a learning process, such as think-aloud protocols or videotaping influence the learning process as students might be more aware of their actions or might feel interrupted (Schraw, 2010). Whereas tracking student behavior might in general not directly influence their activities, adding information of trace data about learners' activities in an online learning environment could help to provide deeper insights into how they apply or adjust learning strategies while learning occurs (Azevedo, 2009; Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Winne & Perry, 2000). Thus, a combination of a multi-method approach to assess learners' self-regulated learning activities seems reasonable (Azevedo, Moos, Johnson, & Chauncey, 2010; Veenman, 2013).

As documented in the second study, students' acceptance to use learning analytics features was high. Nevertheless, students did not rate the perceived learning support accordingly, which might be due to the missing real-time application of learning analytics features. Therefore, it is necessary to implement relevant learning analytics features to validate the given findings and investigate the cohesion of learning analytics and self-regulated learning. The next step of this research project is the implementation of a learning analytics system which allows testing whether and how learning analytics systems are capable of supporting self-regulated learning or if they even hinder it by reducing the learners' responsibility and autonomy (Boekaerts, 1999; Gašević et al., 2015). Due to the ambiguous attitudes towards comparisons with fellow students the relation of learning analytics and motivation to learn needs to be considered in upcoming studies. Especially attention should be paid on the need for autonomy (Deci et al., 1996) as the right measure of support offered through learning analytics systems needs to be scrutinized. This leads to a relevant aspect future research on learning analytics needs to investigate, namely how feedback of learning analytics should be provided to the students to support all components or phases of self-regulated learning. Furthermore, it is necessary to investigate if learners' evaluation of learning analytics features in terms of acceptance and learning support differs regarding their capability to self-regulate their learning to offer the necessary support.

Table 3-5 Learning analytics features related to phases of self-regulated learning

1) Forethought phase	2) Performance phase	3) Self-reflection phase
F2: suggestion of learning partners: can affect motivation and emotions; exchanging about the task can also influence strategy selection	F1: time spent online: supports monitoring time exposure and resource allocation	F3: learning recommendation for successful course completion: helps to evaluate learning and to identify gaps as well as to adjust goals and to plan which strategies can be successful
F8: further learning recommendations: students having difficulties get new approaches (tasks) to understand learning objectives	F2: suggestion of learning partners: supports in terms of help seeking, resource allocation and monitoring as external feedback might be received; can affect volition	F5: timeline showing current status and goal: helps to compare the set goals against learning outcomes and thus lead to strategy adjustment
F9: comparison with fellow students: might affect self-efficacy beliefs and motivation	F3: learning recommendations for successful course completion: helps to better monitor learning progress and apply appropriate resources	F7: prompts for self-assessment: allows to compare learning outcomes with prior set goals leading to potential strategy or goal adjustments
F12: revision of previous learning content: activating prior knowledge might affect task analysis and self-efficacy and thus strategic planning	F4: rating scales for learning material: helps to select fitting learning resources and could foster students critical thinking	F8: further learning recommendations: struggling students get further support to adjust their strategies
F14: reminder for deadlines: helps to be aware of pending tasks and for strategic planning	F5: timeline showing current status and goal: gives feedback about the progress and helps in terms of time management	F9: comparison with fellow students: can affect strategy and goal adjustment
F15: term scheduler, recommending relevant courses matching prior knowledge, requirements and individual scheduling: considers students' prior performance to offer relevant not overcharging tasks (subjects), thus affects emotion, motivation and strategic planning	F6: time expected to complete a task or read a text: facilitates time management	F13: feedback for assignments: can influence students' evaluation and thus lead to goal and strategy adjustments
	F7: prompts for self-assessment: helps to foster students' metacognitive awareness about their learning outcomes and knowledge as it facilitates monitoring; allows repetition of learning content	
	F9: comparison with fellow students: gives feedback about own performance, learning activities and effort compared to others	
	F10: considering students' personal calendar for appropriate learning recommendations: helps in terms of time management	

	F11: newsfeed: enables students to connect learning content with related current news, which can facilitate memorization
	F12: revision of previous learning content: allows learners to repeat basic/prior knowledge and thus connect it to new learning content more easily
	F13: feedback for assignments: helps to align self-monitoring with external feedback
	F14: reminder for deadlines: supports time management

3.5 Conclusion

Learning analytics can provide several benefits to learners and other involved stakeholders (Ifenthaler & Widanapathirana, 2014). The findings of this research project indicate that students perceive value of learning analytics features in terms of learning and are thus willing to use them. However, students were also concerned that learning analytics might be invasive or reduce their autonomy in terms of how to learn.

When implementing learning analytics, the needs and expectations of all stakeholders need to be considered to avoid resistance. The willingness to use can be supported by designing learning analytics features meeting students' needs, highlighting their benefits and functions, as well as by providing transparency regarding the intended purpose, privacy issues, and underlying analyses. Institutions, instructors, students and administrative staff need to be prepared to use and interpret learning analytics systems output (Ifenthaler, 2017).

To provide valid learning analytics to students that support (self-regulated) learning and thus facilitate learning success and retention, further research is inevitable. Additionally, approaches to integrate offline learning into learning analytics analyses may improve the overall validity of such systems. Finally, besides the detailed information and benefits learning analytics can offer, students also need to be aware of their limitations.

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4 The importance of students' motivational dispositions for designing learning analytics

4.1 Introduction

Learning theories such as self-regulated learning highlight the importance of motivation for learning (Boekaerts, 1999; Pintrich, 2000c; Schunk, Pintrich, & Meece, 2008; Zimmerman, 2002). Motivation is a multifaceted concept several disciplines pay attention to as it is considered to be the driver for a person's actions and not obvious from external. Focusing on a cognitive approach, motivation can be defined as "the process whereby goal-directed activity is instigated and sustained" (Schunk et al., 2008, p. 4). This definition implies that motivation is a process as well as goal-oriented and that both initiating activities and persisting in activities are crucial to achieving the designated goals.

Motivational factors, such as interest, autonomy, competence, relatedness, and self-efficacy, determine students' regulation effort towards a learning goal (Eseryel, Law, Ifenthaler, Ge, & Miller, 2014; Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004; Zimmerman & Schunk, 2008). Hence, differences in learning outcomes are related to students' capability to self-regulate their learning, individual characteristics, and motivational dispositions (Schunk & Zimmerman, 2008; Zimmerman, 2002). Especially in highly self-regulated learning environments, such as higher education or online learning, motivation is crucial for successful learning (Chen & Jang, 2010; Joo, Oh, & Kim, 2015; Keller, 2008a; Keller & Suzuki, 2004; Moos & Bonde, 2016). Self-regulated learning processes are considered to be interdependently connected to motivational processes, as motivation affects learning strategy selection, learning processes, and outcomes. Likewise, self-regulation can influence learners' motivation (Lehmann, Hähnlein, & Ifenthaler, 2014; Zimmerman, 1990, 2011; Zimmerman & Schunk, 2008).

In the past few years, higher education has seen various changes, due to larger study cohorts but also higher withdrawals (Mah, 2016), as well as the advancement of applying technologies for learning. One important driver for changing learning and learning environments is the availability of vast amounts of educational data and unforeseen possibilities to make use of them (Long & Siemens, 2011). Learning analytics are a key concept related to this increase in educational data. They use static and dynamic information about learners and learning environments, assessing, eliciting, and analyzing it, for real-time modeling prediction, and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). Current research on learning analytics focusses on technical issues and data processing (Berland, Baker, & Bilkstein, 2014; Costa, Fonseca, Santana, de Araújo, & Rego, 2017), on data privacy (Drachsler & Greller, 2016; Ifenthaler & Schumacher, 2016; Rubel & Jones, 2016; West, Huijser, & Heath, 2016), on developing user systems (d'Aquin, Dietze, Herder, Drachsler, & Taibi, 2014), on relationships between learner characteristics and learning outcome (Ellis, Han, & Pardo, 2017; Gašević, Jovanovic, Pardo, & Dawson, 2017; Liu et al., 2017), or on specific applications for dashboards (Park & Jo, 2015; Schumacher & Ifenthaler, 2018; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). However, linking learning analytics with learning theories is still at an early stage (Marzouk et al., 2016). Additionally, student motivation is not yet sufficiently considered for analyses of learning analytics (Lonn, Aguilar, & Teasley, 2015). In a qualitative study, Corrin and de Barba (2014) investigated how feedback through learning analytics dashboards impacts students' motivation. Their findings indicate that students mostly perceived a positive effect on their motivation in terms of effort regulation or awareness of their progress. However, some participants also indicated that it did not influence their motivation at all. Accordingly, further empirical studies are required to identify the capabilities of learning analytics for facilitating learning processes and especially for supporting and not impairing learning motivation.

To add evidence to this gap in research, the focus of this study was to investigate students' motivational dispositions and its relationship to perceived support from learning analytics systems.

4.2 Theoretical framework

4.2.1 Motivation in (self-regulated) learning processes

Motivation is considered to be a result of an interaction between environmental and individual factors (Cook & Artino Jr, 2016; Hartnett, George, & Dron, 2011; Keller, 2008b; Svinicki & Vogler, 2012). Thus, internal as well as external factors can influence a person's motivation, such as self-efficacy beliefs (Bandura, 1977;

Zimmerman, Schunk, & DiBenedetto, 2017), perceived autonomy (Deci & Ryan, 2008; Deci, Ryan, & Williams, 1996), attributions (Schunk, 2008; Weiner, 1985), value of the task, and expected difficulty in reaching the goal (Eccles & Wigfield, 2002; Engelschalk, Steuer, & Dresel, 2016; Allan Wigfield, Tonks, & Klauda, 2009), goal orientations (Elliot, 2005; Elliot & Hulleman, 2017), academic self-concept, or the design of the learning environment (Keller & Suzuki, 2004).

Self-regulating their learning demands a great effort of students; thus, they need to be motivated to initiate and sustain within these processes (Pintrich, 1999). Self-regulation requires metacognitive monitoring, control of learning activities, and motivational states to reach the designated learning outcomes. Learners need to adjust their behavior, cognition, or motivation accordingly (Lehmann et al., 2014; Winne & Hadwin, 2008). Learning motivation and goal setting in self-regulated learning are influenced by task conditions and requirements, students' beliefs about self-efficacy, outcome expectancies, and individual characteristics (e.g., dispositions, prior experiences, and knowledge) (Winne & Hadwin, 2008; Zimmerman et al., 2017). While engaging in the performance phase, motivation is crucial to maintaining learning activities. Additionally, self-regulated learners use several strategies to control and regulate their motivation, such as (a) extrinsic regulation (self-rewarding, reminding of performance goals), (b) intrinsic regulation (increase task value, interest, or self-efficacy beliefs), (c) volition (change the environment, attention), and (d) information processing (help-seeking, cognitive strategies) (Corno, 1993; Winne & Hadwin, 2008; Wolters, 1998). Thus, motivational constructs are considered to have an impact on self-regulated learning processes (Duffy & Azevedo, 2015; Zimmerman, 2011; Zimmerman & Schunk, 2008).

This study focusses on students' goal orientations and their academic self-concept as crucial motivational components of self-regulated learning (Eccles & Wigfield, 2002; Pintrich, 1999, 2000c). Key aspects of motivational components are described below and will be linked to learning analytics.

Goal orientation

Achievement goals aim to explain "the purpose or reason students are pursuing an achievement task as well as the standards or criteria they construct to evaluate their competence or success on the task" (Pintrich, 2000a, p. 94). They are described as patterns of beliefs and feelings about success, effort, ability, errors, feedback, and standards of evaluation (Elliot, 2005). Thus, achievement goal theories assume that students have different learning behaviors because they have different goal orientations when engaging in learning processes (Cook & Artino Jr, 2016; Dweck & Leggett, 1988; Elliot, 2005; Elliot & Hulleman, 2017; Schunk et al., 2008).

The assumption is that there are two different types of achievement goal orientations (see Table 4-1). (1) Learning goal orientation (also labeled as mastery goal orientation): these learners focus on the intrinsic value of learning, such as gaining new knowledge and skills. Learners who have a learning goal orientation assume that intelligence and skills are controllable via learning activities as success is related to effort whereas failure is considered to be an opportunity to learn (Dweck & Leggett, 1988). These learning goals are divided into (1a) learning-approach goals, where learners focus on gaining competence by seeking challenging tasks and persisting in goal-achievement behavior even when facing obstacles and (1b) learning-avoidance goals when learners try to avoid losing skills or abilities and being wrong, not relative to others but only in reference to themselves or the task (Elliot, 2005; Pintrich, 2000a; Senko, Hulleman, & Harackiewicz, 2011).

(2) Performance goal orientation: these learners focus on achieving better learning outcomes than others and avoid appearing as unintelligent. This goal orientation is associated with perceiving intelligence as being static, avoiding challenges and giving up quickly, as failure is seen as a lack of ability; only if learners are self-confident in their intelligence or competence they seek challenges (Dweck & Leggett, 1988; Elliot, 2005). Performance goals are further divided into (2a) performance-approach goals, as those of students who are willing to show their competences to others or to outperform their peers; and (2b) performance-avoidance goals, related to students who try to hide their incompetency by avoiding challenges or uncertainty. Additionally, work-avoidance goals refer to students' tendency to reach goals by avoiding work or effort at all (Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997; Spinath, Stiensmeier-Pelster, Schöne, & Dickhäuser, 2012). This goal orientation is assumed to be distinct from the above achievement goals as it is specifically characterized by the absence of achievement goal adoption (Elliot, 1999).

Table 4-1 Exemplary overview about the characteristics of achievement goals

	Approach	Avoidance
Learning goal orientation	Learning-approach goals: - develop skills and abilities - understand a task - seek for challenging tasks - develop competence	Learning-avoidance goals: - avoid losing skills and abilities - avoid being wrong - avoid not understanding a task or material - avoid intrapersonal incompetence
Performance goal orientation	Performance-approach goals: - show competence to others by seeking appropriate tasks to appear talented - outperforming peers	Performance-avoidance goals: - avoid showing incompetence to others - avoid challenges

In general, approach goals (learning and performance goal orientation) are positively related to performance or achievement while avoidance goals (learning and performance goal orientation) are negatively related (Van Yperen, Blaga, & Postmes, 2014). Linnenbrink-Garcia, Tyson, and Patall (2008) reported in a meta-analysis that more studies found significant relations of learning-approach goals with achievement than with performance-approach goals, in addition some found negative relations of performance-approach goals with achievement. Further, performance goal orientation is associated with higher academic outcomes in competitive educational contexts whereas learning goal orientation is related to interest and deeper learning strategies (Harackiewicz, Barron, & Elliot, 1998). Performance-avoidance goals are associated to a negative learning outcome (Elliot & Hulleman, 2017). Learners with performance orientation are likely to attribute failure and effort to personal incompetence or low ability and thus as non-controllable (Dweck & Leggett, 1988). Help seeking, which is considered to be a self-regulatory strategy (Zimmerman & Schunk, 2008), is related to the goal orientations of learners, as learning-approach goal oriented learners think of this as a possibility to enhance their competence whereas avoidance-oriented learners might fear showing low ability (Zimmerman & Schunk, 2008). Depending on the context and situation, one goal orientation might be predominant. However, some learners might generally tend to adopt a learning oriented goal approach whereas others are more likely to behave more performance goal oriented (Pintrich, 2000a).

Goal orientations are related to perceived competence as learners who feel highly competent are more likely to adopt approach goals (e.g., 1a or 2a) whereas low perceived competence leads to higher expectancies of failure and adoption of avoidance goals (e.g., 1b or 2b) (Elliot, 2005). A person's competence can be evaluated against (a) an absolute standard, based on the requirements of a task, (b) an intrapersonal standard with reference to past performance or maximum potential performance of the self, and (c) a normative standard which is related to the performance of others (Elliot, 2005; Elliot, Murayama, & Pekrun, 2011).

Academic self-concept

The perceived abilities of learners influence their interest, persistence, motivation to learn, and choice of learning strategies (Cook & Artino Jr, 2016; Schunk et al., 2008). The academic self-concept describes a cognitive representation of a person's perceived abilities in an academic achievement situation (Bandura, 1994; Skaalvik & Skaalvik, 2005). Relevant for learning outcomes is that intrinsic motivation is associated with perceived competence of learners and can be supported by skill-matching but also by challenging tasks and feedback (Hau & Marsh, 2015). Deci and colleagues (1996) postulate a causal effect of the academic self-concept on intrinsic motivation.

When estimating the academic self-concept, a person refers to three reference norms: (a) social reference, comparing own performance with that of relevant others; this reference is crucial for building the academic self-concept since learners rely on external feedback about their performance, such as test results, attributions and, feedback from relevant persons (e.g., teachers, peers, parents) (Dickhäuser, Schöne, Spinath, & Stiensmeier-Pelster, 2002); (b) individual reference, comparing own performance over domains and time; and (c) criterion-based reference, comparing own performance to objective criteria such as learning objectives. Furthermore, the academic self-concept includes (d) performance perceptions of the learner without a reference category (Dickhäuser et al., 2002; Eccles & Wigfield, 2002; Weidinger, Spinath, & Steinmayr, 2016).

The academic self-concept seems to have conceptual analogies with academic self-efficacy beliefs of learners, postulated as vital for motivation in Bandura's (1993) social-cognitive view on learning and motivation (Weidinger et al., 2016). There are, however, differences. While the academic self-concept represents a person's perceived competence within an academic domain, characterized as more past-oriented and relatively stable, academic self-efficacy is a learner's perceived confidence to successfully perform a certain academic task, considered to be more context-specific, future-oriented, and malleable (Bandura, 1977, 1994). Bong and Skaalvik (2003) state that the academic self-concept influences self-efficacy beliefs but not vice versa. Self-efficacy beliefs are built upon prior experiences and outcomes (Zimmerman & Schunk, 2008). However, both concepts are considered to have impacts on intrinsic motivation, strategy use, engagement, persistence, task choice, goal-setting, performance, and achievement (Ferla & Valcke, 2009).

Constructs of personal expectancy comparable to the academic self-concept are included in motivational theories. Such constructs include the expectancy of success in the expectancy value theory of motivation (Bong & Skaalvik, 2003), and also goal orientations, especially the performance-oriented goals are influenced by a person's belief in being able to reach a certain goal. Hence, self-efficacy beliefs or more generally academic self-concept might influence all phases of self-regulated learning as students select tasks or set goals depending on their perceived abilities and differ in persistence as well as in dealing with challenges (Zimmerman & Schunk, 2008). Outcome expectancies are related to self-efficacy beliefs and are a source of motivation as learners will not pursue goals they do not feel capable of reaching (Bandura, 1993; Schunk, 1991).

Motivational design of (online) learning environments

The ARCS (attention, relevance, confidence, satisfaction) model aims to integrate and thus illustrate the relations between the theoretical concepts of volition, motivation, learning, and performance in order to facilitate research and instructional design to generate motivating (online) learning environments (Keller, 2008b). The original model consists of four components (Keller, 2008b; Keller & Suzuki, 2004; Li & Keller, 2018): (1) attention, referring to the level of curiosity aroused; (2) relevance of a given learning objective to a learner, including its perceived value; (3) confidence in the individual belief of being successful in the learning activity, including the attributions assigned to the learning outcome, and (4) satisfaction about the evaluated overall quality of the learning outcome and process. These four components are complemented by volition: self-regulatory strategies to persist in goal-oriented behavior (Keller & Suzuki, 2004).

Thus, the expanded theory of motivation, volition, and performance provides a supplement because it explains how external and internal self-regulatory processes can support learners not only in selecting goals but in acting and persisting to reach their goals (Keller, 2008a). Its motivational foundation is based on the expectancy value theory, self-efficacy beliefs, goal orientation, attribution theory, and assumptions of self-determination theory. In going beyond goal setting and towards action, the model refers to action control theory and volitional strategies. Furthermore, it is assumed that external learning stimuli are processed with reference to cognitive load and information processing theory but are influenced by motivational components. Finally, this process should lead to learners who initiate and sustain learning processes and perform successfully, thus achieving satisfying learning outcomes.

The motivational design process originally consisted of ten steps, including analysis of learners and learning environment, defining motivational goals, design steps in identifying and selecting motivational tactics to reach these goals, implementation, and post-instructional steps to evaluate the design (Keller, 1987, 2008a). Whereas other models (e.g., FEASP-approach (fear, envy, anger, sympathy, and pleasure) (Astleitner, 2000)) more broadly consider emotions in learning in general, this theory aims to support research, diagnosing motivational issues, and designing motivational learning environments.

4.2.2 Motivation in learning analytics

As demonstrated, motivation is a crucial factor in engaging in learning activities and pursuing learning goals. However, combining motivational theory, learning theory, and learning analytics is still at an early stage (Marzouk et al., 2016). Learning analytics provide several benefits to all stakeholders including three perspectives: summative, real-time, and predictive (Ifenthaler & Widanapathirana, 2014). In relation to learners' benefits and motivational dispositions, learning analytics may support for example: (a) evaluating learning outcomes against efforts, (b) monitoring the current progress towards goals, (c) integrating just-in-time feedback from assessments into learning processes, (d) adapting learning activities according to learning recommendations and thus increasing learning success.

To react accordingly and provide motivational interventions, learning analytics require information about the learners, their characteristics, and especially about their current motivational state, as well as the perceived relevance of the learning tasks (Keller, 2008b; Liu et al., 2017). Learning analytics may provide motivational interventions using data about learners, their behavior in the learning environment, and their interaction with the learning material. Because of the high adaptability of a learning analytics system (Ifenthaler & Widanapathirana, 2014), it can react to motivational changes during the learning process.

Learning analytics systems should offer guidance by giving appropriate and personalized feedback on successful and amendable results as learners' self-efficacy beliefs are based on prior success as well as on feedback on their previous performance (Bandura, 1993, 1994; Schunk, 1991; Zimmerman et al., 2017). However, the feedback provided through learning analytics should not be perceived as too intrusive or controlling (Roberts, Howell, & Seaman, 2017) as the perceived autonomy of learners is central for learning motivation (Deci et al., 1996). To take into account students' motivation and the need for autonomy, learning analytics should allow the beneficiaries to set their own learning goals and provide several voluntary learning recommendations to increase students' choice and relevance of learning content. Learning analytics systems should serve appropriate learning recommendations and self-assessments, in line with individual capabilities and ones that do not cause overextension but lead to a challenge and thus to increased curiosity, intrinsic motivation, increased perceived competence, and higher self-efficacy beliefs (Hau & Marsh, 2015; Keller, 2008a). Real-time feedback on current performance and progress towards goals can increase students' perceived confidence in successfully fulfilling the learning requirements and thus lead to strategy adjustments, and ideally to better learning outcomes. However, if students are struggling, the system may provide appropriate guidance on how to reach the designated learning objectives. The feedback could also influence students' dispositions on their learning outcome, leading to changes in upcoming pre-actional phases of motivation (Ifenthaler & Lehmann, 2012). To increase learners' curiosity, various types of learning material such as videos, texts, podcasts, or external links are provided to meet all learners' preferences. Additionally, to increase the relevance of the learning content, learning analytics systems illustrate the connections between different learning content and previous learning artifacts. Furthermore, prompts can be used to investigate and to expand learners' motivation (Bannert, 2009; Ifenthaler, 2012).

Competitive environments might be perceived as reducing autonomy and so are related to a decrease of intrinsic motivation (Deci et al., 1996). A qualitative study investigating students' expectations on learning analytics features revealed differences in students' attitudes towards receiving analyses comparing their performance as it might reduce their motivation (Schumacher & Ifenthaler, 2018). Especially for students who are not performing well in comparison with others, this information might impair their academic self-concept (social reference) and thus their self-efficacy beliefs and motivation. However, a feature comparing one's performance with those of others might be of interest to performance-approach oriented learners.

Considering the assumptions on motivation and (self-regulated) learning of Keller (2008b), Pintrich (2000c), and Zimmerman (2005, 2011), learning analytics can be supportive in initiating and sustaining learning motivation, as summarized in Table 4-2.

Table 4-2 Learning analytics potential support on motivation in the cyclical phases of learning

Pre-action phase

- Providing clear learning objectives and relating them to tasks
  → goals, goal setting; task value, interest
- Connecting learning material to prior knowledge, previous course content, learning objectives, or external data (news, videos)
  → task value, interest, relevance
- Offering skill matching but challenging tasks based on available data
  → curiosity, interest; outcome expectancies; self-efficacy
- Motivational prompts if learners are not beginning to learn or not learning appropriately to reach goals
  → effort initiation
- Comparison with peers and their learning activities
  →self-efficacy; performance goal orientation
- Feedback on predicted learning outcomes
  → expectancies, self-efficacy beliefs
- Feedback on previous learning outcomes and activities
  → self-efficacy; outcome expectations

Action phase

- Analyzing learner's motivational state based on behavior and by using prompts
  → early interventions to increase motivation
- Offering different learning material (videos, slides, texts, external links, news)
  → arouses curiosity; autonomy/choice, interest

- (Prompts) for self-assessments and inform learners about their current state of knowledge not grading
  → autonomy/control; effort regulation; help-seeking; effort initiation
- Just-in-time feedback
  → outcome expectancies, learning actions, rewards, persistence
- Feedback on progress towards learning objectives
  → self-rewards; positive/negative outcomes; reminds of goals
- Providing appropriate learning recommendations on how to reach learning objectives
  → adapt strategies, effort persistence
- Motivational prompts
  → motivation regulation, effort regulation, attention control
- Advising to change learning environment (noise, light etc.)
  → attention control
- Recommendation of learning partners dealing with the same problem
  → help seeking, social reference and embeddedness
- Expected time for completing tasks
  → reward, pausing, monitoring

Post-action phase

- Feedback about learning outcomes
  → attributions, self-efficacy beliefs
- Facilitating learner's evaluation of learning outcomes against goals/standards
  → satisfaction; leading to adaptive/defensive reactions
- Recommendations about improvements for upcoming tasks
  → attributions, increase perceived control of outcomes, adapt strategies, prepare upcoming strategic planning

4.2.3 Research questions and hypotheses

The purpose of this study is to investigate the relationship between students' motivational dispositions and their perceived support of learning analytics systems.

Depending on their goal orientations, students have different reasons for pursuing an achievement task (Pintrich, 2000a), which leads to the use of varying learning strategies and motivational sources. Thus, students' goal orientations also have an impact on their expectations towards support of their learning processes and motivational states. Therefore, it is hypothesized that students' learning goal orientation (Hypothesis 1a), performance-approach goal orientation (Hypothesis 1b), performance-avoidance goal orientation (Hypothesis 1c), and their work-avoidance goal orientation (Hypothesis 1d) are related to their rating of perceived support from learning analytics.

Likewise, learners' anticipated abilities impact their interest, persistence, motivation to learn, and the learning strategies selected (Cook & Artino Jr, 2016; Schunk et al., 2008). Depending on the predominant reference norm on which learners build their academic self-concept, they might demand different support in terms of motivation and learning. Thus, it is assumed that students' academic self-concept based on individual reference (Hypothesis 2a), criterion-based reference (Hypothesis 2b), social reference (Hypothesis 2c), and without reference (Hypothesis 2d) significantly predict their rating of perceived support from learning analytics. Additionally, students' background (i.e., age, gender, final school grade), and study related characteristics (i.e., semester load, current study grade, study program) were reviewed for their influence on how they predicted the anticipated support from learning analytics (Hypothesis 3).

4.3 Method

4.3.1 Participants and design

We recruited a purposive sample of 802 students (472 female, 330 male) from a European university. Most students were enrolled in a Bachelor program (n_{BA} = 588), followed by Master students (n_{MA} = 137), and students in other study programs (e.g., diploma; n_{OTHER} = 77). The participants were enrolled in economics and law (56.6%), STEM (16.1%), languages, culture and arts (13.5%), social sciences (9.7%), medicine (2.6%), and other fields of study (0.9%) [4 missing responses]. Students were asked to participate in an online study that was implemented on the university's server.

4.3.2 Instruments

Learning and achievement motivation scales

The scales for the assessment of learning and achievement motivation (Spinath et al., 2012) measured four factors: learning goal orientation, performance-approach goal orientation, performance-avoidance goal orientation, and work-avoidance goal orientation (31 items; split-half reliability ranging from .73 to .78).

Academic self-concept scale

The academic self-concept scale (Dickhäuser et al., 2002) measures academic self-concept based on four factors: social, individual, criterion-oriented, and no reference norms (22 items; Cronbach's α ranging from .74 to .92).

Expected learning analytics support

The instrument consists of 20 items investigating how learning analytics may support learning (LAS; Cronbach's α = .936). Sample items of LAS are "Learning analytics would help me to track my progress towards my learning goals", "Learning analytics would help me to facilitate my learning activities", "Learning analytics would help me to better analyze my learning outcomes". All items were answered on a 5-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree).

Demographic information

Demographic information included gender, age, course load, study program (15 items in total).

Procedure

Students of various disciplines were invited to participate in the online study, which consisted of four parts. First, students answered questions about their learning and achievement motivation (Learning and achievement motivation scales; 8 minutes). Second, they were asked to disclose information about their academic self-concept (Academic self-concept scale; 7 minutes). Then, they rated benefits they thought learning analytics systems could offer in order to support learning (Expected learning analytics support; 6 minutes). Finally, students revealed their demographic information (Demographic information; 10 minutes).

4.4 Results

Table 4-3 shows the descriptive statistics and zero-order correlations of predictors used in the regression analysis indicating significant correlations between students' background, study characteristics, goal orientations, academic self-concept, and perceived learning analytics support.

Table 4-3 Descriptive statistics and zero-order correlations for students' background, study related characteristics and goal orientations (N = 469)

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Final school grade	-											
2. Semester load	-.062	-										
3. Current study grade	.494***	.042	-									
4. Learning goal orientation	-.089*	.144**	-.132**	-								
5. Performance-approach goal orientation	-.132**	.084*	-.132**	.208***	-							
6. Performance-avoidance goal orientation	-.070	.034	-.007	-.143***	.475***	-						
7. Work-avoidance goal orientation	.073	-.058	.112**	-.337***	.183***	.435***	-					
8. Individual reference	-.040	-.014	-.227***	.240***	.178***	-.051	-.195***	-				
9. Criterion-based reference	-.245***	.053	-.422***	.180***	.275***	-.008	-.032	.546***	-			
10. Social reference	-.259***	.005	-.354***	.063	.252***	.075	.082*	.370***	.729***	-		
11. No reference	-.258***	.071	-.390***	.152***	.244***	.001	-.043	.471***	.828***	.743***	-	
12. Perceived learning analytics support	.113**	.044	.155***	.208***	.260***	.185***	.105**	.116**	.054	.051	-.003	-
M	2.25	30.64	2.25	4.27	3.01	2.31	2.23	4.02	3.63	3.32	3.60	3.44
SD	.59	25.57	.57	.56	.73	.86	.79	.61	.63	.62	.59	.70

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

A hierarchical regression analysis was used to determine whether students' background (age, gender, final school grade), study-related characteristics (semester load, current study grade, study program), goal orientations (learning goal orientation, performance-approach goal orientation, performance-avoidance goal orientation, work-avoidance goal orientation), and academic self-concept (individual reference, criterion-based reference, social reference, no reference) were significant predictors of perceived learning analytics support. The results of the regression analyses for *perceived learning analytics support* are presented in Table 4-4 yielding a ΔR^2 of .183, $F(14, 454) = 8.49$, $p < .001$. With regard to hypothesis 1a, students' *learning goal orientation* positively predicted the *perceived learning analytics support*, indicating that the higher the students' learning goal orientation, the higher the perceived support from learning analytics. Further, students' *performance-approach goal orientation* (Hypothesis 1b) positively predicted the *perceived learning analytics support*, indicating that the higher the students' performance-approach goal orientation, the higher the perceived support from learning analytics. With regard to hypothesis 2a, students' *individual reference* orientation positively predicted the *perceived learning analytics support*, indicating that the higher the students' individual reference norm, the higher the perceived support from learning analytics. Finally, students' *no reference* (H2d) orientation negatively predicted the *perceived learning analytics support*, indicating that the lower students' no reference norm, the higher the perceived support from learning analytics. With regard to hypothesis 3, no significant predictors related to students' background could be identified. However, *current study grade* positively predicted the *perceived learning analytics support,* indicating that the weaker the students' study performance, the higher the *support from learning analytics* is perceived. In addition, *study program* negatively predicted the *perceived learning analytics support*, indicating that students in lower semester levels expect higher support from learning analytics systems.

Table 4-4 Regression analysis for students' background, study related characteristics, goal orientations, and academic self-concept predicting perceived support from learning analytics (N = 469)

Perceived learning analytics support	*B*	*SE B*	*β*
Students' background			
Age	.025	.016	.075
Gender (0 = male)	-.101	.062	-.071
Final school grade	.026	.061	.022
Study related characteristics			
Semester load	.000	.001	.001
Current study grade	.217	.065	.178**
Study program (0 = Bachelor)	-.308	.086	-.178***
Goal orientations			
Learning goal orientation	.257	.060	.206***
Performance-approach goal orientation	.156	.050	.164**
Performance-avoidance goal orientation	.082	.043	.102
Work-avoidance goal orientation	.082	.045	.093
Academic self-concept			
Individual reference	.132	.061	.115*
Criterion-based reference	.101	.095	.091
Social reference	.089	.076	.079
No reference	-.200	.095	-.170*

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

To sum up, Hypothesis 1 is accepted for students' goal orientations (learning goal orientation (H1a), performance-approach goal orientation (H1b)), Hypothesis 2 is accepted for students' academic self-concept (individual reference orientation (H2a), no reference orientation (H2d)), and Hypothesis 3 is accepted for current study grade and study program.

4.5 Discussion

Research on motivation particularly emphasizes the influence of self-efficacy, self-determination, and goal orientation on the quality and outcome of learning (Dickhäuser et al., 2002; Ryan & Deci, 2000; Zimmerman & Campillo, 2003; Zimmerman et al., 2017). Further, research on motivation draws on several well-established theoretical perspectives, such as expectancy value theory (A. Wigfield & Eccles, 2000), attribution theory (Weiner, 1985), social-cognitive theory (Bandura, 1977), goal-orientation theory (Dweck & Leggett, 1988; Elliot, 2005), or self-determination theory (Deci & Ryan, 1991). Contemporary motivational theories influencing research in learning sciences recognize that aspects that motivate one learner might not motivate another (Svinicki & Vogler, 2012). Furthermore, modern theories of motivation presume the intentionality of human behavior: people are motivated when they are willing to achieve a certain future state (Deci & Ryan, 1991).

Especially in online learning environments and higher education motivation of students needs to be considered already when designing the learning environment. Therefore, Keller's theory (2008b) which includes relevant theoretical concepts such as volition, motivation, learning and performance can be used as a guiding framework. As recent empirical findings in the field of learning analytics document, a successful implementation relies on a broad variety of information about individual learners, such as their motivational dispositions as well as individual characteristics (Ifenthaler & Widanapathirana, 2014). Hence, to adapt the learning environment to students' (motivational) needs the design of learning environments can be iteratively informed by learning analytics (Ifenthaler, 2017; Ifenthaler, Gibson, & Dobozy, 2018). In this study, learning goal orientation and performance-approach goal orientation significantly predicted the perceived support from learning analytics. As these two goal orientations are related to either deeper interest and learning strategies or higher academic achievement (Harackiewicz et al., 1998), students assumed more benefits in terms of supporting learning and motivation. However, students with learning goal orientation and performance-approach goal orientation might demand different support (Duffy & Azevedo, 2015). The former might ask for challenging tasks and additional resources, as they are interested in increasing their knowledge and skills (Zimmerman & Schunk, 2008). Whereas the latter might prefer social comparisons related to performance, progress, used material, etc. (Seifert & O'Keefe, 2001) to achieve the designated outcome and outperform others.

The students with performance-avoidance and work-avoidance goal orientation seem not to anticipate support from learning analytics. Nevertheless, it could be especially necessary to point out learning analytics benefit to theses learners as they might particularly risk a lack of motivation to learn or be less able to apply suitable learning strategies and achieve favorable results (Meece, Bluemenfeld, & Hoyle, 1988; Pintrich, 2000b; Wolters, 2003). Thus, further research should investigate differences in terms of motivational dispositions and preferred learning analytics features. Table 4-2 presents potential learning analytics features related to the three phases of self-regulated learning which may support learners' motivation. The identified features can serve as basis for designing learning analytics systems and for further (experimental) studies on potential differences of students' engagement with and perceptions of these features related to their motivational dispositions. Additionally, research should also be complemented by considering other motivational constructs. Support provided in online learning environments which is not aligned with students' needs might even lead to negative learning outcomes (Chen & Jang, 2010). Support such as scaffolding had a positive impact on learning and achievement of students with performance-approach goal orientation but not or rather a negative impact on students' learning outcomes when adopting learning-approach goals (Duffy & Azevedo, 2015). This emphasizes further the necessity to investigate the relation of motivational dispositions and (perceived) support from learning analytics in terms of learning processes and outcomes.

Regarding the academic self-concept beliefs, students with an individual reference norm assume that they could benefit from learning analytics. Students who build their academic self-concept upon comparisons with their own work might be interested in learning analytics for contrasting previous performance with current performance. Surprisingly students with criterion-based and social reference seem not to assume benefits from learning analytics. And furthermore, students whose academic self-concept is based on a more general reference (no reference norm), which is considered to include the other reference norms (Dickhäuser et al., 2002), perceive reverse benefits. Thus, a deeper analysis differentiating the various benefits of learning analytics or relating them to offered learning analytics features might lead to a more profound understanding of learners' perceived support from learning analytics.

Furthermore, the results indicated that students with lower academic performance perceive more support from learning analytics. Thus, learning analytics seem to these students a meaningful support to their performance and how they could improve their learning approach, which both impact motivation as well. The guiding character of learning analytics is also indicated by the result that undergraduate students anticipate more support from learning analytics than more experienced Master students.

The present study has obvious limitations as self-reported measurements are used to assess students' motivational dispositions and as the focus is on only two motivational concepts. Furthermore, the students were not able to use a learning analytics system, thus, the perceived support was based on a hypothetical system, which might lead to biases. Additionally, even though the sample size was appropriate using a purposive sample by actively approaching students to participate in this study without ensuring representativity of age, gender, study subject, etc. might lead to biases due to self-selection and hence to difficulties in generalizability. Learning analytics need to combine trace data and psychological inventories and thus allow further investigation of the reciprocal relation of motivation and self-regulated learning activities of students when engaging in online learning environments (Ellis et al., 2017; Lonn et al., 2015; Winne & Baker, 2013; Zimmerman, 2008). Such a holistic application of learning analytics may lead to a better understanding of motivation and learning processes and thus enables the creation of adaptable and personalized learning environments that meet learners' individual needs (Ifenthaler & Widanapathirana, 2014). However, establishing valid and economic indicators on student motivation for learning analytics requires further research to ascertain when and how to measure motivational states taking account of its' processual character related to the other components of self-regulated learning (Moos & Stewart, 2013). As learning analytics currently already provide feedback to students such as results of comparisons with peers or forecasts about their final course performance (Gašević, Dawson, & Siemens, 2015), the impact of timing and content of feedback on learning motivation needs to be examined in future research. For further insights into students' responses to feedback, analyzing trace data seems to be a promising approach (Zimmerman, 2008). For example, investigating students' behavioral patterns when dealing with learning materials, prompts or analyses of the learning analytics system related to their motivational dispositions might allow a higher adaptivity of learning analytics (Liu et al., 2017).

4.6 Conclusion

Learners differ in their reasons for engaging in achievement tasks and thus seem to expect different support while learning (Schunk & Zimmerman, 2008). The findings of this study indicate that motivational dispositions such as goal orientation and academic self-concept as well as study-related characteristics impact students' perceived support from learning analytics. As the focus of learning analytics is on supporting learning where motivation is a crucial factor, students' motivation needs to be taken into account when designing learning analytics systems. This need is further supported by the assumption of motivation being a result of individual as well as environmental factors (Svinicki & Vogler, 2012). A study conducted by Lonn et al. (2015) found that confronting students at risk in a summer bridge course with feedback from an early warning system led to a decrease of their learning goal orientation. As learning goal orientation is positively associated with intrinsic motivation and learning outcomes, this emphasizes the need to consider motivational dispositions of students when designing learning analytics. Hence, improving alignment with the needs of learners and their individual characteristics, personalization, and adaptivity are considered to be important, and for that, a broad data source is required (Ifenthaler & Widanapathirana, 2014; Schumacher & Ifenthaler, 2018). The appropriateness of learning analytics interventions and feedback is vital as a balance between guidance and autonomy is to be achieved that is not overcharging students' capabilities to self-regulate or impairing their motivation. However, to allow personalized learning analytics features considering students' motivational dispositions, appropriate indicators and data sources (e.g., inventories, physiological measures) need to be identified to make this information available for learning analytics algorithms.

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5 Designing effective means of supporting students' regulation of learning processes through analytics-based prompts

5.1 Introduction

Learning in higher education increasingly takes place in digital learning environments, allowing novel approaches to capture learner behavior when learning actually occurs. This can be used to support learning and further to reconstruct its processes, thus allowing further insights on students' actions without intrusion (Vieira, Parsons, & Byrd, 2018; Winne & Baker, 2013).

Self-regulated learning is considered to be key for successful learning in higher education and likewise in less structured environments, such as digital learning environments (Azevedo, Cromley, & Seibert, 2004; Bannert & Mengelkamp, 2013; Broadbent & Poon, 2015; Cassidy, 2011; Nussbaumer, Dahn, Kroop, Mikroyannidis, & Albert, 2015). Self-regulated learning is conceptualized as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2000, p. 453). However, self-regulating one's learning demands high efforts and skills of learners (Azevedo et al., 2004; Boekaerts, 1999; Lehmann, Hähnlein, & Ifenthaler, 2014; Schmitz, 2001; Zimmerman, 2000). Learners often do not show self-regulatory behavior spontaneously without guidance (Moos & Bonde, 2016; Sonnenberg & Bannert, 2016). Hence, effective means of supporting students' regulation of learning processes and motivation are required, such as the utilization of prompts. Research on prompting focuses on how to design prompts to support self-regulated learning and specifically, on which learning activities should be prompted (Bannert, 2009; Ifenthaler, 2012; Wirth, 2009). However, it is also relevant to know when the learner needs which specific support. Combining learning analytics approaches with means of supporting self-regulated learning would enable adaptive learning environments, offering the learners the required support whenever they needed it.

Research on prompts to support (self-regulated) learning in technology-enhanced learning environments showed varying findings. For example, in an experimental study investigating the use of prompts based on theory of self-regulated learning in a flipped classroom setting, the learners who received the prompts showed significantly higher learning performance than the control group in a pre-post-test plus they used more self-regulation strategies compared to the control group (Moos & Bonde, 2016). An experimental study (Prieger & Bannert, 2018) investigating the impact of metacognitive prompts on learning behavior and learning performance found that students receiving prompts showed significantly different and presumably more systematic navigation patterns within the hypermedia environment than those in the control group but without having an effect on learning performance. Furthermore, the authors found that the effects of prompts are dependent on learner characteristics as participants with lower learning-related competencies profited from metacognitive prompts in terms of their learning behavior and learning performance, whereas students with higher learning-related competencies did not benefit, or were even hampered by the prompts in a hypermedia environment (Prieger & Bannert, 2018). Daumiller and Dresel (2018) found that prompts referring to students' motivation regulation (i.e., strategies used to initiate and persist in learning processes or to raise effort by increasing task value or self-efficacy beliefs (Daumiller & Dresel, 2018)) were effective instructional means, leading to higher task value as part of learning motivation, higher metacognitive control, more task-related learning activities (e.g., cognitive strategies, persistence), and higher learning performance as well as memorization.

To be able to develop evidence-based learning analytics systems that are informed by learning theory and which offer (semi-) automated prompts to learners, further investigation into the relation of prompts and learning performance in technology-enhanced learning environments is necessary. Hence, the focus of this quasi-experimental study is on examining whether cognitive, metacognitive, motivational, or resource-related prompts affect learning performance as well as online learning behavior, and further, if trace data can be used as predictors of learning performance in a digital learning environment. With online learning behavior referring to learning behavior learners show within digital learning environments by interacting with resources and which might be tracked using logfiles.

The first section of this paper focuses on current research on learning analytics in the context of self-regulated learning (5.1.1), and on how to use prompts to support self-regulated learning (5.1.2). Furthermore, the relation of learning analytics, self-regulated learning, and prompts is described (5.1.3). Related to the derived hypotheses (5.1.4), the design of the quasi-experimental study and instruments are described in section 5.2. The findings of the study are reported (5.3), and discussed (5.4) by pointing out the findings' implications, further research needs, as well as limitations of the study, and concluded (5.5).

5.1.1 Learning analytics

Learning analytics offer a promising approach for digital and adaptive learning environments (Aguilar, 2018; Greller & Drachsler, 2012; Ifenthaler & Widanapathirana, 2014). Therefore, learning analytics use static and dynamic information about learners and learning environments, assessing, eliciting, and analyzing them for real-time modeling, prediction, and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). The aim is to better meet students' needs by offering individual learning paths, adaptive assessments and recommendations, or adaptive and just-in-time feedback (Corrin & de Barba, 2014; Gašević, Dawson, & Siemens, 2015; McLoughlin & Lee, 2010) according to learners' motivational states, individual characteristics, and learning goals.

Learning analytics generally rely on information such as learners' behavior in the digital learning environment, and should be supplemented with information about learners' individual characteristics and curricular requirements, and might include external data such as social interrelations or physical data (Ifenthaler & Widanapathirana, 2014). Current learning analytics approaches focus on indicators based on the behavior in the digital learning environment, such as time spent online, access to various types of resources, or reading and writing posts to relate them to learning performance (Mah, 2016). In addition, few other approaches are enriched with learner characteristics such as demographic data or results of assessments, to predict study success (Costa, Fonseca, Santana, de Araújo, & Rego, 2017; Vieira et al., 2018). In a literature review focusing on visual learning analytics, Vieira et al. (2018) found that most studies analyze usage of resources in particular, with only a few studies having a processual approach by trying to understand learning paths or students' learning progress. However, not all collected indicators are (pedagogically) valid and learning analytics only have a limited insight into students' learning as not all learning processes take place in the digital learning environment or can be captured with trace data (Eradze, Väljataga, & Laanpere, 2014; Ferguson, 2012; Ifenthaler & Schumacher, 2016; Wilson, Watson, Thompson, Drew, & Doyle, 2017; Winne, 2017b).

For learning analytics to ideally support self-regulated learning, Winne (2017b) proposes that: a) every operation during learning is tracked; b) the information operated on by a learner is identifiable; c) the traces are time-stamped; and d) the results of the operations are recorded. As learner characteristics, such as prior knowledge, learning strategies, motivational dispositions and prior learning experiences influence how learners interact with learning material (Nakayama, Mutsuura, & Yamamoto, 2014) and how they react to recommendations (Hattie & Timperley, 2007; Shute, 2008; van der Kleij, Eggen, Timmers, & Veldkamp, 2012), such information should be integrated into learning analytics analyses (Gašević, Dawson, Rogers, & Gasevic, 2016; Ifenthaler & Widanapathirana, 2014; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; West, Heath, & Huijser, 2016). Furthermore, many implementations of learning analytics focus on teacher dashboards without offering feedback to the learners (e.g., Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Elkina, Fortenbacher, & Merceron, 2013; Macfadyen & Dawson, 2010; Vieira et al., 2018) or are designed within the discipline of information technology without particularly emphasizing learning theory (Wilson et al., 2017).

Current research on learning analytics focuses on integrating multimodal data for learning analytics, such as learning behavior and physical activity (e.g., body movements, heartrate, electro-dermal activation, facial expressions, eye tracking) (e.g., Azevedo, Taub, & Mudrick, 2018; Di Mitri, Schneider, Specht, & Drachsler, 2018; Worsley & Bilkstein, 2015), on predicting learning performance and retention, applying and comparing different algorithms (e.g., Costa et al., 2017; Howard, Meehan, & Parnell, 2018), or on understanding learning behavior using paths and cluster analyses as well as visualizations of interaction (e.g., Chen, Breslow, & DeBoer, 2018; Hsu, Wang, & Zhang, 2017; Liu et al., 2017) as well as feeding back the analyses and results using dashboards (e.g., Aljohani et al., 2019; Kim, Jo, & Park, 2016; Roberts, Howell, & Seaman, 2017; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018).

However, Marzouk et al. (2016) claim the necessity of a profound link between learning analytics and learning theory to offer valid support to learners. As learning analytics claim to enhance learning processes and optimize learning environments (Ifenthaler, 2015; Siemens, 2010), they need to be underpinned with knowledge from learning theory and empirical findings. To optimize learning processes and environments learning analytics need to feedback their evidence collected to either the learners or the educators to close the loop. However, such feedback needs to be informative, related to learning objectives, and based upon valid inferences to enable the receivers making use of it for improvement (Mislevy & Riconscente, 2005; Nicol & Macfarlane-Dick, 2006; Winne, 2017b). Learning analytics are predominantly applied in higher education settings and by their nature in digital learning environments which are considered to be less structured requiring additional effort of the learners. Hence, in both settings self-regulated learning is considered as key for successful learning processes (Bannert & Mengelkamp, 2013; Draper, 2009). Self-regulated learning theory assumes that highly regulated learners constantly create feedback themselves while monitoring their processes which can be enhanced or modified through external feedback (Butler & Winne, 1995). One possibility to provide such external support motivating learners to use appropriate learning strategies are prompts.

5.1.2 Prompts supporting self-regulated learning

Prompts can be described as "short hints or questions presented to students in order to activate knowledge, strategies, or skills that students have already available but do not use spontaneously" (Wirth, 2009, p. 92). Self-regulated learning is conceptualized as a recursive process in which learners adapt cognitive, metacognitive and motivational processes according to task requirements (Winne, 2017a; Winne & Hadwin, 1998; Zimmerman, 2002). Prompts are a non-directive external support, not providing new information but stimulating the application of known cognitive, metacognitive, motivational or resource management-related strategies during learning (Bannert, 2009). Thus, instructional support on self-regulated learning, such as prompts, should be aligned with learners' strategy knowledge (Thillmann, Künsting, Wirth, & Leutner, 2009). In general, prompts guide learners to reflect on specific aspects of the learning material/task or on their cognitive activities during the learning process, and might further ask them to express these thoughts (Bannert, 2009). Prompts can be designed as questions, incomplete sentences or instructions (Ifenthaler, 2012; Kramarski & Kohen, 2017).

Wirth (2009) proposes a framework to classify prompts according to their (a) *content*: the activities that should be stimulated through prompts (e.g., cognitive or metacognitive learning strategies), (b) the *condition* that must be fulfilled in order that the prompt is presented to the learners: a certain amount of *time*; related to the *task* or based on *previous activities*, and (c) the *method* used for presenting the prompt: *feed forward* prompts – directly referring to the upcoming activities learners are expected to perform – or *feedback* prompts – an indirect method of guiding learners through feedback based on their previous behavior.

Referring to the concept of self-regulated learning and learning strategies (Boekaerts, 1999; Weinstein & Mayer, 1986), c*ognitive prompts* aim to support students' information processing, whereas *metacognitive prompts* focus on activating students' monitoring and controlling of their cognitive activities, such as planning, goal-setting, and evaluating their learning processes and outcomes. Furthermore, *motivational prompts* aspire to enhance motivation to learn, by highlighting targets or giving hints on how to regulate one's motivation, and *resource-oriented prompts* aim to support students in setting up a supportive learning environment or initiating help-seeking behavior.

Prompts need to be aligned with learning theory and instructional intentions (Moos & Bonde, 2016) and presented at the time the learner needs the support in order to avoid additional cognitive processing (Thillmann et al., 2009). Sonnenberg and Bannert (2016) propose using process data to develop effective instructional means. In addition, using trace data of learners allows insights into their behavior and strategy use after receiving an intervention, such as a prompt (Thillmann et al., 2009; Winne & Baker, 2013). Hence, due to the interdependent nature of motivation and self-regulation processes (Zimmerman, 2011) it is crucial, when presenting prompts, to meet learners' needs in terms of external guidance and autonomy, so as not to diminish learners' perceived responsibility or autonomy (Deci & Ryan, 2008; Deci, Ryan, & Williams, 1996). Prieger and Bannert (2018) argue that fixed prompts, which are pre-defined in terms of timing and content, might interrupt the learning process. Furthermore, in line with Cronbach and Snow (1977) that effects of instructional interventions depend on individual characteristics of learners they contend that impacts of prompting depend on learner characteristics. In addition, contextual factors might impact how learners react to external support (Narciss, 2012, 2017). Hence, aspects such as current motivational states, current learning goals, characteristics of the digital learning environment, the learners' physical environments, and the task characteristics need to be considered to present meaningful prompts. As learning analytics have various information available about learners, their characteristics, preferences and behavior (Ifenthaler & Widanapathirana, 2014), this information can serve as a basis for generating prompts to meet students' needs for external regulation and guidance at the right time. Backhaus, Jeske, Pointstingl, and Koenig (2017) presented adaptive prompts to the students based on their self-reported learner characteristics such as work effort and strategy use. However, in their study only an assessment prompt, which asked the participants to assess their own progress, significantly improved learning performance in comparison to the control group.

Based on the current research, further empirical evidence on prompts enriched with trace data is necessary to enable the development of learning analytics systems which provide students with the necessary support.

5.1.3 Synthesis of learning analytics, self-regulated learning and prompts

The underpinning theory of this article is self-regulated learning as it is considered to be relevant for successful learning processes in both higher education and in digital learning environments (Azevedo et al., 2004; Cassidy, 2011) plus it includes a broad perspective on learning processes by emphasizing cognitive, metacognitive, motivational, and behavioral aspects (Boekaerts, 1999; Winne & Hadwin, 1998). Self-regulated learning is either considered to be a cyclical process consisting of a forethought phase, a performance phase and a self-reflection phase (Pintrich, 2000; Zimmerman, 2000, 2002) or consisting of cognitive, metacognitive, and motivational components (Boekaerts, 1992; Pintrich, 2000).

As Winne (2017b) states learning analytics related to self-regulated learning need to include two components: calculating the collected evidence plus recommending what should be changed by giving guiding feedback. However, for being able to deduce valid and informative recommendations, learning analytics need to be grounded in theory on learning, assessment, and feedback to know how learning is considered to take place, to assess the right evidence from the data in relation to the learning objectives (Marzouk et al., 2016; Viberg, Hatakka, Bälter, & Mavroudi, 2018) and feed the contextualized information back to the learners and educators respectively to allow them improve their learning or teaching processes and environments (Clow, 2012). As Bienkowski, Feng, and Means (2012) state learning analytics aim at understanding learning processes in depth by using known methods based on theoretical assumptions of a variety of disciplines and feeding back the information to humans.

To achieve a holistic picture of the individual learner, learning analytics could be enhanced with findings from inventories investigating learners' self-reported strategies plus aligning this with the learning behavior they show within the digital learning environment (e.g., comparing this behavior with patterns associated with success or struggle or their peers) (Ellis, Han, & Pardo, 2017; Gašević, Jovanovic, Pardo, & Dawson, 2017), and adding responses or even sensor data on current emotional states (Di Mitri et al., 2018). Hence, learning analytics can if designed appropriately offer learners the external feedback needed to enhance their self-regulated learning processes or developing such strategies at time and depth required.

In more detail, learning analytics can enhance learners' regulation of learning in all three phases: a) the *forethought phase* by stating clear learning objectives and success criteria of a learning tasks which can impact learners' emotions, motivation and goal setting leading to more strategic planning; b) the *performance phase* by supporting learners in their monitoring by giving additional feedback and recommendations, suggesting to apply alternative learning strategies, as well as reminding them to engage in time management or persistence; and the c) *self-reflection phase* by prompting them to reflect their learning processes in relation to prior set goals and providing suggestions of how to improve for upcoming tasks. As described before prompts are short hints which can be provided to learners during learning, and are considered to support self-regulated learning during all three phases (Moos & Bonde, 2016). However, to be effective such prompts need to be aligned with learning objectives and learner characteristics. Furthermore, they should be presented at the time when they are needed to not interrupt the learning process. Learning analytics offer additional insights into these processes. As Wong et al. (2019) state further experimental studies are required using theory guided approaches to investigate the evidence of learning analytics. To promote this further, the next sections will describe the purpose and design of the present experimental study using prompts underpinned with theory on self-regulated learning enhanced with learning analytics approaches.

5.1.4 Purpose of the study and hypotheses

Trace data are considered to inform instructional design of prompts (Sonnenberg & Bannert, 2016) and to give insights into learners' behavior. Consequently, this quasi-experimental study focuses on (a) investigating how prompts impact learning performance and (b) learning behavior, and (c) if online learning behavior enables an understanding of learning performance.

The assumption that using cognitive, metacognitive, motivational and resource-related strategies is associated with successful learning processes (Pintrich, 2000; Weinstein & Mayer, 1986; Zimmerman, 2001) guided our first two hypotheses.

Hypothesis 1: It is assumed that learners in different prompting conditions vary regarding their learning performance in a *knowledge test* (Hypothesis 1a) and especially *over time* (Hypothesis 1b).

Hypothesis 2: It is furthermore assumed that learners in different prompting conditions vary regarding their learning performance in *transfer tests* (Hypothesis 2a), and especially *over time* (Hypothesis 2b).

Prior studies found that prompts affected learners' navigation patterns within digital learning environments (Bannert, Sonnenberg, Mengelkamp, & Prieger, 2015; Prieger & Bannert, 2018), and that trace data would enable insights into this behavior (Winne & Baker, 2013).

Hypothesis 3: It is hypothesized that the different prompting conditions and the control group differ with regard to their *behavior in the digital learning environment* with focus on the marketing learning unit as indicated by trace data (e.g., views of handout, additional learning material and videos, and their overall interaction; Hypothesis 3a) and that the experimental groups differ regarding the length of the notes taken (Hypothesis 3b).

Furthermore, students' prerequisites such as prior knowledge, motivation, and perceptions lead to differences in their learning behavior and outcomes, thus, such information can be considered for learning analytics analyses (Clow, 2013; Ifenthaler & Widanapathirana, 2014; Nadasen & List, 2017).

Hypothesis 4: It is hypothesized that *academic characteristics*, such as semester, current study grade, prior domain knowledge, perceived confidence and difficulty (Hypothesis 4a), and the *online learning behavior* as indicated by number of views of the handout, additional learning material, video and overall interaction (Hypothesis 4b) significantly predicts participants' learning *performance in the transfer test on marketing*.

Hence, the purpose of this quasi-experimental study is examining if different prompts have an impact on learning performance and online learning behavior. Furthermore, to design digital learning environments enhanced with reliable learning analytics they need to be linked to theory plus need to provide valid insights into learning processes and outcomes. Thus, the study investigates whether trace data can be used for predicting learning performance when controlling for learning behavior outside the digital learning environment.

5.2 Methods

5.2.1 Participants

Initially 135 students from a European university participated in the study. After deleting incomplete or discontinued datasets, a total of *N* = 110 (74 female, 36 male) remained and were used for the hypothesis testing. Participants' average age was 22.68 years (*SD* = 2.82). They were enrolled in either the Bachelor's (65.5%) or Master's (34.5%) program of economic and business education. The participants had studied for an average of 4.86 semesters (*SD* = 2.91). The participants received two credits for participating in the study.

5.2.2 Design

In the university's digital learning environment, a laboratory environment consisting of four classes was implemented. Participants were randomly assigned to the four experimental conditions (see Figure 5-1 for details). The experimental conditions were assigned to the components of self-regulated learning (Boekaerts, 1992, 1999; Pintrich, 2000): *cognitive* (CP; n_1 = 30), *metacognitive* (MP; n_2 = 31), *cognitive, metacognitive, motivational and resource-related* (AP; n_3 = 28), and the *control group* (CG; n_4 = 21). Participants in the CP group received prompts related to cognitive learning strategies (see materials for further details). Participants in the MP group received prompts related to metacognitive learning strategies. Participants in the AP group received prompts related to all learning strategies self-regulated learners are assumed to perform: cognitive, metacognitive, motivational and resource-related. The control group did not receive prompts. ANOVA was used to test the four groups for differences in terms of pre-knowledge, study program, age, and study grade. ANOVA revealed that the groups did not differ with regard to their pre-knowledge related to the learning content $F(3,106) = 1.873$, $p = .139$, study program $F(3,106) = .273$ $p = .845$, age $F(3,106) = 1.241$, $p = .299$, and study grade $F(3,97) = 1.568$, $p = .202$.

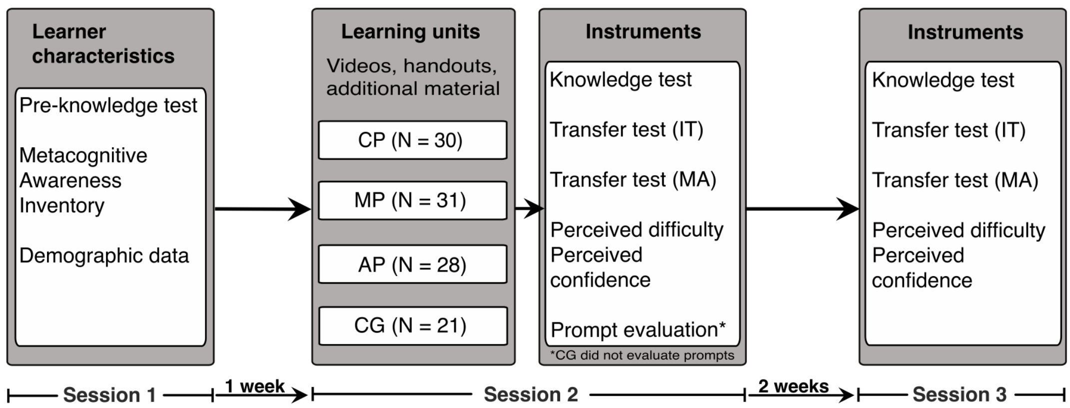

Figure 5-1. Overview about the study design

5.2.3 Materials and instruments

Learning units

Participants were confronted with two learning units in the digital learning environment of the university. The set-up was comparable with online lectures, such as in flipped or blended classroom settings (see Figure 5-2). Students entered the course and were presented two lectures of a value-based management course, *IT-governance* and *marketing*. Each course folder contained the corresponding video lecture, the related handout and material with additional information. The video lectures showed the lecturer and relevant visualizations. The duration of the lecture video in *IT-governance* was 11:43 minutes, and the lecture section on *marketing* was 13:29 minutes. The learning units were selected due to their variety of difficulty, with *IT-governance* considered a more complex and unfamiliar topic and *marketing* as a more common topic, generally perceived as being easier.

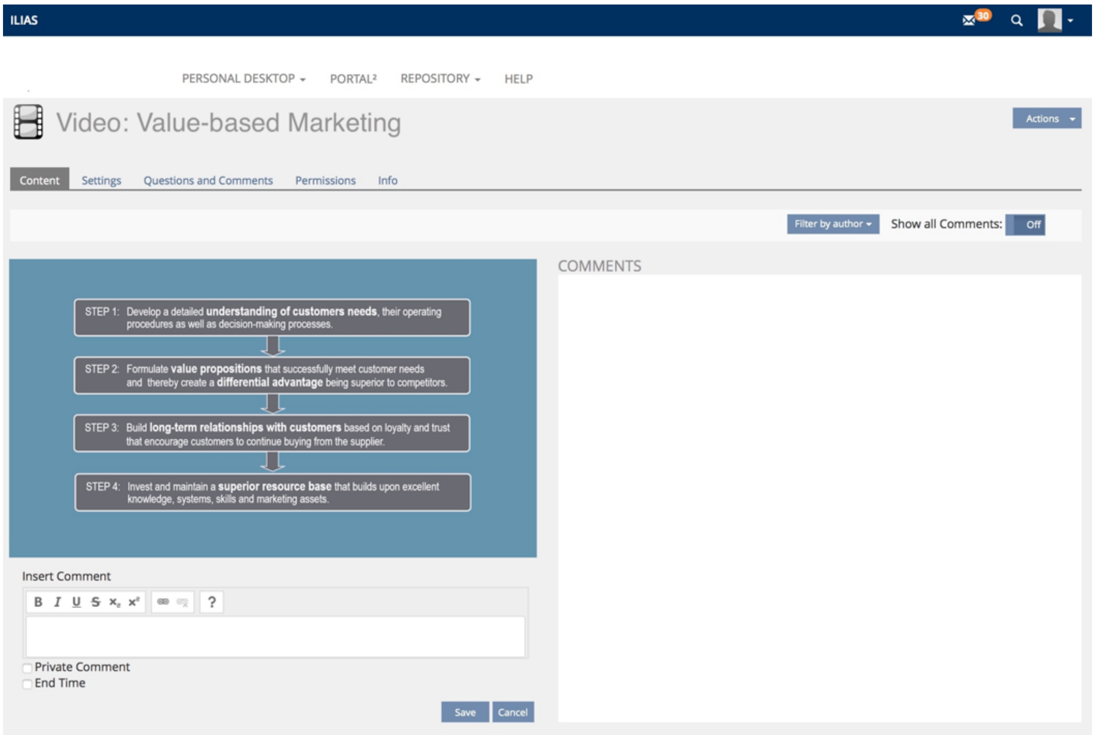

Figure 5-2. Digital learning environment

Cognitive, metacognitive, motivational and resource-related prompts

Based on self-regulated learning theory (Boekaerts, 1992, 1999; Pintrich, 2000; Zimmerman, 2002) prompts were designed as shown in Table 5-1. The prompts were either embedded in the digital learning environment interface or during the videos. The prompts were either related to a navigation decision, to the content based on instructional decisions, or related to a certain point of time in the video or learning period. The prompts were shown to the students in form of a pop-up window as an overlay in the digital learning environment (see Figure 5-3), with some showing optional text boxes or answers on a rating scale. Depending on the experimental group participants were facing a different number of prompts embedded in each learning unit, the *CP group* received four in each unit, the *MP group* received five in each unit, and the *AP group* received six in each unit plus one in the middle of the study. However, it needs to be noted that learners did not have encountered all prompts embedded as they only had limited time for learning and received most prompts only when showing the required navigation or learning behavior (e.g., accessing a resource connected to a prompt, watching the video to a certain point of time). After the learning period of 50 minutes, all groups, including the control group, were guided by a prompt to come to an end and to proceed to the survey.

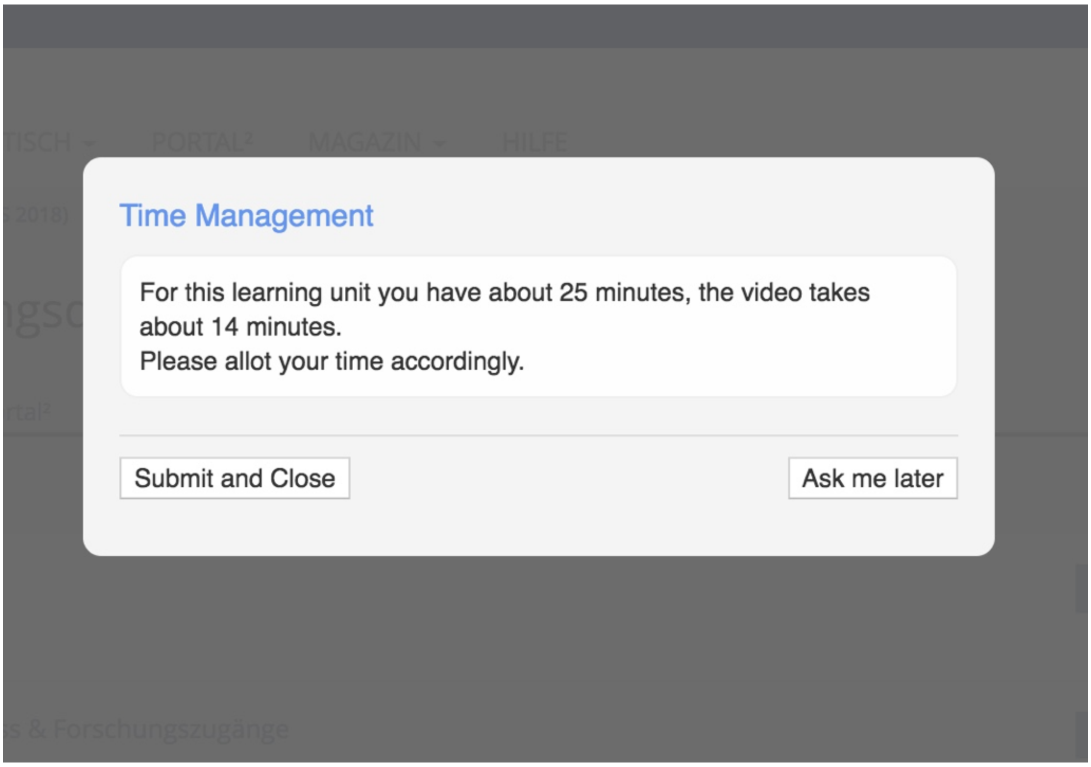

Figure 5-3. Sample prompt

Table 5-1 Sample prompts for each prompting condition including time of presentation and learning unit

Prompts	Time of presentation	Unit
Cognitive prompts		
Take notes on the content of the video. Write down your notes in the comment field.	When opening the video	IT; M
Think about the concepts presented and if they appear to be coherent and reasonable. Write down your critical thoughts and questions.	During the video	M
Metacognitive prompts		
Please think about the strategies you used whilst watching the video. Multiple answers are possible. (Possible answers: a) Scrutinizing the content presented; b) Listening; c) Repeating parts of the video; d) Creating related examples; e) Taking notes; f) Extracting the main content; g) Relating the content to prior knowledge; h) Asking yourself questions)	After the video was finished	IT
Reflect on the main contents of the video. Write down your thoughts.	After the video was finished	M

All prompts		
For this learning unit you have about 25 minutes, the video takes about 12/14 minutes. Please allot your time accordingly.	When opening the learning unit	IT; M
Try to focus your attention on the content.	During the video	M
There are additional resources in the digital learning environment you can use to better prepare yourself for the final test.	After video was finished	IT; M

Knowledge test

The pre-knowledge test consisted of eight single-choice questions related to the upcoming learning content. At the point of measurement two, the initial questions were used again and supplemented with eight additional single-choice questions to measure declarative knowledge. The same 16 single-choice questions were used for the third measurement point. A sample question was "What is a federal mode of IT-governance? – Joint decision-making between central IT, top management, and the lines of business." For each correct single-choice question, one point was scored. For analyses, the overall knowledge test results were used percentagewise.

To assess transfer knowledge participants were confronted with a writing assignment for each learning unit at t_2 (350 words expected, max. 3 points) and again at t_3 (250 words expected, max. 3 points). A sample task was "Please describe in your own words how IT governance supports value creation in a company. Please refer to constructs of the learning material.". In addition, at t_2 and t_3, participants rated the perceived difficulty of each learning area and how well prepared they felt for the upcoming assessment.

Two independent raters scored the responses to the transfer tasks with which participants were confronted for each learning unit at measurement points t_2 and t_3. Points were assigned based on the quality of responses (0 = not sufficiently described; 1 = only a short description or with significant mistakes; 2 = a good description of the concepts; 3 = a very good description, supplemented with additional examples). In case of non-uniformly rated transfer tasks, the two raters discussed the scoring and either adjusted or kept their score. Among the two raters an interrater reliability of K = .91 for *transfer knowledge IT* at t_2, K = .94 for *transfer knowledge marketing* at t_2, K = .96 for *transfer knowledge IT* at t_3, and K = .97 for *transfer knowledge marketing* at t_3 was found.

Learner characteristics

Learner characteristics include *personal* characteristics about learners such as age, gender, socio-demographic information, *academic* characteristics such as prior knowledge, learning goals, learning strategies, *social/emotional* characteristics referring to group dynamics or individual emotions (e.g., self-efficacy, motivation), and *cognitive* characteristic such as mental procedures or attention span (Drachsler & Kirschner, 2012).

To investigate participants' metacognitive awareness, the *Metacognitive Awareness Inventory* (Schraw & Dennison, 1994), containing 52 items answered on a Thurstone scale (0 = no; 1 = yes) was used. The two dimensions of the inventory include 1) *knowledge about cognition* (17 items, Cronbach's α = .644), and 2) *regulation of cognition* (35 items, Cronbach's α = .800). Knowledge about cognition refers to declarative knowledge, procedural knowledge and conditional knowledge. Regulation of cognition includes planning, information management, comprehension monitoring, debugging strategies and evaluation.

Participants further stated demographic information such as age, study program (Bachelor's or Master's program), semester, course load, current study grade (current GPA), etc.

Evaluation of prompts

Participants who were confronted with prompts evaluated them by answering nine items including two subscales: evaluation of perceived learning support through the prompts (5 items, Cronbach's α = .836), and negative perceptions associated with the prompts (4 items, Cronbach's α = .851). Sample items to investigate learning support were: "The prompts encouraged me for reflection" or "The prompts supported my learning processes". Sample items investigating if learners perceived the prompts negatively such as distracting or too often were "I perceived the prompts as disturbing" or "Prompts were too often". All items were answered on a 5-point Likert scale with 1 = "I do not agree at all" and 5 = "I fully agree". Hence, high numbers in perceived learning support would indicate that learners perceive high learning support whereas high numbers in negative perceptions would indicate that learners evaluated the prompts highly negative.

Trace data

While interacting with the digital learning environment, participants' navigation was tracked. For this research paper the following indicators were used: interaction with the digital learning environment indicated by number of views of resources (handout for each learning unit, additional learning material, video views, overall interaction), and the number and length of written notes taken in IT and marketing learning units.

Procedure

The participants were randomly assigned to the four experimental groups. The study consisted of three measurement points: t_1 as an on-site investigation, t_2 took place on-site and one week later, and t_3 was implemented as an online investigation accessible for one week, two weeks after t_2 occurred. At t_1 participants received an introduction and completed a *pre-knowledge test* (8 single-choice questions; 12 minutes), the *metacognitive awareness inventory* (52 items; 12 minutes), and *demographic data* (14 items; 5 minutes). At t_2 participants were confronted with two *learning units* in the domains of marketing and IT governance (50 minutes). Each learning unit consisted of a video lecture (13:29 minutes marketing; 11:43 minutes IT governance), the related handout and additional material. Participants were instructed to prepare themselves for a subsequent knowledge test with the material provided. They were then confronted with a *knowledge test* including the questions of t_1 and additional eight questions (16 single-choice questions; 20 minutes) and had to pass two *transfer tasks* related to the two learning units (2 writing tasks; 25 minutes). In addition, the participants rated the *perceived difficulty* of the learning content and their *confidence* (5 items per unit; 3 minutes) plus if being in an experimental condition *evaluated the prompts* they received (9 items, 3 minutes). In t_3 participants again completed the *knowledge test* used in t_2 (16 single-choice questions; 20 minutes) and answer two *transfer tasks* related to the learning material (2 writing tasks, 20 minutes) as well as reporting the *perceived difficulty* and *their confidence* (5 items per unit; 3 minutes).

5.3 Results

An alpha level of .05 was used for statistical tests and partial η^2 (small effect: $\eta^2 < .06$, medium effect $.06 \leq \eta^2 \leq .13$, strong effect $\eta^2 > .13$).

5.3.1 Hypothesis 1 declarative knowledge

A repeated-measures MANOVA was computed with dependent variable declarative knowledge, within-subject factor time (t_1, t_2, t_3) and the experimental conditions of the prompting groups (CP, MP, AP, CG) as between-subject factor (see Table 5-2 for descriptive statistics and Figure 5-4). MANOVA showed a significant within-subject effect for time, Wilk's Lambda = .384 $F(2, 105) = 84.300$, $p < .001$, $\eta^2 = .616$ but no interaction effect of time and the experimental conditions Wilk's Lambda = .934 $F(6, 212) = 1.216$, $p = .299$. Pairwise comparisons using Bonferroni correction showed significant differences between measurement point t_1 ($M = 40.90$; $SD = 15.41$) and t_2 ($M = 61.25$; $SD = 13.61$) $p <. 001$, between t_1 ($M = 40.90$; $SD = 15.41$) and t_3 ($M = 56.25$; $SD = 13.70$), $p < .001$ as well as between t_2 ($M = 61.25$; $SD = 13.61$) and t_3 ($M = 56.25$; $SD = 13.70$), $p < .001$. To check for differences between the experimental conditions post hoc univariate ANOVA were conducted for each measurement point. As indicated before, no significant differences for pre-knowledge at t_1 between the experimental conditions was found $F(3,106) = 1.873$, $p = .139$. Furthermore, no significant differences between the experimental conditions at t_2 $F(3,106) = 1.874$, $p = .138$, and t_3 $F(3,106) = 1.785$, $p = .154$ were found.

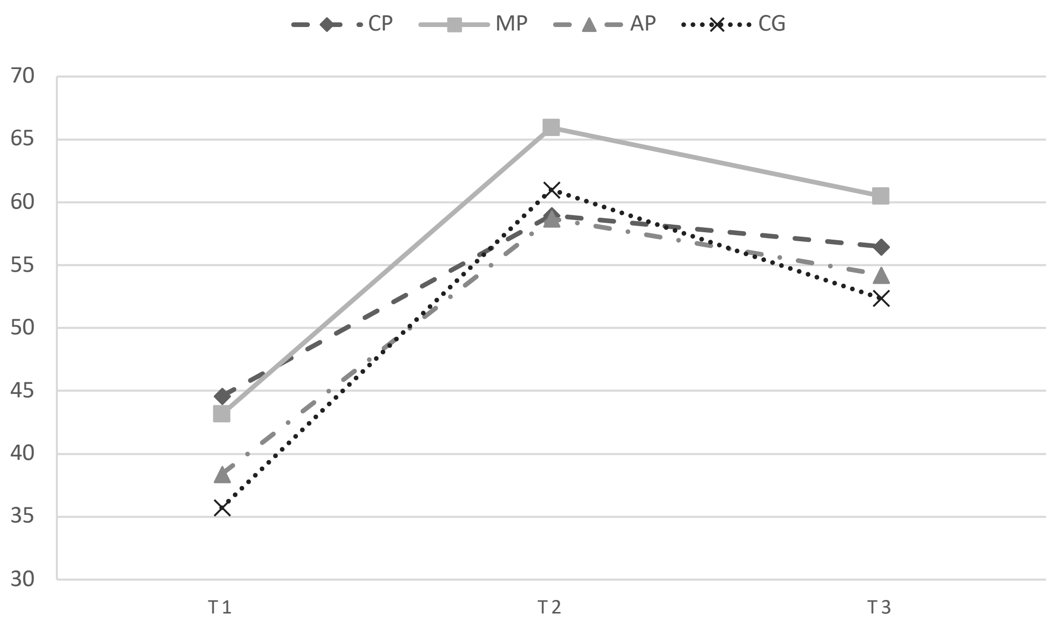

Figure 5-4. Declarative knowledge for each experimental condition over time

To test for changes over time for each group, repeated-measures ANOVA was used. Significant differences in terms of declarative knowledge over time were found for the *CP group* $F(2,58) = 16.764$, $p < .001$, $\eta^2 = .366$. Post-hoc comparisons using

Bonferroni correction revealed significant differences between t_1 (M = 44.58; SD = 15.63) and t_2 (M = 58.95; SD = 13.99) p <. 001, between t_1 (M = 44.58; SD = 15.63) and t_3 (M = 56.45; SD = 13.38) p <. 001, but not between t_2 (M = 58.95; SD = 13.99) and t_3 (M = 56.45; SD = 13.38) p = .804. For the *MP group* significant differences regarding declarative knowledge over time were found F(1.62,48.63) = 35.474, p < .001, η^2 = .542. Post-hoc comparisons using Bonferroni correction revealed significant differences between t_1 (M = 43.14; SD = 14.00) and t_2 (M = 65.92; SD = 13.09) p <. 001, between t_1 (M = 43.14; SD = 14.00) and t_3 (M = 60.48; SD = 12.64) p <. 001, as well as between t_2 (M = 65.92; SD = 13.09) and t_3 (M = 60.48; SD = 12.64) p = .044. For *AP group* significant changes of declarative knowledge over time were found F(2,54) = 24.327, p < .001, η^2 = .474. Post-hoc comparisons using Bonferroni correction showed significant differences between t_1 (M = 38.39; SD = 14.80) and t_2 (M = 58.70; SD = 13.32) p <. 001, between t_1 (M = 38.39; SD = 14.80) and t_3 (M = 54.24; SD = 14.33) p <. 001, but not for t_2 (M = 58.70; SD = 13.32) and t_3 (M = 54.24; SD = 14.33) p = .237. For the *control group* significant differences of declarative knowledge over time were found F(2,40) = 33.915, p < .001, η^2 = .629. Post-hoc comparisons using Bonferroni correction showed significant differences between t_1 (M = 35.71; SD = 16.90) and t_2 (M = 61.01; SD = 13.39) p <. 001, between t_1 (M = 35.71; SD = 16.90) and t_3 (M = 52.38; SD = 14.04) p <. 001, as well as between t_2 (M = 61.01; SD = 13.39) and t_3 (M = 52.38; SD = 14.04) p = .030.

Given these findings for declarative knowledge, Hypothesis 1a is rejected and Hypothesis 1b is accepted for *MP group* and *CG,* and partly accepted for *CP* and *AP group*.

5.3.2 Hypothesis 2 transfer knowledge

A repeated-measures MANOVA was computed with dependent variables transfer knowledge in IT, and transfer knowledge in marketing, within-subject factor time (t_2 and t_3), and the experimental conditions of the prompting groups (CP, MP, AP, CG) as between-subject factor (see Table 5-2 for descriptive results and Figure 5-5). MANOVA showed a significant between-subject effect for the experimental conditions Wilk's Lambda = .843 F(6, 210) = 3.122, p = .006, η^2 = .082 and a significant within-subject effect for time Wilk's Lambda = .839 F(2, 105) = 10.077, p < .001, η^2 =

.161. No significant interaction effect was found for time and group Wilk's Lambda = .892 $F(6, 210) = 2.061$, $p = .059$.

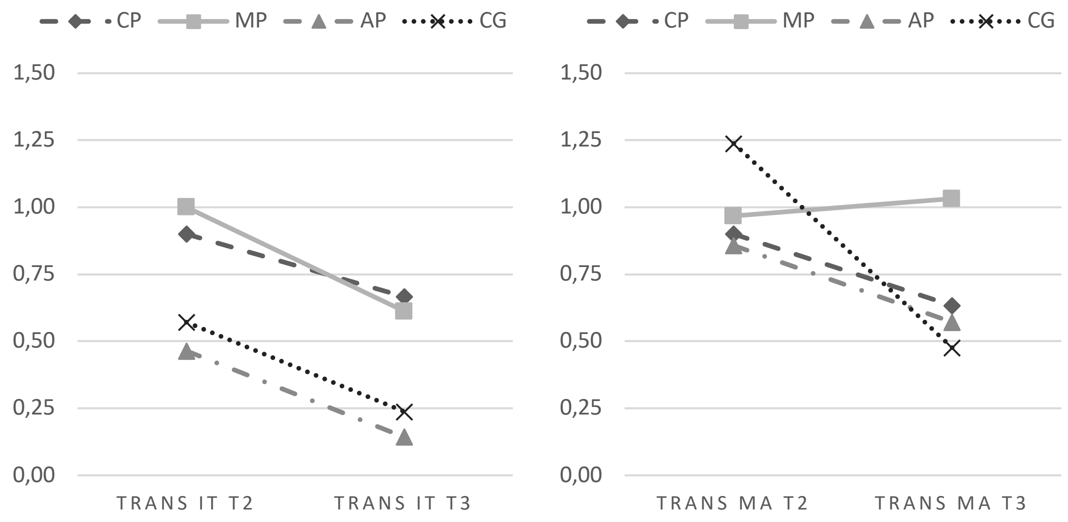

Figure 5-5. Transfer knowledge for each unit and each experimental condition over time

Table 5-2 Descriptive statistics for declarative knowledge, transfer knowledge for each learning unit, perceived confidence and difficulty for each learning unit per measurement point (t)

t	Variables	CP (*N* = 30)		MP (*N* = 31)		AP (*N* = 28)		CG (*N* = 21)	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	Declarative knowledge	44.58	15.63	43.15	14.01	38.39	14.80	35.71	16.90
2	Declarative knowledge	58.96	13.99	65.93	13.09	58.71	13.32	61.01	13.39
	Transfer knowledge IT	.90	.84	1.00	.89	.46	.69	.57	.68
	Transfer knowledge MA	.90	.66	.97	.84	.86	.97	1.24	.83
	Confidence IT	2.00	.74	2.23	.88	2.11	.79	1.95	.67
	Confidence MA	2.47	.86	2.74	.96	2.46	.96	2.29	.85
	Difficulty IT	3.20	1.03	3.16	1.13	3.39	.74	3.48	.81
	Difficulty MA	2.77	.90	2.74	.89	2.96	.69	3.33	.73
3	Declarative knowledge	56.46	13.38	60.48	12.64	54.24	14.34	52.38	14.04
	Transfer knowledge IT	.67	.80	.61	.72	.14	.36	.24	.54
	Transfer knowledge MA	.63	.72	1.03	.84	.57	.84	.48	.93
	Confidence IT	1.90	.71	2.19	.91	2.29	.85	1.76	.70
	Confidence MA	2.13	.82	2.58	.99	2.54	.84	2.24	1.14
	Difficulty IT	3.03	.76	3.58	1.09	3.25	.75	2.90	1.14
	Difficulty MA	2.73	.78	2.97	.80	3.04	.69	2.67	1.11

Note: CP = cognitive prompt group, MP = metacognitive prompt group, AP = all prompt group, CG = control group, declarative knowledge (percentage-wise), transfer knowledge (measured 0 to 3), perceived confidence (Confidence IT and MA per measurement point, 5-point Likert scale), and perceived difficulty (Difficulty IT and MA per measurement point, 5-point Likert scale)

Post hoc univariate ANOVA revealed significant differences between the two measurement points for transfer knowledge in IT $F(1, 5.46) = 16.189$, $p < .001$, $\eta^2 = .132$, and transfer knowledge in marketing $F(1, 5.24) = 11.921$, $p = .001$, $\eta^2 = .101$. Furthermore, a significant interaction effect for time and group for transfer knowledge in marketing $F(3, 1.42) = 3.24$, $p = .025$, $\eta^2 = .084$ was found.

One-way ANOVA revealed significant differences between the experimental groups for transfer knowledge in IT at t_2 $F(3,106) = 2.944$, $p = .036$ and for transfer knowledge at t_3 using Brown-Forsythe correction $F(3,89.62) = 4.973$, $p = .003$. No significant differences between the groups were found for transfer knowledge in marketing at t_2 and t_3. However, Tukey post-hoc tests showed no significant differences for transfer knowledge in IT at t_2 for the experimental groups. Only the difference between the *AP* ($M = .46$, $SD = .693$) and *MP groups* ($M = 1.00$, $SD = .894$), $p = .053$ was slightly above statistical significance. At t_3 significant differences in IT were found between *AP* ($M = .14$; $SD = .356$) and *MP* ($M = .61$; $SD = .715$), $p = .029$, *AP* ($M = .14$; $SD = .356$) and *CP* ($M = .67$; $SD = .802$), $p = .012$.

For changes over time on a group level, paired t-tests were applied for each group and each transfer test. For the *CP group* no significant difference was found for transfer knowledge IT at t_2 ($M = .90$; $SD = .845$) and t_3 ($M = .67$; $SD = .802$), $t(29) = 1.88$, $p = .070$ but for transfer knowledge marketing at t_2 ($M = .90$; $SD = .662$) and t_3 ($M = .63$; $SD = .718$), $t(29) = 2.28$, $p = .030$. For the *MP group* no significant differences were found for transfer knowledge IT between t_2 ($M = 1.00$; $SD = .894$) and t_3 ($M = .61$; $SD = .715$), $t(30) = 2.04$, $p = .050$, nor for transfer knowledge marketing between t_2 ($M = .97$; $SD = .836$) and t_3 ($M = 1.03$; $SD = .836$), $t(30) = -.338$, $p = .738$. For the *AP group* significant differences were found for transfer knowledge IT between t_2 ($M = .46$; $SD = .693$) and t_3 ($M = .14$; $SD = .356$), $t(27) = 2.20$, $p = .036$. No significant differences were found for transfer knowledge marketing between t_2 ($M = .86$; $SD = .970$) and t_3 ($M = .57$; $SD = .836$), $t(27) = 1.68$, $p = .103$. For the *control group* significant differences were found for transfer knowledge IT between t_2 ($M = .57$; $SD = .676$) and t_3 ($M = .24$; $SD = .539$), $t(20) = 2.32$, $p = .031$. Furthermore, a significant difference was found for transfer knowledge marketing for the *control group* between t_2 ($M = 1.24$; $SD = 831$) and t_3 ($M = .48$; $SD = .928$), $t(20) = 3.07$, $p = .006$.

Based on these findings for transfer knowledge, Hypothesis 2a is accepted for IT at t_2 and t_3 but not for marketing. Hypothesis 2b is accepted for transfer knowledge for IT and marketing.

5.3.3 Hypothesis 3 differences in trace data for the prompting conditions

To determine whether the different experimental conditions vary regarding their online behavior within the marketing learning unit (views of handout and additional material, views of the video, and overall interaction) multivariate analysis of variance was used (see Table 5-3 for descriptive statistics). Results indicate that there are significant differences between the groups Wilk's Lambda = .665 $F(12, 272.80) = 3.794$, $p < .001$, $\eta^2 = .127$. ANOVA revealed significant differences between the groups for *views of the handout*, $F(3,106) = 3.084$, $p = .032$, $\eta^2 = .079$, and for *views of the additional learning material* $F(3,106) = 8.418$, $p < .001$, $\eta^2 = .192$. No significant differences were found for *video views* $F(3,106) = 1.097$, $p = .354$ and for the *overall interaction* in the learning unit marketing $F(3,106) = 2.117$, $p = .102$. Post-hoc comparisons using Bonferroni correction showed significant differences for views of the handout between the *AP group* ($M = .50$, $SD = .694$) and *CG* ($M = 1.05$, $SD = .384$), $p = .034$. With regard to views of the additional learning material significant differences were found between *AP group* ($M = .18$, $SD = .390$) and *CG* ($M = .90$, $SD = .436$), $p < .001$, between *CP group* ($M =.43$, $SD = .568$) and *CG* ($M = .90$, $SD = .436$), $p = .008$, and between *MP group* ($M = .52$, $SD = .570$) and *CG* ($M = .90$, $SD = .436$), $p = .045$.

Table 5-3 Descriptive statistics for views of handout, additional material, videos, overall interaction, number and length of notes taken (referring to the marketing learning unit)

Variables	CP (*N* = 30)		MP (*N* = 31)		AP (*N* = 28)		CG (*N* = 21)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1) Number of views of handout	.70	.75	.87	.72	.50	.69	1.05	.38
2) Number of views of additional material	.43	.57	.52	.57	.18	.39	.90	.43
3) Number of views of video	1.30	.95	1.74	2.21	1.29	.98	1.10	.30
4) Overall interaction	6.87	4.14	8.71	4.85	8.61	5.65	6.14	1.49
5) Number of notes taken	2.07	2.64	1.10	2.36	3.46	4.67	0.00	.00
6) Length of notes taken	310.10	362.22	171.42	378.03	491.89	686.92	0.00	.00

As participants in the control group, not receiving any prompts, did not take notes during the marketing learning unit, further analyses were conducted to test for differences between the experimental groups with regard to the length of notes taken within the marketing learning unit. ANOVA revealed significant differences for the length of notes taken $F(2,86) = 3.126$, $p = .049$, $\eta^2 = .068$. Post-hoc comparisons using Bonferroni corrections showed significant differences for the length of notes taken in the marketing unit between *AP group* ($M = 491.89$, $SD = 686.92$) and *MP group* ($M = 171.42$, $SD = 378.03$), $p = .043$, but not for the *CP group* ($M = 310.10$, $SD = 362.22$) and the other groups.

Hence, Hypothesis 3a is accepted for the number of views of the handout and the additional material, and rejected for number of views of the video and the overall interaction within the marketing learning unit. With regard to the length of notes taken Hypothesis 3b is accepted.

5.3.4 Hypothesis 4 predicting transfer test results in marketing

Table 5-4 shows the descriptive statistics and zero-order correlations of the predictors used in the regression analysis. To investigate whether (a) students' study related characteristics (semester, current study grade, prior knowledge in marketing, perceived difficulty and confidence of the marketing learning unit) and (b) their online learning behavior (views of handout, additional material, video, and overall interaction) could significantly predict their learning performance in the transfer test, linear regression analysis (see Table 5-5) was used, yielding a $\Delta R^2$of .334 $F(9,91) = 6.571$, $p < .001$. With regard to *academic characteristics* participants' *semester* was a significant positive predictor, current *study grade* was negatively predicting, and their *perceived confidence in marketing* was a positive predictor of participants' transfer test result. Regarding *trace data* only participants' number of *views of the handout* was a significant positive predictor of learning performance.

Table 5-4 Descriptive statistics and zero-order correlations of predictors used for linear regression analysis predicting the results of the transfer test in marketing

Variable	1	2	3	4	5	6	7	8	9	10
1) Transfer test result marketing	-									
2) Semester	.265**	-								
3) Study grade	.309**	-.033	-							
4) Prior knowledge in marketing	.049	.096	-.071	-						
5) Perceived difficulty	-.128	.080	.044	-.110	-					
6) Perceived confidence	.406***	-.032	-.028	-.018	-.134	-				
7) Views of handout	.223*	.003	-.136	-.137	.009	-.055	-			
8) Views of additional material	.140	.086	.001	-.057	.205*	-.091	.557***	-		
9) Views of video	-.029	-.224*	-.020	.033	-.029	.148	.059	.010	-	
10) Overall interaction	.052	.020	.032	-.089	-.021	.186*	.378***	.214*	.471***	-
N	101	101	101	101	101	101	101	101	101	101
M	1.01	5.07	2.35	31.43	2.89	2.50	.77	.50	1.42	7.91
SD	.831	2.81	.598	16.82	.835	.934	.662	.559	1.43	4.63

* $p < .05$; ** $p < .01$; *** $p < .001$

Based on these results, Hypothesis 4a is accepted for semester, current study grade, and perceived confidence and rejected for prior knowledge in marketing and perceived difficulty of the learning unit. Further, Hypothesis 4b is only accepted for number of views of the handout and rejected for number of views of the additional material and the video as well as the overall interaction within the learning unit.

Table 5-5 Regression analysis for academic characteristics, and online learning behavior predicting results of the transfer test in marketing (N = 101)

Transfer test result marketing	*B*	*SE B*	*β*
Academic characteristics			
Semester	.081	.025	.273**
Study grade[1]	-.343	.116	-.247**
Prior knowledge in marketing	.001	.004	.025
Perceived difficulty	-.099	.085	-.100
Perceived confidence	.389	.076	.438***
Online learning behavior			
Views of handout	.274	.136	.218*
Views of additional material	.126	.152	.085
Views of video	.004	.057	.006
Overall interaction	-.023	.019	-.130

Note. * $p < .05$, ** $p < .01$, *** $p < .001$;

[1] Due to German grading system, a smaller value indicates a better grade

5.4 Discussion

The purpose of this study was to investigate (a) if different prompting conditions had an impact on declarative and transfer learning performance, (b) if the prompts entail different learning behavior and (c) if trace data can inform learning performance. Therefore, a quasi-experimental design was administered and repeated-measures (multivariate) analyses of variance as well as linear regression analyses were used.

5.4.1 Summary of findings

Findings indicate that all participants had a significant increase of *declarative knowledge* between t_1 and t_2 and an expected decrease in t_3. However, no significant differences between the prompting conditions were found for declarative knowledge, indicating that the different prompts did not significantly affect participants' learning performance for declarative knowledge.

With regard to *transfer knowledge,* significant effects were found for the experimental groups and for changes over time. However, on a multivariate level no significant interaction effect was found. With regard to changes over time, significant effects were found for IT and marketing and an interaction effect for the prompting condition and time for transfer knowledge in marketing. Further analyses revealed significant differences between groups only for IT but not for marketing. These differences were found for the *AP group* which showed significantly lower transfer knowledge than the *MP* and *CP groups*.

With focus on different *navigation behavior* multivariate analyses of variance were used to investigate if there are differences between the experimental conditions in viewing the material provided in the marketing unit (handout, additional learning material, video, overall interaction). Findings indicate significant differences between the groups in viewing the handout and the additional material. However, no significant differences were found for video views and the overall interaction with the marketing learning unit.

With regard to the *views of the handout* related to the marketing learning unit the *control group* viewed the handout significantly more often than the *AP group*. Regarding the *views of the additional material* the *control group* viewed the material significantly more frequently than all experimental groups. Based on the descriptive results the participants mainly interacted with the video compared to the handout and additional material. Most participants started to watch the video at least once (77.3%) or twice (15.5%), only three participants did not start watching it. In contrast 35.5% of the participants did not view the handout, and 54.5% did not click on the additional material.

With focus on *academic characteristics and trace data* and their predictive possibilities to inform learning analytics systems, learning performance with focus on transfer knowledge in marketing at t_2 was investigated using linear regression analysis. Findings indicate that being in a higher semester, having a better current study grade, and perceiving higher confidence in marketing are associated with a higher learning performance in the transfer test in marketing. Referring to trace data only viewing the handout more often was related to better test results.

5.4.2 Findings on prompting and learning performance

Based on the results of repeated-measures MANOVA, the prompts shown to the participants did not impact their learning performance regarding declarative knowledge and might have impacted their transfer knowledge in IT. These findings are comparable to those of Müller and Seufert (2018), who also found no significant effects of prompts on recall and comprehension, but on transfer knowledge. Post-hoc tests revealed that the *AP group* receiving cognitive, metacognitive, motivational and resource-related prompts was outperformed by the other experimental groups. Further, correlation analyses revealed positive correlation between the *MP group* and declarative (r = .216, p = .023) and transfer knowledge in IT at t_2 (r = .190, p = .047), whereas belonging to the *AP group* was negatively related to transfer knowledge in IT (r = -.209, p = .028). One reason might be that the participants in the *AP group* received too many or too great a variety of prompts in a relatively short learning period, leading to higher mental efforts or distraction (Bannert, 2007). However, besides the suggestion that learners should receive the support they need at the time they need it without increasing cognitive load (Sweller, 2011; Thillmann et al., 2009), no further recommendation of how many prompts are effective was found. Referring to the information available from studies using prompts the number of prompts varied across studies and across conditions within the studies. For example Backhaus et al. (2017) confronted learners with one to three of five possible prompts within e-modules of circa ten minutes, only one type of the prompts was related to increased test performance. In a study using reflective prompts learners had 35 minutes of learning time in a hypermedia learning environment and were prompted for metacognition as they should reflect and express each navigation decision within the environment leading to higher transfer performance compared to the control group but not to significant effects for performance in recall and knowledge (Bannert, 2006). In a study investigating short- and long-term effects of prompts, learners were designing their own metacognitive prompts before the learning occurred and should choose eight moments in time for receiving them during a 40 minutes learning period in a hypermedia learning environment. Results indicated differences between the prompted group and the control group with regard to their navigation patterns and their transfer test performance directly after the learning period and in a subsequent learning period without prompts, but no effects on recall and comprehension were found (Bannert et al., 2015). Moos and Bonde (2016) presented prompts related to planning (3 prompts), monitoring (4 prompts) and reflection (5 prompts) asking learners to verbalize in a learning session of approx. 45 minutes resulting in more self-regulated learning activities and higher test performance compared to the control group. Müller and Seufert (2018) confronted their participants with six prompts (3 cognitive and 3 metacognitive) within each of the two learning periods of thirty minutes resulting in increased performance in the first transfer test compared to the control group. Hence, the number of prompts (see second subsection of section 5.2.3 for further details) participants were confronted with in this study was comparable with the amount in other studies. Based on the data available we further analyzed participants' perceptions on the prompts with regard to perceived learning support and negative perceptions about the prompts. With regard to perceived learning support where on a scale of 1 to 5, a low result indicates low perceived support and a high result high perceived support, the *AP group* evaluated the prompts related to learning support below the middle of the scale with M = 2.71 (SD = .82), the *CP group* perceived a comparable learning support with M = 2.91 (SD = .81), whereas the *MP group* reported a higher perceived learning support M = 3.30 (SD = .85). With regard to negative perceptions about the prompts a low number is related with low negative perceptions and a high number with high negative perceptions. The *CP group* reported relatively low negative perceptions with M = 1.42 (SD = .89), followed by the *MP group* reporting still relatively low negative perceptions related to the prompts with M = 1.69 (SD = 1.05), and with the *AP group* reporting the highest negative perceptions of the prompts with M = 2.07 (SD = .86). One-way ANOVA revealed significant differences between the groups for perceived learning support through prompts $F(2,86) = 3.843$, $p = .025$, $\eta^2 = .082$, and for negative perceptions regarding the prompts $F(2,86) = 3.525$, $p = .034$, $\eta^2 = .076$. Tukey-HSD post-hoc tests revealed that *AP group* perceived significantly less learning support than the *MP group,* $p = .022$, and had significantly more negative perceptions than the CP group, $p = .026$. For both analyses, no other significant differences between the groups were found.

We further analyzed participants' perception of having received too many prompts on item basis. Results showed, that *AP group* perceived more than all other groups having received too many prompts M = 2.00 (SD = .903), *MP group* M = 1.55 (SD = 1.27), and *CP group* M = 1.07 (SD = 1.08). One-way ANOVA revealed significant differences between the groups $F(2,86) = 5.247$, $p = .007$, $\eta^2 = .109$ with the *AP group* perceiving significantly more prompts than the *CP group*, $p = .005$. These results are in line with the number of prompts presented to the participants and further support our assumption that *AP group* might have received too many or too great a variety of prompts. However, participants' perception of having received too many prompts is still relatively low on a scale from 1 to 5 with 5 indicating strong agreement on having received too many prompts. Comparably, the *AP group* perceived less learning support through the prompts than especially the *MP group*. Hence, future research might further investigate the effects of the number of prompts and performance for example by using an experimental setting with different amounts of prompts, a think-aloud approach to gain insights into students' perceptions or by additionally measuring cognitive load.

In addition, for not being interruptive Molenaar and Roda (2008) argue that prompts should be in line with the learner's current goals and activities, whereas Wirth (2009) argues that prompts provide only limited information to the learner, thereby only insignificantly interrupting learning processes. To further prevent interruptions of learners machine learning approaches could be applied for predicting a moment in which learners are more likely to be in need of or to react and engage with the content prompted by using variables such as learners' current goals, emotional states, their past behavior or behavior indicating that learners are struggling but also demographic data (Pielot et al., 2017).

Further reasons why the varying prompting conditions might have had no considerable effect on learning performance might be due to the limited learning period, which did not allow the application of many different strategies, or may be due to the fact that learners who have already studied for an average of 4.86 (*SD* =2.91) semesters have already established a relatively rigid learning behavior which will not be affected by temporary prompts. Furthermore, Prieger and Bannert (2018) found that learners with higher skills did not benefit from metacognitive prompts regarding learning performance, compared to those with lower skills. In this study, learners stated relatively high metacognitive awareness (knowledge about cognition *M* = .76; *SD* = .15; regulation of cognition *M* = .70; *SD* = .15; with a possible maximum of 1.0), hence, participants might already have known when to apply which strategy and might have felt distracted by the prompts. However, as indicated above, correlation analyses showed that being in the *MP group* was positively related to learning performance in declarative knowledge and transfer knowledge in IT, indicating that the metacognitive prompts were somehow related to learning performance, a finding mirrored by other studies (e.g., Kauffman, 2004; Lehmann et al., 2014; Nückles, Hübner, & Renkl, 2009). Nevertheless, the average learning performance, especially in transfer tests but also in declarative knowledge, was rather low, indicating that the learning period was too short or participants did not take the task seriously. Thus, future studies should investigate prompts in authentic learning scenarios.

5.4.3 Findings on prompting and learning behavior indicated by trace data

To gain further insights if different prompts affect learners' behavior in a typical digital learning environment, multivariate analyses of variance were used.

Based on the trace data available for the marketing learning unit findings indicate that the control group significantly differs from the experimental groups with regard to viewing the additional learning material and from the *AP group* in terms of viewing the handout.

However, with focus on number and length of notes taken in the marketing unit descriptive statistics show that the prompt asking participants to take notes did impact their behavior as the *control group* did not take notes in contrast to all prompting conditions. In addition, when comparing the experimental groups, the *AP group* significantly took more notes than the *MP group*. But with regard to transfer knowledge in marketing the prompted note taking did not seem to have a positive effect on learning performance, as indicated by previous studies (Nye, Crooks, Powley, & Tripp, 1984; Peverly, Brobst, Graham, & Shaw, 2003). Hence, it is necessary to further investigate the content and quality of the notes taken. Furthermore, even though solely the *AP group* received a prompt with the information, that there is additional learning material available, this group accessed the additional material least of all. One reason might be that they received many prompts and were busy in taking notes as indicated by the descriptive statistics. However, the *control group* viewed the handout and additional material the most but had the lowest overall interaction with the learning unit.

Summarized, the findings on trace data are ambiguous, as prompts to take notes seemed to have an effect, but the *AP group* did not follow the prompt pointing to the additional material. Potentially, the *control group* applied their own strategies and browsed more efficiently trough the learning unit as indicated by the overall interaction, whereas the prompted groups relied on the guidance offered through the prompts possibly inferring their own learning strategies. The results from this quasi-experimental study make it difficult to infer how to design prompts as guidance for learner by not impairing their self-directedness or established strategies. Especially, when considering that interventions in higher education should support processes of self-regulated learning and learning performance. On a descriptive level the *control group* showed the highest test performance related to the transfer test in marketing at t_2 compared to the experimental groups. Hence, it might be possible that learners might have been interrupted by the prompts or have had available sufficient strategies to face the learning tasks. But when looking at the transfer test results in marketing at t_3 the *control group* showed the lowest test performance and highest decrease whereas the *MP group* showed a slight increase and best performance. Comparable, the *control group* showed a high increase in declarative knowledge from t_1 to t_2 but performed worst at t_3, whereas *MP group* showed the best performance at t_2 and t_3. In addition, further evidence is required with regard to successful navigation patterns, for example, non-linear navigation based on learners' current needs versus navigating through the digital learning environment in a more linear way (Prieger & Bannert, 2018).

5.4.4 Findings on trace data informing learning performance

One major aim of learning analytics is to use learners' behavior in digital learning environments for predicting learning performance (El-Rady, Mohamed, & El Fakharany, 2017). However, referring to learning performance in the marketing transfer test only participants' number of views of the handout of the learning unit could significantly predict their performance. More relevant for predicting learning performance were academic characteristics of the participants such as the semesters studied or their perceived confidence. However, when facing the issue that many current learning analytics systems do not even refer to additional information about learners (Vieira et al., 2018), this might significantly reduce their validity.

In sum, in this quasi-experimental study, trace data did not, as hoped, provide explanation for learning performance. However, it needs to be kept in mind the limitedness of the trace data in this study as it was only possible to track participants' initial click on the resources which opened in another window of the browser not allowing to track further interaction such as scrolling the material.

Given these findings on trace data, and considering that learning analytics have only limited data available (e.g., not all indicators can be captured through the system or the system has no access to learner characteristics) and furthermore, that the data available are affected by learning processes outside the digital learning environment, learning analytics might only offer very limited insights into students' learning processes (e.g., Ferguson, 2012; Wilson et al., 2017; Winne, 2017b). Hence, having only available small datasets as in this study, automated support through learning analytics might be limited compared to having available large datasets. Thus, the role of the teacher as mediator between learning analytics results and the interventions the learners receive needs to be further examined. But as such data are complex teachers require high data literacy to be capable of interpreting the data and deducing appropriate interventions (Greller & Drachsler, 2012; Ifenthaler, 2017; Vieira et al., 2018).

Digital learning environments in higher education to date are limited, as they only allow data to be captured on online behavior, for example, accessing a folder or downloading the slides. At the most, they can track the length of time students spend watching videos or passing self-assessments, and they might be aggregated to behavioral patterns. But as the systems do not offer sufficient learning opportunities, any actual learning tends to take place outside the system, leading to biases in the predictions. Therefore, it is necessary to ensure that "offline" learning can be integrated into the learning analytics system. For example, by prompting students to reflect on their learning activities, and to track their learning time, quality, and the resources used. In addition, learners could be asked to take related tests to have information about their current knowledge. At least, learners' self-awareness about their learning activities should be triggered and they should be informed that learning analytics results can be biased for different reasons to avoid demotivation or suspicion. Hence, most of the data available cannot be related to cognitive learning processes. Consequently, inferring from these data on learning requires further empirical evidence (Ferguson & Clow, 2017). The most promising ways of predicting which students are at risk, or their expected learning performance, may be information on learner characteristics and results of self-assessments, and only to a negligible effect, information about when and how often students accessed resources. However, feeding back test results or other analyses, potentially selected by the teacher, enables learners to monitor and to increase their awareness which might enhance their self-regulated learning processes. Such processes can be further enhanced with the digital learning environment offering learners the possibility to set individual learning goals including related materials and a deadline.

Though, enabling learning activities in digital learning environments to be recorded, such systems first need to become more flexible and support things learners would otherwise do on paper or using other programs (e.g., text editors, highlighting tools, mind map app) and, at a higher level, need to offer tools for planning and goal-setting. In addition, in order to achieve improved availability of information about the learning processes, such systems should be highly integrated and enable personalization, which is also related to students' demands of an 'ideal' analytics supported digital learning environment (Schumacher & Ifenthaler, 2018).

5.4.5 Limitations and further research

This study shows several limitations, for example the experimental setting allowed only a limited learning time and limited learning material, resulting in restricted possibilities for tracking learning behavior or validly inferring strategy use from trace data. Even though the university's common digital learning environment was used and participants were told that they have to pass the knowledge tests to receive the credit points, the learning scenario is not comparable to real learning settings. For example, motivational dispositions such as goals are relevant factors for successful learning processes (Schunk, Pintrich, & Meece, 2008), in this quasi-experimental approach, learners' motivation and goals may differ from those they have in authentic learning situations.

Prompts in this study were not adaptive or personalized based on learners' current behavior or their characteristics, raising the issue that prompts that are supportive for one learner might not be helpful for another, due to different prerequisites or characteristics (Backhaus et al., 2017; Lin & Lehman, 1999; Prieger & Bannert, 2018). Further analyses might investigate if relations of prompts, learner characteristics and learning performance exist. In addition, participants were only confronted by prompts during t_2, which, in total, took about 90 minutes. Hence, they were not familiar with receiving prompts, used them only for a short time and received many prompts. However, confronting students with prompts over a longer period might reduce the possible benefits of prompts related to learning performance which

Nückles, Hübner, and Renkl (2008) refer to as over-prompting. In addition, it needs to be further analyzed how many prompts the learners were actually facing during their individual learning paths.

Nevertheless, the experimental setting allowed to control for possible external learning behavior of the participants, making the results on the insufficient predictive power of online trace data even more significant. The digital learning environment used for this experiment is a well-known system among European universities, however, current tracking is limited to track clicks in the system. Many digital learning environments used in higher education, however, are comparable or even less complex than the learning scenario used in this experimental setting, and learning analytics are applied in such systems for identifying students at risk or predicting learning performance (Zhang & Almeroth, 2010). Consequently, when designing new digital learning environments they should offer authentic learning opportunities, and possibilities to capture learners' behavior need to be considered and implemented at the very beginning.

As participants of this quasi-experimental study were only from one university, findings cannot be generalized, but might be investigated further including students from more universities.

Hence, future research should investigate prompts in real learning settings, which will be the next step in this research project. Particularly, research on learners' reaction to prompts should be in focus using trace data. As no adaptive or personalized prompts were used in this study, referring to Backhaus et al. (2017), the system will offer adaptive prompts to the learners based on their (self-reported) learning characteristics and their learning behavior in the online system. For example, when students only download the lecture slides, they will receive a prompt referring to the lecture recordings, the self-assessments, or further readings. Furthermore, upcoming analyses might investigate individual navigation patterns related to the learning performance or the prompts received.

5.5 Conclusion

The purpose of this quasi-experimental study was to investigate the effect of prompts on the learning performance in declarative and transfer knowledge tests, as well as on learning behavior, and to examine whether and how trace data can inform predicting learning performance.

Findings indicated that prompting did not affect declarative knowledge and only had an impact on transfer knowledge in IT. However, differences in learning behavior were found between the control group and the experimental groups. Furthermore, the power of trace data to inform predictions on learning performance was rather limited. In this study, learning performance with regard to transfer knowledge in marketing were only predicted by the frequency of views of the related handout.

Ferguson and Clow (2017) claim that learning analytics still lack empirical evidence, this study, in using a quasi-experimental approach and by reporting 'negative' findings, highlights the potential limitations of learning analytics especially when facing small datasets, and aims to encourage upcoming studies to use experimental study designs.

Prompts in this research might have not been efficient, as they were not related to students' characteristics or behavior, resulting in inappropriate support. However, information based on trace data might be helpful in generating effective instructional means and should be investigated further.

Still, research in learning analytics and how they support students at higher education institutions is scarce. Research in learning analytics needs to further investigate how technology-driven interventions may support learning and what role the educator may take between algorithm-based recommendations and informative feedback to the individual student.

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6 Linking assessment and learning analytics to support learning processes in higher education

6.1 Introduction

In higher education, summative assessments are still predominant and formative assessments for supporting learning are associated with additional workload for the facilitators (Broadbent, Panadero, & Boud, 2017). Nevertheless, assessments (in higher education) are increasingly considered as a means to support learning processes (Cartney, 2010) and can be enhanced by applying educational technologies (Carless, 2017). As Shute and Becker (2010) stated, a shift from collecting numbers to insights into processes of learning and instruction is preferable. Therefore, assessment needs to be an ongoing process of collecting data from different contexts feeding back the inferences for adjusting instruction, and learning (DiCerbo, Shute, & Kim, 2016). However, in order to elicit valid evidence, assessments need to be designed carefully by following a principle-based design approach (Mislevy, Almond, & Lukas, 2003; Shute, Leighton, Jang, & Chu, 2016).

In higher education self-regulated learning is the key to successful learning (Cassidy, 2011; Draper, 2009). Self-regulated learning can be defined as “an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment” (Pintrich, 2000, p. 453). During this process, which is mostly assumed to be cyclical (e.g., Zimmerman, 2000) learners set goals, analyze the task and incorporate the criteria of success. During learning, learners monitor their progression and adjust learning strategies accordingly. They create feedback internally, which can then be enhanced with external feedback (Butler & Winne, 1995). Formative as well as self-assessments are considered to be related to self-regulated learning (Hattie & Timperley, 2007; Panadero, Jonsson, & Botella, 2017; Paris & Paris, 2001).

As learning in higher education is increasingly facilitated through digital learning environments, learners’ behavior can be tracked using learning analytics. Learning analytics aim at optimizing and modeling learning processes, learning environments and educational decision-making by assessing, eliciting, and analyzing dynamic information about learners and learning environments (Ifenthaler, 2015). Therefore, learning analytics collect a variety of data, such as how timely learners access resources, their performance in self-assessments, their digital interactions with peers, access to library resources, their geolocation, but also individual demographic information, and can be enriched with self-reported data from surveys on learning strategies or motivational dispositions (R. A. Ellis, Han, & Pardo, 2017; Gašević, Jovanovic, Pardo, & Dawson, 2017). Based on data collected and the resulting analyses, adaptive and personalized feedback can be offered to learners whenever they need it. As feedback is more effective when it provides learners with information on how to improve (Hattie & Timperley, 2007), solely giving learners an overview about how they performed in a test is not sufficient. Hence, feedback should be enhanced with additional recommendations. For example, learners testing their current knowledge with self-assessments could receive feedback on how they performed both overall, and in more detail related to each learning objective. Furthermore, they could receive additional recommendations on content or topics that need revision, as well as on any additional related learning resources. Based on learners' online learning behavior, learning analytics might also recommend changing learning strategies, such as a timely recapitulation of the lectures.

In summary, learning analytics might be capable of supporting the proposed ongoing assessments of learners' knowledge and learning behavior across different contexts and of giving informative feedback for improvement. In addition, learning analytics can also enhance and support teachers in their assessment practice, by allowing an ongoing collection of evidence and enabling them to adjust their teaching to learners' needs. Due to the availability of large datasets on student performance the data could be also used for informing institutional or governmental decision-making (Ifenthaler, 2015). However, even though applying learning analytics for enhancing assessment seems to be fruitful, related research and theory contribution are still at an initial level (F. Martin & Ndoye, 2016).

Hence, the purpose of this paper is to provide an overview on how assessment can be combined with learning analytics with the aim of supporting self-regulated learning processes of students in higher education. Therefore, relevant aspects of assessment and assessment design, the role of feedback related to assessment and self-regulated learning, plus current perspectives on learning analytics, will be introduced. A conceptual framework will be derived, based on the theory, and suggestions will be made as to how learning analytics features could assist this framework. This paper concludes with a discussion of the model and an outline of upcoming research needs.

6.2 Assessment

6.2.1 Assessment in higher education

This section gives an overview about assessment frameworks, as well as practices, requirements and constraints of assessments in the context of higher education. Furthermore, links between assessment and self-regulated learning are introduced.

Definitions of assessment differ and may be distinguished by focusing either on the process or the product of assessment (Webb, Gibson, & Forkosh-Baruch, 2013). In this regard, the process refers to the assessment activities and the product refers to the results of the assessment (e.g., a label of judgement, score) (Black & Wiliam, 2018; Webb et al., 2013) or alternatively, the assessment focuses either on a learning process or on a learning product (e.g., essay) (Falchikov, 2005). Furthermore, depending on the functions of the assessments their definitions differ (see section: 6.2.2). The basic cyclical assessment process consists of three phases: (1) eliciting evidence, (2) interpreting evidence, and (3) taking action (Wiliam & Black, 1996).

To further strengthen the connection to pedagogy and contextualize assessment, Black and Wiliam (2018) propose an enhanced framework of assessment (Figure 6-1). They further emphasize an integrative view on formative and summative assessment which are distinguished based on the "*kinds of inferences being drawn from assessment outcomes*" (Black & Wiliam, 2018, p. 553, emphasis in original) either related to the current status or related to actions for improvement. Their assessment model is considered to be cyclic and entails six components. It starts with (1) pedagogical and instructional approaches and (2) underlying theories of learning, going on to include (3) contextual characteristics, such as discipline, institutional policies, the learning environment and outcomes. These are culturally valued and promoted (Bennett, 2011) and influence (4) the planning and design of assessments (Bearman et al., 2016), which should be guided by design principles (Mislevy et al., 2003). The (5) assessment itself is then implemented and provided to the learners, having either a formative or summative function, depending on how the evidence is used. The evidence may inform (6) external summative testing. This is mostly associated with high-stakes tests, which, as well as being determined by contextual factors, may also impact them (e.g., adjustments of curricula or policies).

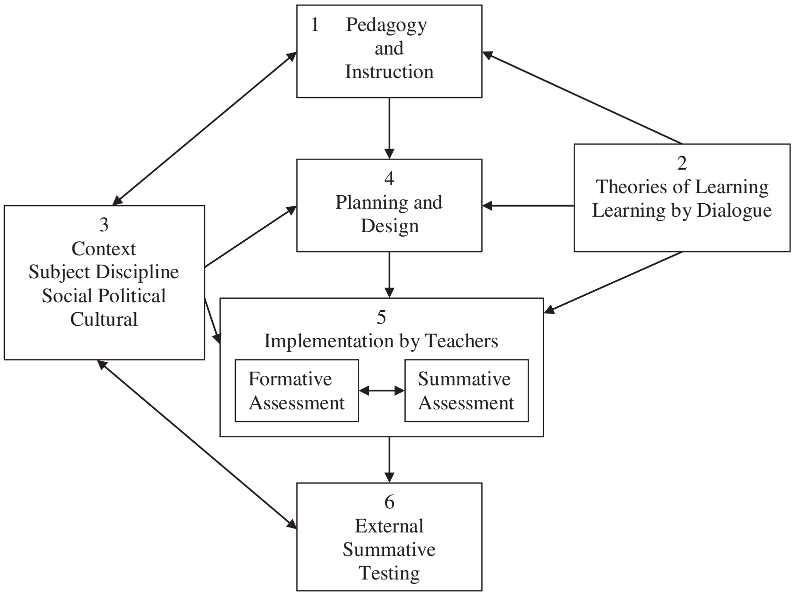

Figure 6-1. Model of assessment integrating pedagogy (Black & Wiliam, 2018, p. 556)

Assessment in higher education has several functions, such as certificating students' performance by assigning grades, evaluating learners' progress and giving support on how to make improvements, ascertaining quality of teaching courses and curriculum, and providing information for the institution or accreditation (Sadler, 2010a). In higher education assessment is most commonly associated with grading or certification (Boud, 2007). Due to lager study cohorts with heterogenous prerequisites, however, the aspect of giving individual support becomes increasingly relevant (Bosse, 2015; Tolstrup Holmegaard, Møller Madsen, & Ulriksen, 2017). Assessment methods used in higher education include portfolio assessments, written and oral examinations and group assessments and diaries, and assessment modes focus on self- and peer-assessment, and formative, continuous and summative assessments, as identified by a literature review on relevant assessment practices in higher education related to the Bologna process (Pereira, Assunção Flores, &

Niklasson, 2016). Self-regulated learning is both a goal of and a necessity for successful learning in higher education (Cassidy, 2011; Nicol, 2009), and assessment practices (Panadero et al., 2017) plus related feedback (Nicol & Macfarlane-Dick, 2006) are considered to support learners' self-regulation. Self-assessments in particular are discussed within the context of higher education as they are related to all components of self-regulated learning (Paris & Paris, 2001) and foster learners' responsibility towards learning (Bennett, 2011). For example, Panadero et al. (2017) used a meta-analytic approach to find that self-assessments produced a positive impact on students' self-regulated learning strategies, yielding small to medium effect sizes (d = .23 to d = .65). Furthermore, formative assessment in higher education focuses on peer-assessment as a means of supporting learning (Cartney, 2010). Peer-assessment is thought to increase learners' responsibility and autonomy for their learning and help gain a better understanding of what is relevant for achieving high quality learning products (Cassidy, 2006; Webb et al., 2018).

However, to be able to perform in self- and peer assessments but also to react to feedback, students are considered to require capabilities of feedback literacy (Carless & Boud, 2018) including evaluative judgment (Panadero, Broadbent, Boud, & Lodge, 2018). Evaluative judgement is described as "being able to judge the quality of one's own and others' work" (Tai, Ajjawi, Boud, Dawson, & Panadero, 2018, p. 468) and is relevant in estimating achievements of standards and criteria related to produced artifacts, such as an essay or programming task. Evaluative judgement can be fostered through engaging students in self-and peer-assessment practices, by emphasizing their justifications for their judgments (Boud & Molloy, 2013; Tai et al., 2018). Conversely, it supports learners in self-regulating their learning (Panadero et al., 2018). In summary, processes related to self- and peer assessment as well as evaluative judgement and feedback literacy are closely related to learners' self-monitoring and self-evaluating activities described in models of self-regulated learning (e.g., Winne, 2011, 2017a; Zimmerman, 2000).

As summative assessments in particular, but also formative assessments can have vital consequences for learners (Shute et al., 2016), assessments need to be reliable and valid (Shute & Becker, 2010). Particularly, (complex) skills cannot be measured directly, as it is only possible to infer learners' skills, knowledge, competences and learning processes based on their observable behavior (Bennett, 2011; Mislevy et al., 2003). Hargreaves (2007, p. 186) emphasizes, that "validity of [formative] assessment for learning depends on how far the interpretation and use of the assessment actually leads to further learning". However, it is furthermore crucial to design the assessment based on principles to enhance the validity of the evidence generated (DiCerbo et al., 2016). As validity is an interplay between "evidence and theory support[ing] the interpretations" (AERA, APA, & NCME, 2014, p. 11) scores cannot be interpreted without theoretical underpinnings. As it is not obvious why learners do not respond correctly, Bennett (2011) suggests offering a sufficient number of tasks focusing on the same aspect from multiple sources or investigating the reasons for choosing answers in order to recognize patterns of students' errors, so that interventions are designed appropriately.

Due to large cohorts in higher education and limited resources, assessments used for providing feedback are constrained (Boud & Molloy, 2013; Nicol, 2009). Hence, economic assessment practices need to be found both to meet the requirements of having summative assessments resulting in students' certificates and other accreditation processes and also to support students' learning with formative assessments and feedback. In meeting these constraints and requirements, Broadbent et al. (2017) divided the required summative assessments into multiple assignments and enhanced them with formative elements by using annotated rubrics, exemplars, and personalized formative audio feedback to support students' learning and self-assessment. As learning analytics aim at providing adaptive and personalized feedback to individual learners it might be a meaningful enhancement of current assessment practices in higher education, which will be described in section 6.3 on learning analytics.

6.2.2 Functions of assessment

In the literature, at least two major functions of assessment are discussed: formative and summative assessment (e.g., Bennett, 2011; Black, 2013; Shute & Becker, 2010; Webb & Ifenthaler, 2018). The summative assessment is often taken at the end of a learning unit or course and mostly related to some kind of judgement where a learner's performance is related to the predefined objectives with the purpose of grading or certification (Shute & Becker, 2010). Benefits of summative assessment are that "(a) it allows for comparing learner performances across diverse populations on clearly defined educational objectives and standards; (b) it provides reliable data (e.g., scores) that can be used for accountability purposes at various levels (e.g., classroom, school, district, state, and national) and for various stakeholders (e.g., learners, teachers, and administrators); and (c) it can inform educational policy (e.g., curriculum or funding decisions)" (Shute & Becker, 2010, p. 8). The aforementioned functions of summative assessment may be further expanded by an evaluative function, focusing on "Evaluating the quality of educational institutions or programs" (Wiliam & Thompson, 2008, p. 59).

Formative assessment as an ongoing cyclical process (Wiliam & Black, 1996) can be defined as "assessment that is specifically intended to provide feedback on performance to improve and accelerate learning" (Sadler, 1998, p. 77). Furthermore, formative assessment should support the adaption of teaching activities to learners' needs (Black, Harrison, Lee, Marshall, & Wiliam, 2003). Following Wiliam and Thompson (2008, p. 63), formative assessments include defining a shared understanding of standards and criteria of learning outcome ("Where the Learner Is Going"), assessing learning evidence ("Where Is the Learner Right Now"), and giving feedback on how to achieve the pre-set outcomes ("How to Get There"), by involving the teacher, the peers and the learners themselves.

However, formative and summative assessment are not fully distinct concepts, as, for example, summative test results may be used as feedback for learners, resulting in a change of students' learning behavior, even though this was not the primary intention (Bennett, 2011; Black & Wiliam, 2018; Smith, 2007). Alternatively, they might result in changes of instructional processes (Bennett, 2011). In addition, when learners prepare for an exam or interact with the assessment tasks (Bennett, 2011) reflective processes might be initiated. Hence, both functions of assessment are considered to be on a continuum, and it is proposed that the same tools (e.g., tests, essays) can be used for both but applied with a different focus (Black & Wiliam, 2018; Wiliam & Black, 1996). Hence, so as not to exclude evidence from assessments used for a primary summative purpose but applied in a formative way (Wiliam, 2011), Black and Wiliam (2009, p. 9) adjusted their definition of formative assessment to the following: "practice in the classroom is formative to the extent that evidence about student achievement is elicited, interpreted, and used by teachers, learners, or their peers, to make decisions about the next steps in instruction that are likely to be better, or better founded, than the decisions they would have taken in the absence of the evidence that was elicited". This definition is more learner-centered as the authors highlight that they associate instruction with teaching *and* learning (Black & Wiliam, 2009) and emphasize decision making, based on evidence.

In order for assessment activities to support students' learning processes, Wiliam (2011) highlights two aspects: a) the assessment needs to be designed in such a way that the generated evidence can be acted upon, by not only showing the gap but by pointing out, how improvements can be made and b) that learners react to the feedback by initiating activities accordingly. However, learners' reaction to the feedback provided based on formative assessment will be influenced by their individual characteristics, like their capacity to self-regulate their learning (Butler & Winne, 1995) as well as motivational constructs, such as perceived self-determination (Deci, 1992) or attributions of failure and success (Schunk, 2008; Weiner, 1985). Hence, learners should perceive some kind of autonomy and control when taking assessments (Bevitt, 2015), and the feedback given should engender learners' responsibility, autonomy and competence so that they are motivated for behavioral change. Boud and Molloy (2013, pp. 704-705) emphasized the agency of learners within the process of assessment by stating that "there is an educative purpose of assessment to inform the practice of learners so that not only do they have the capabilities to produce work that meets the standards of others, but also they can make their own informed judgements about the process of production of that work, drawing upon the full range of resources available to them." To promote such learning-oriented assessments which facilitate both functions – certification and learning – Carless (2007) describes three components: a) assessment tasks as learning tasks, which refer to the designated learning outcomes and are spread across the learning or course period; b) involving students by enabling them to understand the learning goals, engage with the criteria and standards as well as evaluate themselves and their peers; and c) feedback as feedforward, by providing timely feedback with recommendations for upcoming activities.

However, to gain valid inferences about learners' progression based on their observable behavior as well as using these inferences to deduce appropriate assumptions and interventions, and to achieve a trans-contextual standard which is necessary to combine evidence from different contexts, assessments need to be designed carefully (DiCerbo et al., 2016). Therefore, principles of assessment design will be described further.

6.2.3 Assessment design

To be able to infer from assessment data on students' learning, assessments need to be designed following design principles (Shute et al., 2016). Several frameworks exist, such as the Assessment-Triangle (Pellegrino, Chudowsky, & Glaser, 2001), Assessment Engineering (Luecht, 2013), the Four Building Blocks (M. Wilson, 2005) or the Evidence-centered Assessment Design (e.g., Mislevy et al., 2003; Mislevy & Riconscente, 2005). The Assessment Triangle (Pellegrino et al., 2001) consists of three interdependently connected assessment elements focusing on evidence-based reasoning: a) *cognition* includes assumptions about learners' representations of knowledge and competence development as well as underlying learning theories; b) *observation* encompasses the multifaceted tasks or methods used to let learners demonstrate knowledge and skills which need to be designed with a purpose and aligned with the cognitive model for providing the correspondent evidence; and c) *interpretation* involves methods used for inferring from the observable assessment data from various sources on learners' knowledge and skills (as defined in (a) the cognition model).

The Evidence-centered Assessment Design framework prevails in the context of technology-enhanced assessments (Webb & Ifenthaler, 2018). The reason for this is that it considers advances of learning sciences and technology and highlights the need for assessment measures to be aligned with the new complexity (Mislevy et al., 2003), such as the integration of evidence from different contexts and measures as well as over time (Almond, 2010). Hence, for linking learning analytics and assessment, this framework seems promising as it synthesizes different models which is in line with the holistic learning analytics framework developed by Ifenthaler and Widanapathirana (2014). Using a principle-based approach guided by learning theory increases the coherence of the *inferences* from *observations* on the *interpretations* of the intended assessment constructs and thus increases the assessments' validity (Nichols, Kobrin, Lai, & Koepfler, 2017). In addition, the Evidence-centered Assessment Design framework is described in reasonable detail making it usable for application.

The Evidence-centered Assessment Design framework consists of five layers (Mislevy & Riconscente, 2005): (1) *domain analysis* includes knowledge about the domain and about what is relevant in order to perform valued tasks in this domain; (2) *domain modeling* defines the relevant elements of the assessment (underlying theory, claims of assessment and defining data to be collected), based on the domain analysis, and states how they can be elicited and observed. Hence, it is about "what an assessment is meant to measure, and how and why it will do so" (Mislevy & Haertel, 2006, p. 8); (3) *conceptual assessment framework* focuses on designing the elements of an assessment considering different models as a blueprint (as described below in more detail); (4) *assessment implementation* refers to putting the prior templates into concrete terms by "authoring tasks, fitting measurement models, detailing rubrics and providing examples, programming simulations and automated scoring algorithms" (Mislevy & Riconscente, 2005, p. 24) and determining how the tasks and scaffolds will be presented to the learners; (5) *assessment delivery* refers to presenting the assessment to learners by selecting a task or activity, presenting it according to the task model and collecting the work product, processing the response by identifying evidence related to the assessment purpose (evidence model), including giving optional task-level feedback to learners. All evidence collected is accumulated for summative assessment and feedback (based on evidence model), leading to an update of the probabilistic assumptions of the *student model*. This information again feeds into activity selection, such as further instruction or new assessment tasks. All information required for the processes of assessment delivery is stored in the *task/evidence composite library*. All related processes and the task/evidence composite library interact and update each other dynamically in each step.

For operationalizing and designing an assessment, Mislevy et al. (2003) describe the *Conceptual Assessment Framework,* containing several intertwined models:

- The *student model* includes the “variables related to the knowledge, skills and abilities we wish to measure” (Mislevy et al., 2003, p. 6). Learners’ knowledge in a certain domain is estimated by inferral from their observable behavior, related to assigned tasks or situations applying probabilistic models, but further influenced by external variables such as environmental or personal conditions (e.g., noise, motivation).
- The *evidence model* “provide[s] detailed instructions on how we should update our information about the student model variables given a performance” (Mislevy et al., 2003, p. 8). This contains *evaluation standards*, how scores are assigned to learners’ work products (e.g., rubrics, automated scoring procedures); and how the collected variables relate to the assumptions in the *student model* and to the overall performance level of a targeted proficiency (*measurement model*).
- The *task model* describes the sets of tasks designed based on domain modelling, their key features and how to present them to the learners to obtain valid data (e.g., considering circumstances influencing performance). The tasks need to be designed to elicit the behavior that is expected from the learners to infer on their knowledge.
- The *assembly model* concerns the representation of a broad variety of tasks to enable a valid inferral of learners’ proficiency, based on their processing of the tasks, as indicated in the *student model*. Hence, it “orchestrates the interrelations among the Student Models, Evidence Models, and Task Models” (Mislevy & Riconscente, 2005, p. 20) and would serve as the basis for adaptive testing.

Nichols et al. (2017) describe three characteristics constituting principle-based assessment designs: 1) *construct-centered approach* meaning that the constructs which should be assessed are defined and guide the design process; 2) *engineering towards intended interpretations and uses*, which implies that the assessments are designed to collect evidence and interpret it using measurement and probabilistic models to infer on the assessment targets; and 3) *explicit design decisions and rationales* supporting an explicit and transparent design process, including detailed definitions of the targets of inference, the stimuli used to elicit them, and of the evidence collected and the way in which it is evaluated and accumulated to infer on the assessment targets. Furthermore, a principle-based approach integrates both formative and summative functions of assessments as they focus on being informative to the learner regardless whether graded or not (Shute et al., 2016). Therefore, however, not only the assessment needs to be delivered to the learner but also feedback needs to be provided to support learning from assessments.

6.2.4 Feedback in assessment

As described before, assessments might be carried out either externally (e.g., by teachers, peers, educational technologies) or in the form of self-assessments internally by the learner. The information gathered will be evaluated against pre-defined assessment criteria, standards or learning objectives. In the case of external assessment, the result and optional actions for improvement need to be somehow communicated to the learner (Narciss, 2008, 2017). Hence, the feedback provided can be described as the expression of the assessed, contextualized and interpreted assessment evidence including information about how to make improvements in terms of reaching the favored outcome (Ramaprasad, 1983; Sadler, 2010b). Feedback therefore can have *cognitive* (information processing), *metacognitive* (self-evaluation or reflection) and *motivational* (encouraging effort and persistence) functions (Narciss, 2008; Narciss et al., 2014). Feedback might be provided on four levels – the task performance, the process of solving the tasks, the level of self-regulation, and the self-level about the learner’s person (Hattie & Timperley, 2007). However, for some authors, in order to be considered as feedback, this information needs to be actually *used* to close the loop (e.g., Ramaprasad, 1983; Sadler, 1989), thus leading into some kind of adapted learning activities.

However, the feedback provided will not necessarily lead to changes in learners’ behavior (Cartney, 2010; Hattie & Timperley, 2007). In line with learning theoretical assumptions of cognitivism (Piaget, 1975) it is not sufficient only to present the feedback information to the learner, as the information needs to be interpreted and processed and is further influenced by individual prerequisites (e.g., prior knowledge, educational background, learning history, attribution patterns, goal setting, learning strategies, beliefs) (Butler & Winne, 1995; Evans, 2013; Nicol, 2009; Nicol & Macfarlane-Dick, 2006; Sadler, 2010b). In particular, if the external feedback is contradictory to the internal feedback or beliefs the external information needs to be integrated into learners' cognitive representations to reduce potential perceptions of discrepancies (Butler & Winne, 1995; Piaget, 1975). Thus, as Narciss (2012, 2017) states, besides the type, quality and the source of the external feedback, individual characteristics of the learners and their learning behavior, as well as contextual factors of the learning setting (e.g., learning objectives and tasks) also determine the effectiveness of the feedback provided. Hence, learners need to be capable and willing to interpret and react upon the feedback provided, as well as actively seeking feedback (Hattie & Timperley, 2007; Narciss, 2008). As Boud and Molloy (2013, p. 709) state "The challenge for learners is not only to acquire understanding of the appropriate standards and criteria and monitor their performance against these, but also to find new opportunities to put this learning into practice and find ways of judging their own work." Hence, if learners encounter problems cognitively in understanding the feedback and deriving appropriate actions, or if motivational constraints mean they refuse to react to the feedback, the feedback process might not result in improved learning behavior. Furthermore, feedback should not be a one-way activity from teacher to learner but should consider the learner as an actively involved agent. This process can be enhanced through discussions to achieve a shared understanding and social construction of standards, criteria and quality of work (Carless, Salter, Yang, & Lam, 2011; Nicol & Macfarlane-Dick, 2006; Sadler, 2010b). These prerequisites make it challenging to provide meaningful feedback that supports individuals in their learning. However, feedback is also considered to increase learners' motivation to learn (Butler & Winne, 1995; Hattie & Timperley, 2007; Narciss, 2008) and improve learners' self-regulatory skills (Nicol & Macfarlane-Dick, 2006). Furthermore, their capability to understand, interpret and make use of feedback can be trained, as discussed in the field of feedback literacy (Carless & Boud, 2018). To promote the social construction of feedback peer-feedback is a practice used in higher education to foster the engagement of students with the assessment criteria and the standards, encouraging them to give meaningful feedback to others and learn from others' work (Cartney, 2010; Cassidy, 2006).

Feedback is considered to be a key component of formative assessment (Hattie & Clarke, 2019; Sadler, 1989), and, if provided appropriately, is vital in supporting successful learning processes (Sadler, 2010b; Shute, 2008). Hence, Nicol and Macfarlane-Dick (2006) identified seven principles of good feedback practice to foster self-regulation. These principles include feedback, that (1) allows learners to know what is expected from them, (2) supports their self-regulation through self-assessments and reflection, (3) provides high quality information (e.g., related to criteria, timely, corrective advice, useable limited quantity) about their learning and (4) on how to improve, (5) is constructed in a social interaction between the involved parties, (6) considers and supports motivational concepts, and (7) gives teachers information about how to adjust instruction to meet learners' needs. Butler and Winne (1995) emphasize that, to foster self-regulated learning, feedback should support learners' monitoring processes, increasing their awareness about these processes, calibrating internal judgments, choosing appropriate strategies, and adopting suitable goals as the anchor of their monitoring activities. Hattie and Timperley (2007) state that feedback is most efficient when it is not directed on a personal level but rather when it focuses foremost on task performance, then on the process of working on the task, and finally on the self-regulation of these processes. Furthermore, no one level should be overemphasized.

However, besides all presumed positive impacts of feedback on students' achievement, teachers are faced with limited resources and increasing numbers of students with heterogenous prerequisites, constraining their possibilities to provide supportive and personalized feedback to the learners (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019). With regard to offering individual support to learners, learning analytics are a promising approach.

6.3 Learning analytics in higher education

Definitions of learning analytics mostly focus on collecting data about learners and learning environments in order to use this information for understanding and optimizing learning processes and environments and educational decision-making (e.g., Ifenthaler, 2015; Siemens, 2010). However, learning analytics are often not defined or distinguished precisely from the related of concepts academic analytics and educational data mining (Ifenthaler, 2015), which are all at the intersection of computer science, education, and statistics (Romero & Ventura, 2013). Educational data mining is more focused on the automatic detection of new patterns, whereas learning analytics are concerned with assessing known assumptions in the data collected, including human judgement (Bienkowski, Feng, & Means, 2012). Academic analytics use aggregated educational data to support institutional decision making, such as resource allocation or retention planning (Ferguson, 2012).

Papamitsiou and Economides (2014) identified that studies using learning analytics or educational data mining focus on a) identifying and modeling learning behavior; b) using indicators for predicting performance; c) increasing teachers' and learners' reflection and awareness; d) early prediction of dropout and retention or identification of related learning engagement; e) improving assessments by making them adaptive and providing feedback; and f) recommending resources either for the learners or, technically, for analyses. In a recent literature review on educational data mining and learning analytics in higher education Aldowah, Al-Smarraie, and Fauzy (2019) classified current applications into four main dimensions: 1) *computer-supported predictive analytics* consider a variety of factors, including learners' behavior and achievements in assessments to predict dropout and retention and to implement interventions accordingly, plus they focus on evaluating learning material to adjust their quality and fit to learners' needs as well as determining their impact on performance; 2) *computer-supported learning analytics* include the identification of collaboration and self-learning processes using data on learners' interaction with the digital learning environment; 3) *computer-supported behavioral analytics* identify patterns and preferences and detect irregular or successful behavior; and 4) *computer-supported visual analytics* facilitate the understanding of the complex analyses and enable the derivation of interventions, as well as providing insights into the learning processes to both learners and teachers.

Therefore, a variety of data is collected: *behavioral data* of learners, from their navigation within the digital learning environment using logfiles (e.g., login, time online, access of resources), their use of the library resources; data on *social interaction* (group work, discussions); *external data* such as geolocation, access to buildings; *socio-demographic information* (e.g., age, sponsorship, educational background); *self-reported data* from surveys (e.g., learning strategies, motivational disposition) or *learning artefacts and performance* (e.g., assignments, self-assessments, forum discussions) (e.g., Ifenthaler & Widanapathirana, 2014; Sclater, Peasgood, & Mullan, 2016). Based on the data collected, learning analytics allow insights into students' interactions with the learning resources or learning processes (Vieira, Parsons, & Byrd, 2018; Winne & Baker, 2013). Therefore, the heterogenous data need to be pre-processed to allow the application of data mining methods and algorithms, in order to identify behavioral patterns or relationships within the data, for example (Romero & Ventura, 2013). The analyses allow retrospective as well as real-time insights, and also aim to provide predictive forecasts (Daniel, 2015; Ifenthaler & Widanapathirana, 2014). However, predictive analytics using machine learning require datasets containing a certain amount of historical learning behavior to train the algorithms for valid predictions of unseen test datasets (Brooks & Thompson, 2017; T. Martin & Sherin, 2013). As learning is always related to the context in which it occurs, inferences and algorithms which were valid for data from one context or previous cohorts might not result in valid analyses in other contexts or cohorts (Greller & Drachsler, 2012; Macfadyen & Dawson, 2012; West, Heath, & Huijser, 2016). In addition, learning and teaching in higher education mostly take place face-to-face or blended, resulting in small or incomplete datasets, due to learning processes outside the digital learning environment (Ifenthaler & Schumacher, 2016; Schumacher & Ifenthaler, under review; A. Wilson, Watson, Thompson, Drew, & Doyle, 2017).

Hence, learning analytics and its related concepts are complex and are intended to provide insights into the multifaceted and complex domain of learning and teaching.

Aiming to illustrate the interrelatedness of the various sources and stakeholders of learning analytics, Ifenthaler (2015, 2019) proposes a holistic framework (see Figure 6-2). Based on rather static curricular information influenced by governmental and institutional requirements learning objectives are defined, learning settings and assessments are designed. Curricular requirements impact the digital learning environment, the teachers and their instruction, and vice versa, teachers' characteristics influence the curriculum and micro-level design of the (digital) learning environment. Within this, learners, with their individual characteristics, social relatedness and physical prerequisites, interact with each other and the resources, thus generating a huge variety of data. This static and dynamic information needs to be structured and integrated in the learning analytics engine to be analyzed based on pedagogical theoretical assumptions using different data mining methods and algorithms for comparisons, predictions or to identify patterns. To achieve adaptive and personalized learning environments this information is provided via the digital learning environment to the learner in form of visualizations, prompts (short hints or questions), recommendations or other feedback such as digital badges. Besides this, the information gained could also be mediated through the teacher, either to feed it back to the learner or to adjust the learning environment according to the learners' needs. In line with academic analytics, the information can further be used for reports to different stakeholders for different purposes (e.g., decision-making, resource allocation, curriculum changes).

However, learning analytics are still not sufficiently guided through knowledge from learning theory and empirical evidence (Marzouk et al., 2016). Instead of focusing on the relevant theory-driven indicators (Wong et al., 2019) and the prevailing aim of learning analytics *supporting learning processes* (Clow, 2013; Gašević, Dawson, & Siemens, 2015) technical elaborated systems are created or algorithms are applied using all data available. In addition, learning analytics still suffer from a lack of evidence that they are actually capable of supporting learning (Ferguson & Clow, 2017; Viberg, Hatakka, Bälter, & Mavroudi, 2018).

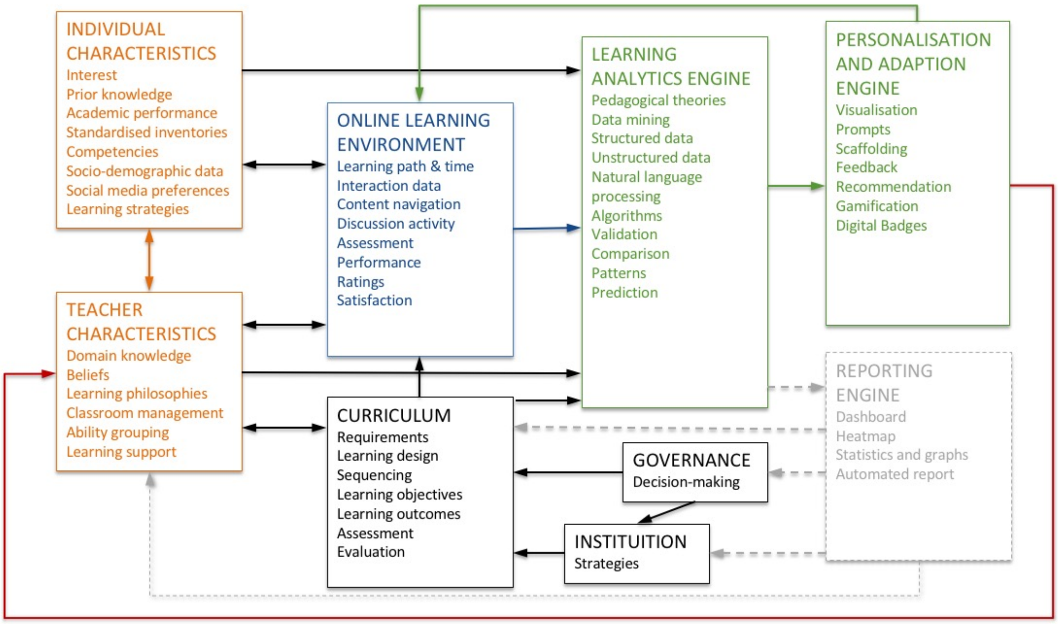

Figure 6-2. Holistic learning analytics framework (Ifenthaler, 2019)

However, learning analytics offer a huge potential for adaptation and personalization of digital learning environments (Aguilar, 2018; Greller & Drachsler, 2012; Ifenthaler & Widanapathirana, 2014). But, if learning analytics systems should provide feedback to learners on how to improve learning, their current performance and their learning processes need to be validly assessed. Hence, the further theoretical synthesis of current assumptions about learning processes and the possibilities learning analytics can offer is necessary and reasonable. In the next section this aim will be promoted further by highlighting potential links of assessment, feedback and learning analytics under consideration of theory on self-regulated learning.

6.4 Informative assessment using learning analytics

By referring to the Assessment Working Group at EdusummIT 2011, Webb et al. (2013) propose a definition of digitally enhanced assessments "as those that integrate 1) an authentic learning experience involving digital media with 2) embedded continuous unobtrusive measures of performance, learning and knowledge (…) which 3) creates a highly detailed (high resolution) data record that can be computationally analysed and displayed so that 4) learners and teachers can immediately utilize the information to improve learning". Sub-items 2, 3, and 4 in particular, are related to the application of learning analytics. However, to identify, capture and analyze the relevant data using appropriate assessment measures and link them to targeted performance, learning processes and knowledge, these assessments need to be designed following principle-based approaches. Shute et al. (2016) outlined a vision of "ubiquitous, unobtrusive, engaging, and valid" (p. 53) assessment, including continuous data collection and integration of learners' interactions with different learning resources in different learning environments to gain increased evidence about learners' skills and competences across contexts. They further emphasize that assessment should "(a) support, not undermine the learning process for learners; (b) provide ongoing formative information […]; and (c) be responsive to what is known about how people learn" (p. 52). Learning analytics might be capable of assessing cross contextual learning processes without being intrusive (Vieira et al., 2018; Winne, 2017b) and can be further enriched with multiple sources, such as peer-assessment and -feedback, self-assessments and -reflections. To meet sub-items (b) and (c), learning analytics need to be further aligned with theory on learning, feedback and assessment (Marzouk et al., 2016; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018). However, only few publications specifically focus on the link of assessment and learning analytics (e.g., C. Ellis, 2013; Ifenthaler, Greiff, & Gibson, 2018; F. Martin & Ndoye, 2016). C. Ellis (2013) states that assessment analytics allow learning performance and progress to be measured over time, along with individual, social, and standard-based comparisons. She further suggests that assessment analytics should include aspects such as completed degrees, progression results, module results, individual assessment results, achievements compared to learning objectives and criteria, plus strengths and weaknesses of a student's work. F. Martin and Ndoye (2016) assign learning analytics techniques and data measures to four types of assessments used in digital learning environments and investigate their application. Ifenthaler et al. (2018) highlight the potential of enhancing (large-scale) assessments using learning analytics, especially for providing immediate feedback to learners and teachers as well as for processing the immense amount of data.

Shute and Becker (2010) adapted the needs for contemporary assessment from the National Research Council (NRC, 1996) to highlight the differences of foci on assessment. The shift from assessing learning outcomes to assessing learning processes to acquire relevant skills and knowledge is of key importance. As Pellegrino et al. (2001, p. 27 f.) state, assessments are static as they only “provide ‘snapshots’ of achievement at particular points in time, but they do not capture the progression of students’ conceptual understanding over time, which is at the heart of learning”. Shute and Becker’s (2010) work was carried over and enhanced with aspects on how learning analytics might support the enhanced focus on assessment (see Table 6-1).

Table 6-1 Changing assessment foci (Shute & Becker, 2010, p. 4) and enhancing the focus on assessment with learning analytics

Less focus on assessment	More focus on assessment	Supporting assessment through learning analytics
Learning outcomes	Learning processes	Learning analytics enables the tracking of learners’ behavior within digital learning environments and thus adoption of a processual view on learning.
What is easily measured	What is most highly valued	Learning analytics allow implementation of a great variety of measures, and, if designed and implemented following a principle-based approach, learning analytics can support the measurement of highly valued learning approaches and outcomes by focusing and accumulating relevant indicators based on the underlying evidence model to give an overall indicator for performance, skills, knowledge or competencies.
Discrete, declarative knowledge	Rich, authentic knowledge and skills	Learning analytics enable evidence from various tasks to be capture and integrate, using multiple data sources within numerous contexts. By tracking learners’ complex problem-solving behavior, their performance and behavior in educational games or collaborative tasks transfer of knowledge and multiple skills can be assessed.
Content knowledge	Understanding and reasoning, within and across content areas	Learning analytics might help gain an understanding of whether learners integrate knowledge from different contexts by referring to an intertwined assessment design mapping the various learning objectives and measurable indicators across courses. A holistic representation of learners’ knowledge, skills and competencies can be derived and might possibly be enhanced with knowledge and skills learned in informal contexts.
What learners do not know	What learners understand and can do	Learning analytics allow feedback concerning both what learners currently know and are capable of (performance-oriented; feedback), and where and how they can further improve their capabilities and skills by providing

		recommendations (process-oriented; feedforward).
By teachers alone	By learners engaged in ongoing assessment of their work and that of others	Digital learning environments using learning analytics allow frequent self-assessments with immediate feedback, this feedback can be enhanced with teacher feedback or peer-feedback through relevant tools (e.g., different tasks for the same learning objective assessed from different perspectives and combined in joint feedback).

Different assessment types are predominant in certain disciplines, depending on the discipline's practices and the valued knowledge, skills and competences or learning goals (Knight, 2006). For example, Neumann, Parry, and Becher (2002) assign assessment types to the different disciplines, distinguishing hard and soft as well as pure and applied: Hard pure disciplines, such as natural sciences and math, focus on frequent knowledge assessments with specific, close and norm-referenced assessment types, such as calculations. Soft pure disciplines, such as social sciences and arts, put more emphasis on learners' understanding, judgement and integration of complex knowledge including continuous assessments, essays, projects, oral examinations, but also on declarative knowledge using multiple-choice tasks. Hard applied disciplines like engineering focus on factual knowledge using multiple-choice tests in rigorous and ongoing assessments for elimination but also on complex problem solving and application and integration of knowledge. Soft applied disciplines like education or management focus on developing professional practice and problem-solving, assessments include essays and project-reports and are enhanced by peer- and self-assessments to foster self-reflectory and practical skills. Hence, the practices and assessment needs are different. F. Martin and Ndoye (2016) list four commonly applied types of online learning assessments, a) comprehension-type assessments such as multiple-choice, b) discussion boards to promote collaboration and interaction, c) reflection-focused assessments highlighting the solution process (e.g., essays), and d) project-based assessments integrating different skills to reach an authentic product. While single- and multiple- choice assessments may be easy to analyze, the focus should not be on easily assessable, but on valued learning outcomes (Shute & Becker, 2010). Relevant within the debate on 21st century skills are projects engaging learners in behavior that is difficult to measure as the constructs, some of which are on a group level, are latent including behavioral, cognitive and affective components (Webb et al., 2018).

Neither assessments (Bennett, 2011) nor learning analytics (West et al., 2016) can be interpreted without considering their context. Indeed, learning behavior within different contexts is a crucial indicator when it comes to recording holistic skills and competences, especially those occurring cross-contextually (DiCerbo et al., 2016). Hence, to obtain valid results, the characteristics of the different contexts (e.g., course format, level of self-directedness) and tasks (e.g., difficulty, complexity, assessed skills) need to be considered in the analyses. Thus, in order to assess these complex constructs involving different types of assessments varying over disciplines, a principle-based assessment design framework is necessary for guiding systematic design and valid integration into learning analytics. Furthermore, by defining how the measured indicators are related to the assessment goals as well as how to proceed with incomplete data would further enhance the validity of learning analytics. In addition, this would support the need for a more theory-driven approach of learning analytics (Bienkowski et al., 2012; Ferguson, 2012; Marzouk et al., 2016) which could be reasonably enhanced with educational data mining techniques for identifying unknown patterns and findings within the trace data. However, to close the feedback loop the assessed evidence needs to be translated into feedback, either through the system or the teacher, considering the different demands of each individual learner as described in the following section.

6.4.1 Feedback based on learning analytics

Feedback in learning analytics systems is mostly provided through dashboards, and research predominantly focuses on investigating satisfaction, design and usability aspects, performance, comparisons with peers, and engagement (e.g., Aljohani et al., 2019; Park & Jo, 2015; Roberts, Howell, & Seaman, 2017; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Verbert et al., 2014). Providing feedback using learning analytics is not limited to the use of dashboards as it can be provided by using prompts, by teachers sending feedback messages based on learning analytics results, or by suggesting additional resources when presenting the results of self-assessments. However, only few empirical studies (Howell, Roberts, & Mancini, 2018;

Pardo et al., 2019) or conceptual papers (Sedrakyan et al., 2018) focus in particular on how feedback using learning analytics had an impact on learners' affect and resilience (Howell et al., 2018) or on learners' satisfaction with feedback and academic achievement (Pardo et al., 2019). However, current learning analytics systems often do not provide information to learners but only to the teachers (Macfadyen & Dawson, 2010; Vieira et al., 2018). But, to close the loop as proposed in the discussion on formative feedback and assessment, learners need to be informed about how they are performing, how they can improve and where they should go to (Hattie & Timperley, 2007; Wiliam & Thompson, 2008). Feedback provided through learning analytics should incorporate learning theory to not diminish learners' willingness to react upon it by not considering motivational dispositions (Lonn, Aguilar, & Teasley, 2015; Schumacher & Ifenthaler, 2018b), prior knowledge and other prerequisites. Hence, especially with a focus on fostering students' self-regulated learning capacities, learning analytics need to be designed carefully, taking into account theory and empirical findings about the interplay of cognition, metacognition, motivation, and behavior.

Feedback based on learning analytics in particular often provides students with information on their current performance, comparisons or even an estimated final grade (outcome feedback), but most systems do not provide informative process-oriented feedback to learners as to how they can improve their learning processes (Sedrakyan et al., 2018). However, to provide the process-oriented feedback, learning analytics need to understand why learners did not meet the requirements. Therefore, a huge variety of tasks assessing the same skill or competency need to be offered (Bennett, 2011). The tasks should be developed and accumulated based on the Evidence-centered Assessment Design framework. Further information about why learners did not perform well can be collected by asking learners to reflect on their answers, judge their learning, by integrating a task on assessing their understanding of the underlying concept, or by identifying behavioral patterns which might be related to misunderstandings, gaming the system or other non-productive behavior (Chen, Breslow, & DeBoer, 2018; Hsu, Wang, & Zhang, 2017; Liu et al., 2017; Verbert, Manouselis, Drachsler, & Duval, 2012).

Assessments are considered to determine what learners are learning (Boud & Falchikov, 2007; Gibbs & Simpson, 2005). Learners might also feel incited to *learn for the data* – i.e. to achieve good learning analytics results, instead of focusing on what is actually relevant to learn (Nistor & Hernández-Garcíac, 2018). Furthermore, learners might increasingly rely on data and feedback provided through learning analytics (Corrin & de Barba, 2014). Thus, it needs to be kept in mind that a key focus of higher education is to engender students with high capabilities of self-regulated learning. Hence, the feedback provided through learning analytics needs to be based on the assumption that the learners, as agents, are responsible for their own learning (Boud & Molloy, 2013). Therefore, feedback should promote learners' self-assessment capabilities, and their competences in evaluative judgement which are relevant for academic success and life-long learning. Consequently, learning analytics should be linked to resources promoting the adequate application and improvement of learning strategies (e.g., rehearsal or elaboration) (Black, McCormick, James, & Pedder, 2006; Weinstein & Mayer, 1986), and other academic competencies such as technology proficiency or research skills (Mah & Ifenthaler, 2018). For example, relevant online or university courses could be recommended, based on digital learning behavior or self-reported learning strategies. Prompts could guide learners' self-regulation with input such as "What are your goals for today?", "Have you already set up a study plan?" or "Try to link new concepts from the text to concepts you already know.". Furthermore, a function to set individual learning goals and assign material to those could support planning and monitoring. In addition, learning analytics should engender learners to engage in reflection and critical thinking, which might be supported through prompting self-regulated learning strategies (Kramarski & Kohen, 2017; Müller & Seufert, 2018; Prieger & Bannert, 2018). Based on learners' answers to such prompts, teachers can generate evidence on students' progress (Wiliam & Thompson, 2008).

Most research favors immediate feedback over delayed feedback, however findings vary and might depend on the feedback level (task, process, regulation, self) or on the type of task, as well as on learners' prior knowledge (e.g., Butler & Winne, 1995; Evans, 2013; Hattie & Clarke, 2019; Hattie & Timperley, 2007; Kulik & Kulik, 1988;

Shute, 2008). Further, it is assumed that learners are activating their own reasoning capabilities if they do not receive feedback immediately (Schroth, 1992) or if they receive less feedback (Hattie & Clarke, 2019). Hence, considering learners as agents learning analytics systems might allow them to demand feedback whenever and in the depth they want it. To foster self-regulation learners should also be prompted to reflect about their answers, solutions and products, to write down open questions or to reflect on where they are heading and any improvements that can be made.

As the interpretation of feedback is also dependent on learners' prerequisites (Evans, 2013), learning analytics might enable the provision of adaptive and personalized feedback to learners considering their prior knowledge, their current motivational states or current goals. Learners' reactions to feedback might not be as intended, as they might reject the feedback, abandon or change the goal, or change their behavior (Kluger & DeNisi, 1996; Wiliam, 2011). Using trace data enables further investigation of learners' behavioral reactions to feedback, which could be enhanced with self-report data by prompting them with simple questions on their perceptions of the feedback or their current emotional or motivational states. When learning analytics are used to provide automated feedback learners, need to be made aware of the potential shortcomings of the underlying analyses, for example by prompts such as "Based on the data available in our analyses it seems you have not worked on the study material for a while. Hence, it would be reasonable to catch up. If you have worked on the material offline, you might like to confirm your activities by answering the following questions. Or you can take a self-assessment to test your knowledge of the material." Furthermore, the feedback provided should be on aspects which are in the control of the learner and are thus malleable. Feedback is a powerful tool for supporting learning but can also have unfavorable results (Hattie & Clarke, 2019). Hence, knowledge about learners' reactions to feedback is furthermore relevant to design supportive (digital) learning environments (Evans, 2013).

6.4.2 Developing an integrative assessment analytics framework

A processual framework of the interplay between principled-based designed (formative) assessment, feedback, and learning analytics is presented in Figure 6-3, which integrates conceptual approaches on assessment (Black & Wiliam, 2018;

DiCerbo et al., 2016; Shute & Becker, 2010; Wiliam, 2011), assessment design (Almond, 2010; Mislevy et al., 2003; Mislevy & Riconscente, 2005), assumptions on feedback related to assessment (Gibbs & Simpson, 2005; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Nicol & Macfarlane-Dick, 2006) and the holistic framework of learning analytics (Ifenthaler, 2015, 2019). The process is assumed to be cyclical and includes the assessment design, data collection during learning in the digital learning environment and assessments within multiple contexts, evaluative and interpretative components, a feedback model, learners' and teachers' reactions, plus the holistic learning analytics framework. The relationship between the models is reciprocal – together they are adaptive to the learners' needs and progress, as well as to curricular changes or instructional adjustments. Following the Evidence-centered Assessment Design (Mislevy et al., 2003; Mislevy & Riconscente, 2005) the assessment is designed considering governmental, institutional and curricular requirements. This information is embedded in and aligned with the learning analytics engine and the digital learning environment to collect relevant data, and to aggregate the evidence collected according to the assessment purpose. To clarify expectations, the overall learning goals, criteria of success and standards are shared and discussed with the learners and are referred to as feed up (Hattie & Timperley, 2007). Learning analytics could provide this information on different levels of detail for a learning unit, a (self-) assessment, entire courses or programs enhanced with exemplars or rubrics. Following DiCerbo et al. (2016) data collection is an ongoing process within multiple contexts. Therefore, learning products or processes are collected over multiple tasks, learning opportunities and within the digital learning environment. As (Bennett, 2011) suggests, several assessment tasks should be available and applied to assess the same construct (assembly model and assessment delivery in the Evidence-centered Assessment Design). In addition, learner characteristics can be collected, based on self-reported data and enhanced with behavioral data, information which is also used to update the student model. Further, contextual factors such as the assessment situation should be considered, as this can influence learners' behavior. Based on the evaluation standards in the evidence model, the behavior shown or learning products provided are scored, and, by relying on the measurement model, are related to the assessed skills, competence or knowledge. Here task level feedback can be provided to the learners, as proposed by Mislevy et al. (2003), and should be about misconceptions or misinterpretations of the task, instead of focusing on lacking knowledge (Hattie & Timperley, 2007). The evidence collected from various tasks and over multiple contexts needs to be accumulated based on assumptions in the evidence model (e.g., weighting) and related to the specific assessment purpose (Almond, 2010). This in turn also updates the student model and its underlying probabilistic assumptions. Furthermore, the previous step supports the summative assessment function by assigning grades or certifications, and the formative function by deriving suggestions for improvement. In addition, the summative function might also entail suggestions for improvement. In general, these suggestions might be derived either by the teacher or a digital learning environment informed by this integrated framework, but can be enhanced with feedback from peers. To connect the assessment process with the other entities (e.g., learner, teacher, institutional) feedback (based on theoretical assumptions of feedback) on how to close the gap between current performance and the designated goals needs to be provided (e.g., suggestions for improvement and/or grades). As suggested by Hattie and Timperley (2007), the feedback provided should focus on the task, if this has not yet been done, on the process, on learners' self-regulation, and ideally not on the personal level. As learning analytics enables the collection of more than only performance indicators, feedback can also be provided on the process and on self-regulation. Based on learners' proficiency and knowledge, learning analytics could provide as detailed and timely feedback as necessary, or allow the learner to choose when to receive feedback. It can also give recommendations on when to ask for feedback and how to use it. By using prompts, additional evidence on motivational and emotional states can be collected, but also regulatory hints can be provided (Bannert, 2009). The learners influenced by their characteristics will interpret the feedback and react to it, by changing either their behavior or the goal, by abandoning the goal or by rejecting the feedback (Kluger & DeNisi, 1996; Wiliam, 2011). To increase the likeliness that the feedback is used as intended, learning analytics integrate all information on the learners to provide (adaptive) feedback considering learners' current goals, knowledge, learning activities, motivational states or needs. However, the feedback and learners' reaction to it might furthermore influence the teacher's behavior, the instructional process and the digital learning environment, which should all be adapted to the learners' needs, according to Nicol and Macfarlane-Dick (2006). If the assessment has a formative function, another assessment or learning period might follow, in which additional evidence about learners' skills, competences, and knowledge will be collected. This information could be used to assume learners' progress and use of feedback. As feed forward is considered the most relevant for learning (Hattie & Timperley, 2007) the learners are further provided with information about where they should go next. Learning analytics can recommend further learning material or learning paths (Ifenthaler & Widanapathirana, 2014) related to the evidence collected and the learning objectives. In both formal and informal learning contexts related to the discussion of lifelong learning a new assessment cycle, which should be integrated into learning cycles, will begin and will be influenced by the previous. However, it should be kept in mind that both assessment and feedback require either prior knowledge or instruction to be useful (Hattie & Timperley, 2007).

Learning analytics are related to this framework as they can, in particular, support the ongoing data collection over tasks and contexts as well as the integration of the data into a unique model of skills, knowledge and competencies, as suggested by DiCerbo et al. (2016). For example, the learning analytics system needs to be able to draw on the information in the student and evidence model in order to know what data are in the scope of collection and measurement, as well as how the data are related and interpreted (Mislevy & Riconscente, 2005; Shute, Rahimi, & Emihovich, 2017). Furthermore, by using external or sensor data, contextual variables such as noise, the location of the learning environment or physical resources used can be integrated into the analyses. By collecting enough variables, the probabilistic models in the principle-based assessment design allow students' performance in a certain domain to be forecast (Mislevy et al., 2003), which is in line with aims of learning analytics which focusing on predicting performance, retention or dropout (Papamitsiou & Economides, 2014; Sønderlund, Hughes, & Smith, 2019). Based on the assembly and student model, the learning analytics system can provide the challenging but not overdemanding tasks to the learners, enabling adaptive (self-) assessments (Shute et al., 2016, as demanded in sub-item (c) in section 6.4). Learning analytics are currently lacking a sound integrative framework, especially with regard to which indicators need to be collected and how, based on these indicators, inferences on learners' performance, competencies and skills can be made. In addition, this approach makes it possible to provide tasks for each domain and student model as well as the ability to go beyond assessments using solely single- or multiple-choice tasks (Almond, 2010), as these do not validly assess the valued 21st century skills (Shute et al., 2016). As the task model contains a plethora of tasks, not only summative but also formative assessments and additional assessment-feedback loops can be provided (Almond, 2010), as demanded by Shute et al. (2016, sub-item (b) in section 6.4). Furthermore, learners might choose a certain amount of formative tasks focusing either on a learning product or process that should be part of their final grade (Webb et al., 2013) and explain why they chose this task (e.g., good performance, learning product or a perceived learning gain). As no "one-size-fits-all" learning analytics system exists (Gašević, Dawson, Rogers, & Gasevic, 2016) and the context is relevant for each discipline, a unique assessment design mapped to the available learning analytics indicators needs to be developed to satisfy the different assessment needs of the disciplines. This might also facilitate the integration of assessments from different disciplines as for example in multidisciplinary study programs. Likewise, with regard to interdisciplinary and non-cognitive skills developed independently of the domain, the snippets of evidence can be integrated into an overarching competency model and using the learning analytics reporting engine, a competency overview for each learner could be provided at any time.

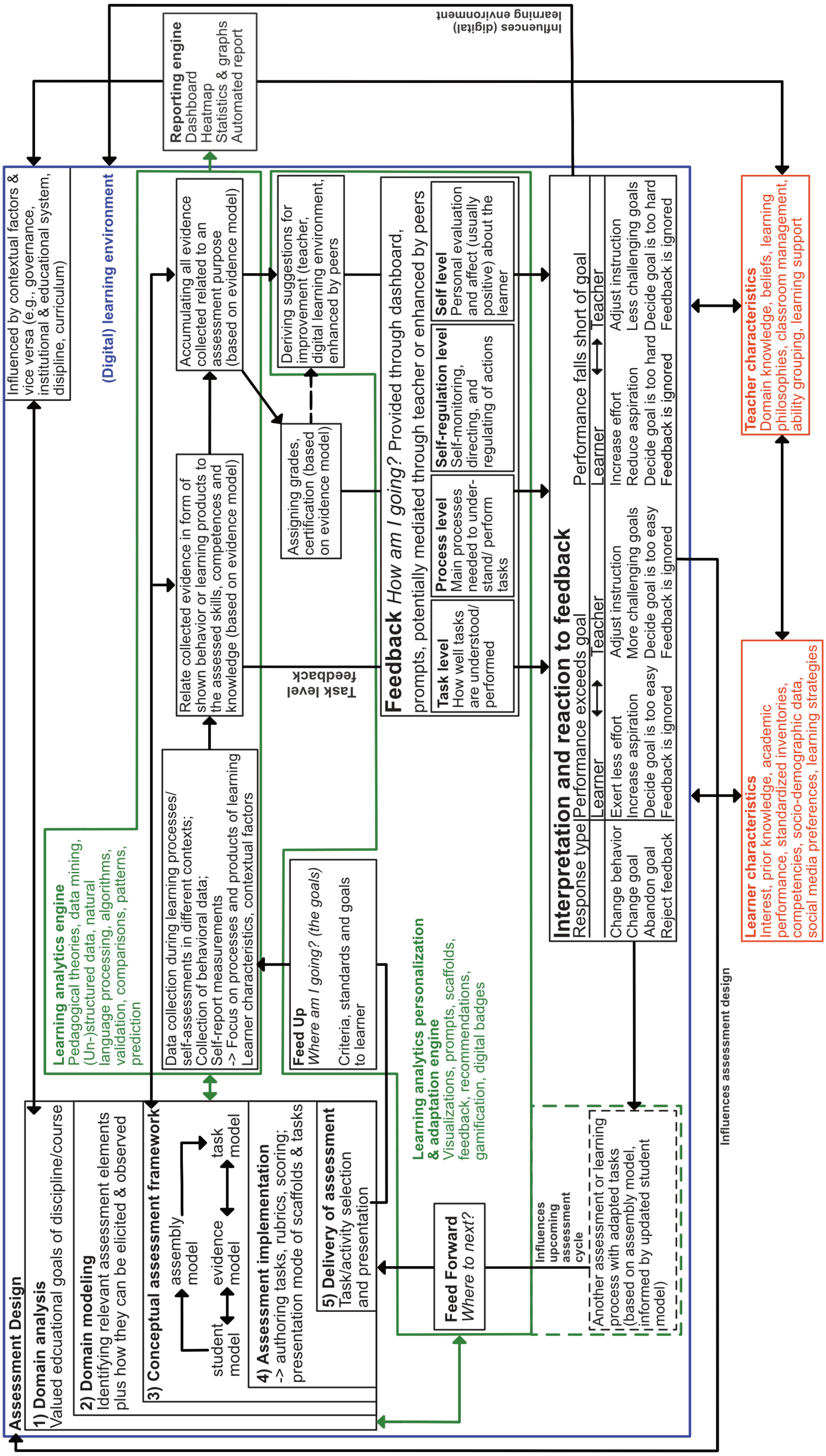

Figure 6-3. Integrative processual assessment framework using learning analytics

6.4.3 Learning analytics features for informative assessment

Following the statements on informative assessment of Forster (2009), and Fogarty and Kerns (2009), a definition of informative assessment using learning analytics is outlined. Assessment enriched with learning analytics enhances assessments with ongoing data collection over multiple contexts including (self-) assessment results, learning behavior and other relevant variables resulting in additional evidence. Furthermore, it is aimed at closing the feedback loop by using the evidence to provide recommendations on improvement or to support learners' self-monitoring. Additional information is provided to teachers and other stakeholders that can be used to adjust and enrich teaching and assessment practices as well as institutional processes. This approach also aims to narrow down the distinction of formative and summative assessments, as both are capable of providing additional evidence as well as further emphasizing the cooperation of learners and teachers. In addition, the use of learning analytics enables further the investigation of learners' reaction to feedback. Hence, such assessments are grounded in principle-based designs, include data from different contexts to gain insights into how learners learn and understand, use the data to provide feedback on improvement and analyze how the feedback is used to adjust learning and teaching processes. To highlight these features and emphasize that this type of assessment underpinned with data is going beyond traditional summative and formative assessment, the term *in*formative assessment is used. Exemplar implementations are described to illustrate how learning analytics and a principle-based designed assessment approach can enhance each other and provide the necessary feedback to learners and teachers.

To facilitate *peer-assessments* and related feedback, learning analytics could be applied. Learners could upload their assignments, which would then be automatically assigned to their peers on the course. As Cassidy (2006) states, support and training is necessary to foster students' capability and comfort related to peer-assessments which can be enhanced with learning analytics. For example, they can be supported by offering a catalogue of the rubrics and standards related to the assignment, plus a feedback-checklist based on principle-based assessment design. To enable the peer-reviewers to give more helpful feedback, which can be actively used for improvement, the feedback could be analyzed with regard to the feedback practice (Pinheiro Cavalcanti et al., 2019) or with a focus on the recommendations provided for improvement (Xiong, Litman, & Schunn, 2012) using sentiment analysis and natural language processing. Based on these analyses, the quality of the feedback provided could be evaluated to foster students' engagement in peer-assessments and feedback. In addition, the assignment could be compared to an expert solution for providing recommendations to the learners or the peers. If the assessment is designed to be formative, the learner's updated version could be compared to the feedback provided to gain insights into how the feedback was used, enhanced with an additional self-report by the learner of how useful they perceived the feedback in improving the assignment. The peer-feedback and related analyses, the information on the use of the peer-feedback and its perceived impact on the work, along with the automated analyses comparing the assignment with the expert solution, can be aggregated for the teacher, thus facilitating the identification of learners who might be at risk, and enabling the teacher to use the evidence generated to derive appropriate interventions (Cartney, 2010). By providing these additional analyses, the teacher might be able to give additional support to learners at risk, even in larger courses.

When it comes to supporting *self-assessments*, the system could provide learners with the learning objectives, rubrics and standards. Additionally, Carless (2007) suggests providing learners with feedforward – or feedback in advance – detailing common mistakes or problems faced by earlier cohorts in dealing with the same assignments. Comparably, providing learners with exemplars (Broadbent et al., 2017; Sadler, 1989) from previous cohorts as a "good practice" can be used as feedforward and to clarify how standards and criteria can be applied. According Boud and Molloy's aim (2013) to increase learners' agency in assessment and feedback processes when handing in assignments, learners could be prompted by the system to include a statement evaluating their own performance against the requirements and to detail their learning processes (internal monitoring in self-regulated learning), which could be supplemented with external feedback via the tutor. While writing the evaluation statement, learners might reflect on their learning process and products, and potentially adjust them before handing them in for final assessment. To include assessment tasks as learning tasks, as proposed by (Carless, 2007) to support both functions of assessment, the learning analytics system could provide several tasks related to each learning objective (from task model) and prompt the learners throughout the whole course to take the assessments. The feedback provided to the learners should include advice as to the learning objectives where further learning is required, and should be enhanced with recommendations on relevant materials. Furthermore, a social component could be included as the system might recommend whom to ask for support with particular difficulties (Webb et al., 2018).

Academic writing skills are relevant for performance in higher education (Mah & Ifenthaler, 2018) but are challenging, especially for novice learners (Wingate, 2006), who struggle with structuring or referencing. Automatic analyses using natural language processing could provide learners with immediate formative feedback on the syntax, word choice, mechanics or citations based on rubrics and criteria (J. Wilson & Andrada, 2015).

However, not only learners should use the feedback to adjust their learning – teachers should also use the evidence and feedback to *adjust their teaching*. If learning analytics were based on comprehensive assessments, they could provide teachers with an aggregated overview about learners' competences and knowledge relevant for the course and either provide learners with additional resources to prepare for the required standard for successful participation or adapt the course material to the cohort's needs. If the pre-knowledge is too far away from the requirements, the system could alert the teacher or the student, prompting a counseling or offering a different learning path with further preparatory courses. To guide learners' expectations of the course in advance the system could provide them with detailed course objectives, information about how they will be assessed, short introductory materials and learning strategies suited to the course design plus preparatory learning offers. Furthermore, learning analytics can support teachers during the course period by enabling them to continuously monitor their students' learning processes, progress and needs and to use this information to adjust their instruction accordingly (Evans, 2013). A function enabling learners to rate the difficulty of the provided material or to record their need for help could be offered. Based on this evaluation or the information why learners did not successfully perform in tasks (see section 6.4.1), teachers could either provide additional material (e.g., videos) through the digital learning environment. Likewise, if several students face the same difficulties, teachers could recapitulate related content in the face-to-face session.

Working on *collaborative projects* and tasks are common assessments and collaborative learning in a supportive culture (Wiliam & Thompson, 2008) or communities of practice (Lave & Wenger, 1991) is considered to be supportive in generating, receiving and understanding feedback (Evans, 2013). Learning analytics can support the grouping processes by recommending appropriate networks, or at least enable identification of the network in which learners are engaging in (Clow, 2013). Moreover, if the system allows collaboration learning analytics enable gaining additional insights to be gained into group working and solution processes. To gain a better understanding of who contributed in which way to the solutions, the collaborative development of products or online group discussions can be analyzed. In addition, group regulation processes and the roles taken on by learners can be analyzed (Volet, Vauras, Salo, & Khosa, 2017). Furthermore, offline data could be added – for example, if students are working together in person, the system could enable all participants log in and track their presence. If groups are facing difficulties, conflicts or are behind schedule, the teacher could provide additional support or prompt the less active group members to engage more (van Leeuwen, Janssen, Erkens, & Brekelmans, 2014). To analyze collaboration or networks within courses or distributed learning settings, social network analyses or analyses of discussion posts are often used (Ferguson & Buckingham Shum, 2012; Hernández-Garcíac, González-González, Jiménez-Zarco, & Chaparro-Peláez, 2015). The data collected could further be used to infer on learners' collaborative skills.

6.5 Implications and future research

The integrative framework serves as an initial description of the relationships between learning analytics, principle-based assessment design, and feedback. It needs to be taken into account that such frameworks are always a simplification of the underlying processes and concepts. Furthermore, to investigate its usefulness and evidence the framework needs to be set into practice. In addition, several conceptual limitations and technical requirements are associated with the proposed approach. Learning analytics only provide very limited insights into learning processes (Ferguson, 2012; Winne, 2017b). To date, most digital learning environments used in higher education scarcely support actual learning, it is difficult to infer on learning processes based on the trace data collected (A. Wilson et al., 2017). Thus, digital learning environments need to offer learning opportunities and holistic systems, for example by including tools for collaboration, communication, text processing applications, literature management systems interacting with the university's library resources, and highlighting and annotation tools for reading materials (Schumacher & Ifenthaler, 2018a). Furthermore, cognitive processes where learners are thinking about or integrating new information cannot be tracked by learning analytics as "doing nothing in the system" could also indicate that the learner is grabbing a coffee. As most learning takes place outside the digital learning environments, solutions need to be found to integrate these data. Learners' activities in other programs, such as text processing, the internet browser or communications, could be tracked and integrated but this would raise severe privacy concerns. If the data were to be collected through learners' self-reports on their learning behavior and their use of the materials, this would result in reduced accuracy and validity. In addition to the incompleteness, the datasets in educational settings are comparably small with regard to other disciplines. Hence, algorithms might not produce valid analyses calling for the need to apply different algorithmic approaches which can serve both small and large datasets (Baker, Martin, & Rossi, 2017). However, although learning analytics allow additional insights into learning, their incompleteness needs to be considered in the analytical models. To make the analyses more significant and less error-prone, inclusion and exclusion criteria for using or weighting indicators for analyses need to be defined (evidence model). For example, if a learner only pasted a response to the textbox, no information about the actual processing of the learning task can be provided (e.g., checking for mistakes, process of changing the text during writing, estimated time on task). If a learner only downloaded the material but was not online frequently the system should enhance the data available with self-reported data investigating learners' perceptions of their learning progress, which can be further enriched with hints to make them aware of the additional learning material. In particular, if learners with "unengaged" online behavior are successful in assessments, they might have available sufficient learning strategies to successfully learn outside the digital learning environment. Using additional inventories to assess their learning strategies might provide further insights. Hence, when teachers receive information about their students' progress also information about the aforementioned limitations need to be included (e.g., required data were not available, analyses based on self-reports), to prevent teachers from misinterpretation and initiating inappropriate interventions. In summary, this further highlights the need to assess a huge variety of different snippets of evidence about learning behavior in order to aggregate it to a more fine-grained picture which is, if interpreted correctly a major benefit of learning analytics. Furthermore, as cognitive learning processes are difficult to measure using learning analytics and data to infer on learning is limited, validly designed and implemented (self-) assessments are becoming even more important especially as predictors for performance or dropout.

As learning analytics aim to support learning and instructional processes they need to provide feedback to both learners and teachers, which is currently still limited (Macfadyen & Dawson, 2012; Vieira et al., 2018). The feedback in some cases includes limited visualizations (F. Martin & Ndoye, 2016) and should, instead of focusing only on descriptions of performance indicators provide, recommendations for improvement (Sedrakyan et al., 2018). Furthermore, the analyses and visualizations are complex and not easy to understand (Aguilar, 2018; Greller & Drachsler, 2012), much less enabling the receivers to derive actionable knowledge and understanding of their limitedness and biases. To increase the probability of reaction, feedback needs to be presented in a way that the target groups understand (Park & Jo, 2015; Sedrakyan et al., 2018). For example, Corrin and de Barba (2014), using a qualitative approach investigating students' interpretations of feedback (performance in assessments, frequency of access of the learning management system) provided through learning analytics dashboards, found that students reported using the feedback to adjust their learning, but could not explain how the changed behavior would impact their learning. Van Horne et al. (2018) found that the frequency of checking a learning analytics dashboard more extensively was not associated with positive effects on learning performance and suggested enhancing them by prompting learners to use additional timely strategies, instead of only focusing on external feedback after learning had occurred. Thus, the feedback and digital literacy of the target groups of learning analytics need to be fostered, but also additional research is necessary on improving the feedback provided, both in terms of usability and feedback practice. Plus, learners should be encouraged to use self-regulatory strategies to create internal feedback and assess themselves to monitor their learning processes, instead of being dependent on extensive external feedback sources. Further research investigating learners' understanding of feedback provided through learning analytics, their knowledge about their limitedness and their ability to use this feedback proactively to adjust their learning behavior is needed. Investigating their reactions could be enhanced by using trace data supplemented with self-report data.

In particular, teachers need to be developed further in data literacy (Greller & Drachsler, 2012; Ifenthaler, 2017; Vieira et al., 2018) so that they can act as a mediator between learning analytics and the learners as referred to by Ito (2019) as "extended intelligence". Further research is required on how teachers understand and actually use the additional information to improve their instruction and provide additional support to learners.

Research has shown that assessments are related to negative emotions of learners (Carless, 2017). As Shute et al. (2016, p. 55) state "one risk associated with our vision (of ubiquitous assessment) is that students may come to feel as if they are constantly being evaluated, which could negatively affect their learning and possibly add stress to their lives". Hence, learners might perceive constraints in their "natural" learning activities or their motivation. Thus, learners in higher education should be aware of and be in control of what data are collected, who has access to the data, and for which inferences which data are used (Ifenthaler & Schumacher, 2016; Pardo &

Siemens, 2014; Slade & Prinsloo, 2013). As the focus of formative assessments and learning analytics is on supporting learning, students need to have the possibility to test themselves and receive formative feedback. However, traditional summative assessments could be enhanced with additional evidence from continuous data collection, especially on learning processes. But learners need to be conceded with high autonomy in choosing which assessments or data should be integrated for final grading, so as not to compromise their need for self-determination. Due to the contextualization of disclosure (Nissenbaum, 2010) and the fact that teachers would gain very deep insights into learners' strengths and weaknesses based on cross-contextual assessments using learning analytics, the information needs, at the least, to be deidentified in order to prevent prejudices or biases which might be promoted further through the underlying algorithms (Bienkowski et al., 2012; Slade & Prinsloo, 2013; A. Wilson et al., 2017). Hence, further research is needed to investigate learners' perceptions about the ongoing assessments of their learning processes and their perceived choice so that learning is not impaired or diminished.

In the end, the implementation of such holistic approaches faces several challenges with regards to technology, organizational change, curriculum development, and stakeholders' readiness. In order to realize ongoing and cross-contextual data collection and measure competences across courses, curricular changes are required. To derive potential learning paths, it needs to be defined how the courses relate to a certain study program and to other study programs, and which prerequisites are required to study a course. Learning objectives need to be assigned to each course, to each learning resource, and each assessment task. Following the Evidence-centered Assessment Design, assessments need to be designed or re-designed. To meet all these requirements standards across the institution or even across institutions need to be developed. Hence, huge curricular changes are necessary. Furthermore, the curriculum and operationalizations need to be mapped onto the learning analytics system and the underlying algorithms. Therefore, the interfaces of the institutional IT infrastructure need to be defined and implemented (e.g., curriculum profile, student profile, learning profile) (Ifenthaler & Widanapathirana, 2014; Schumacher, Klasen, & Ifenthaler, 2019). Thus, to realize such institutional change processes, change management is vital, the institutional culture needs to be open to evidence-based approaches, the stakeholders need to be willing and prepared and corresponding resources need to be available (e.g., time, infrastructure) (Macfadyen, Dawson, Pardo, & Gašević, 2014; Schumacher et al., 2019; Tsai & Gašević, 2017)

6.6 Conclusion

This paper aims to synthesize assessment, feedback and learning analytics. Therefore, theory on assessment and how assessment is implemented in higher education was described. Furthermore, assessment serves at least a formative and a summative function, which should both be used to be informative for learners as well as for learning and instructional processes. To design such informative and valid assessments supported through technology, principle-based assessment designs are considered to be a promising approach. However, for assessments to be informative, the results and derived recommendations for improvement need to be provided to learners and teachers as feedback, feedforward or feedup. To be effective, this feedback needs to consider learners' prerequisites, such as prior knowledge, motivational and emotional states or learning goals. Due to the increased use of digital learning environments the possibilities of learning analytics can provide information about learners' prerequisites and can be applied to analyze learning processes and environments aiming at supporting and optimizing them. However, learning analytics still suffer from a lack of theoretical foundation and empirical evidence.

In increasingly complex learning environments various cognitive, meta-, and non-cognitive skills are required for problem-solving, which makes it difficult to infer from learners' behavior to the skills in focus (Baker et al., 2017). The underlying constructs plus the associated behaviors of learners are overlapping (Webb et al., 2018). Furthermore, related assessments are still limited and lacking empirical evidence (Shute et al., 2016). Hence, combining the possibilities of learning analytics approaches with a principle-based assessment design can serve as a basis, as it aims to define the interrelatedness of the constructs and consider how the behavioral evidence and performance can be accumulated and related to each assessment target. Furthermore, this approach allows learning analytics to be better embedded into theory of learning and cognition which would support its validity and might increase its evidence. By developing an integrative framework, aimed at synthesizing current perspectives on assessment, feedback and learning analytics, and by providing some exemplary implementations, this aim was promoted further.

However, even though learning analytics enable broad support to be offered to learners, it must be borne in mind, that the learners are the agents for their learning processes. As such, their digital and feedback literacy needs to be fostered to enable them to evaluate the validity of the results and decide how to react to the feedback provided. Hence, learning analytics should provide additional information to support evidence-based decisions and increase self-reflection and awareness.

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7 Discussion and further research

To give an overview about the contribution of the thesis, the findings will be summarized in five major topics (section 7.1.) roughly related to the research aims, described in section 1.2. Results referring to the detailed research questions and hypotheses are presented within each related chapter. Based on the findings implications (7.2) for the design of learning analytics will be derived. Furthermore, limitations of the thesis will be discussed to identify current research needs (section 7.3). Finally, the thesis will be concluded in section 7.4.

7.1 Findings on advancing learning analytics research and development

7.1.1 Findings on learners' perceptions and expectations of learning analytics

The first two studies (study 1 and 2, paper 1) contribute to the research need to integrate the expectations, perceptions and opinions on learning analytics of the different stakeholders and in particular of students (Tsai & Gašević, 2017; West, Luzeckyj, Toohey, Vanderlelie, & Searle, 2020). Findings of the qualitative study (study 1) indicate that students first of all have a positive attitude towards learning analytics. Even though attitude is not included in common technology acceptance models (e.g., Venkatesh, Morris, Davis, & Davis, 2003) other research suggests that a positive attitude towards using a technology can be a precursor of utilizing a technology (Moran, Hawkes, & El Gayar, 2010). In addition, participants of study 1 expressed a variety of features that learning analytics could offer. Moreover, in line with findings of a previous study participants would prefer holistic systems (Ifenthaler & Schumacher, 2016) integrating several applications and functions for all study processes. However, findings also revealed several concerns learners have with regard to learning analytics. For example, participants addressed privacy issues and raised concerns related to motivation such as comparison with peers, too much surveillance and reduced autonomy which is in line with findings of a comparable study (Roberts, Howell, & Seaman, 2017). Participants preferred learning with printed texts and discussed a function that includes learning outside the digital learning environment for valid analyses and feedback. Likewise, other research indicates that students perceive analyses of their digital learning behavior not relevant when the course is predominantly realized face-to-face or learning is occurring outside the digital learning environment (Bennett & Folley, in press; Verbert et al., 2014). Furthermore, participants highlighted that individual learners might have different demands resulting in the need to offer highly adaptive and personalized systems which is in line with findings of other research (Bennett & Folley, in press; Roberts et al., 2017). With regard to learning support, participants demanded sufficient self-assessments to assess their current knowledge related to the learning objectives but also connected learning resources such as highlighted keywords in the learning material linking to additional resources. In addition, functions to learn and discuss with peers plus suggestions to connect with potential learning partners were brought up.

Based on quantitative findings (study 2), the features participants were most willing to use, referred to simple reminders of deadlines, materials offering learning content for revision plus self-assessments with immediate feedback. With regard to the perceived learning support through the potential features participants rated the self-assessments with feedback, learning recommendations for successful course completion plus a timeline showing their current status towards the learning objectives the most helpful. Furthermore, findings indicate that perceived learning support through a feature, the perceived usefulness, the ease of use, and related privacy perceptions are positively related to participants' willingness to use this feature. The perceived benefits of a technology such as the perception of learning support and users' willingness to use a certain feature are relevant factors for actual use and thus for successful implementation (Ifenthaler & Schweinbenz, 2013; Lee, Yoon, & Lee, 2009; Venkatesh et al., 2003).

Hence, the findings of study 1 and 2 as well as the fifteen identified learning analytics features may serve as guidance for designing learning analytics and for directing future research.

7.1.2 Findings on supporting (self-regulated) learning

With regard to the expected support through learning analytics participants in the first qualitative study (paper 1) described features that could potentially support self-regulated learning within all phases. Hence, findings suggest that learners might demand support during all phases of self-regulated learning and not only during the actual learning phase. Furthermore, participants of study 2 perceived significantly different support through the 15 distinctive learning analytics features.

As suggested, prompts are considered to support learning in digital learning environments (Daumiller & Dresel, 2018; Devolder, van Braak, & Tondeur, 2012; Moos & Bonde, 2016). However, referring to the quasi-experimental study (paper 3, chapter 5) investigating how different prompts based on self-regulated learning theory might support learning performance with regard to declarative and transfer knowledge as well as over time, the support through the prompts was limited. Results indicate that the different prompts had no impact on participants' learning performance regarding declarative knowledge. With regard to transfer knowledge slight effects of the prompts were identified as significant differences between the groups were found for the IT learning unit (for both post-test measurement points) plus significant interaction effect of time and group was found for the marketing unit. Likewise, other studies found that cognitive and metacognitive (Müller & Seufert, 2018) or metacognitive (Bannert & Mengelkamp, 2013; Bannert, Sonnenberg, Mengelkamp, & Prieger, 2015) prompts had an effect on transfer knowledge but not on recall or comprehension. Even though the effects of the prompts on learning performance were rather limited, the different prompts seem to have affected participants' digital learning behavior as indicated by significant differences with regard to usage of resources or note taking. This supports comparable findings of prior research investigating metacognitive prompts, indicating that the prompts had an impact on digital learning behavior but this in turn did not influence learning performance (Prieger & Bannert, 2018). In study 4 findings on participants' perceived learning support through the prompts reveal moderate results. Overall, referring to the data of study 4 it might be assumed that metacognitive prompts seem to be more effective than cognitive prompts or a combination of cognitive, metacognitive, motivational and resource-related prompts. Participants receiving metacognitive prompts had higher results in the declarative knowledge test, and in the transfer test in IT at t_2 plus had a slight performance increase with regard to transfer knowledge in marketing from t_2 to t_3. Furthermore, these participants reported perceiving more learning support through the prompts than the other two groups. However, these results were predominantly on a descriptive level demanding further research as discussed in section 7.3.2. In addition, these findings might be in contrast to previous research which favored cognitive or a combination of cognitive and metacognitive prompts over metacognitive prompts alone with regard to learning outcome (Berthold, Nückles, & Renkl, 2007). As the prompts provided were not tailored to the participants they might have not supported them as intended, which will be discussed further in section7.3.2, or learners might have ignored the prompts.

7.1.3 Findings on learner characteristics with regard to learning analytics

In this thesis the third study (paper 2, chapter 4) contributed to findings on learners' perceived learning support through learning analytics considering their motivational dispositions but also personal and academic characteristics. Findings indicate that students in undergraduate courses and with lower study performance plus with learning and performance-approach goal orientations as well as with an academic self-concept based on an individual norm anticipated higher support through learning analytics. Also, the qualitative findings of study 1 suggest to at least consider students' preferences when providing feedback to the learners as indicated through the ambiguous thoughts about comparisons with peers on performance and learning progress plus the demand for high personalization of the system. Further analyses of the data collected in study 2 (Schumacher & Ifenthaler, 2017) indicate that the perceived learning support through a certain learning analytics feature was related to the manifestation of participants' self-regulated learning strategies. Moreover, findings of study 4 suggest that academic characteristics of learners are relevant predictors of learning performance whereas trace data only to a limited extent. Likewise, other research enhances learning analytics models for predicting performance with learners' dispositions or additional self-report instruments (e.g., Ellis, Han, & Pardo, 2017; Tempelaar, Rienties, & Giesbers, 2015). Also, that the prompts, which were not tailored to learners' needs and characteristics, did not impact learning performance as expected, suggests integrating learner characteristics for offering adaptive support. As participants in study 4 reported comparably high metacognitive awareness they might have not been in need of the support provided or required different support. Hence, findings of this thesis suggest that learners' characteristics, preferences, and needs should be considered in the models of learning analytics.

7.1.4 Findings on using trace data for informing learning performance

Findings of study 4 contribute to one of the predominant aims of learning analytics, using digital learning behavior for predicting learning performance (Aldowah, Al-Smarraie, & Fauzy, 2019; Papamitsiou & Economides, 2014). As in study 4 (paper 3, chapter 5) a quasi-experimental study design was used, it allowed to control for learning behavior outside the digital learning environment. However, findings of study 4 analyzing the predictive power of trace data in a learning unit were limited as only participants' views of the handout were significantly predicting their learning performance. Predictors that were more relevant were academic characteristics (e.g., current GPA, perceived confidence or the semesters studied). Furthermore, results of study 4 indicate that the prompts had an impact on learners' note taking behavior (length of notes) but this was not related to learning performance suggesting to scrutinize the value of the trace data which are easy to access and analyze.

Thus, by using a quasi-experimental approach the thesis provides a contribution to the demand of enhancing the empirical evidence of learning analytics (Ferguson & Clow, 2017). In addition, the findings with regard to the use of trace data for predicting learning performance suggest that learning analytics might be limited at least when analyzing small datasets. Other studies investigating trace data for predicting learning performance in authentic courses showed diverse findings with regard to relevant indicators for example, reading and posting messages, content creation, quiz efforts, and files viewed (Zacharis, 2015), or regular study time, numbers of late submissions, number of access to online sessions, and reading the course information package (You, 2016), as well as course logins, lesson reading activity, time spent on lesson quizzes and scores on these quizzes (Strang, 2017). In addition, Gašević, Dawson, Rogers, and Gasevic (2016) found that significant predictors differ depending on the instructional design of a course and the discipline. However, studies using controlled experimental conditions for investigating the potential of trace data for predicting learning performance within common higher education digital learning environments seem to be limited. Summarized, this further emphasizes the need for additional studies (using experimental designs), and for developing learning analytics guided through learning theory (Marzouk et al., 2016; Wong et al., 2019).

7.1.5 Contribution to theoretical foundation of learning analytics

This thesis contributes to the theoretical foundation of learning analytics by linking learning analytics with theory on self-regulated learning, motivation, assessment and feedback. In the first paper, the identified learning analytics features were assigned to the three phases of self-regulated learning and described how their functionalities could serve or impact the related processes (see Table 3-5). As the motivational component of self-regulated learning is currently not considered sufficiently in the arena of learning analytics (Lonn, Aguilar, & Teasley, 2015; Wong et al., 2019) this was the focus of the third paper. Theoretical contribution included an outline of learning analytics that consider motivation by design by referring to the ARCS model (Keller, 2008; Keller & Suzuki, 2004). Furthermore, the potential support learning analytics can offer with regard to motivation was assigned to each phase of self-regulated learning (see Table 4-2). As the impact of learning analytics on students' motivation is discussed ambiguously and might depend on learners' dispositions (e.g., Aguilar, 2018; Corrin & de Barba, 2014; Kim, Jo, & Park, 2016; Lonn et al., 2015; Toohey et al., 2019), this work might serve as an initial guidance for considering learners' motivation when designing learning analytics. The theoretical contributions of this thesis might be particularly relevant when considering that learning analytics are at the intersection of several disciplines (Sclater, Peasgood, & Mullan, 2016) with computer science and educational science presumably being predominant (Dawson, Gašević, Siemens, & Joksimovic, 2014). Furthermore, the interdisciplinarity of learning analytics is challenging (Kitto, Buckingham Shum, & Gibson, 2018; Kitto, Lupton, Davis, & Waters, 2017), entailing that several endeavors to develop learning analytics might be driven from disciplines not related to learning sciences; or at least do not consider learning theory sufficiently (Gašević, Dawson, & Siemens, 2015; Tsai & Gašević, 2017; Viberg, Hatakka, Bälter, & Mavroudi, 2018). In addition, learning analytics not guided through theory might use all data available trying to detect patterns or relations to achieve a good model fit but without scrutinizing whether these data are meaningful with regard to the purpose of learning analytics (Lerche & Kiel, 2018; Rosé, McLaughlin, Liu, & Koedinger, in press). As learning analytics focus on understanding and supporting learning processes, referring to empirical and theoretical approaches of assessing learning processes and products seems reasonable (paper 4). Hence, a major theoretical contribution of this thesis is the development of an integrative assessment analytics framework (see Figure 6-3). This framework might guide upcoming design of learning analytics systems and increase their validity and learning support by offering self-assessments.

7.2 Practical implications

Based on the studies conducted and the theoretical considerations several implications can be deduced. A major implication is that learning analytics systems need to be holistic with regard to both, the functionalities they offer but also the data they are referring to. It is further indicated that learning analytics systems should be developed based on learning theory and consider the users and their characteristics to meet their needs and provide meaningful and adaptive support. As the integration of data collected is not only a technical challenge but also a challenge for operationalization principle-based assessment design might increase the validity of the results for deducing meaningful interventions. To illustrate potential implications of this thesis, holistic learning analytics supporting cognition, metacognition, and motivation will be outlined. As the author participated in the project developing the learning analytics system LeAP (Learning Analytics Profiles)[1] the section will end by providing some insights into the system to further illustrate practical implications.

Offering digital learning environments comprising several intertwined functionalities such as text processing and annotation, planning or communicating would not only facilitate learning but also data collection and integration. With regard to the components of self-regulated learning holistic learning analytics systems should investigate and support cognition, metacognition and motivation.

[1] https://www.bwl.uni-mannheim.de/en/ifenthaler/research/leap-learning-analytics-profile/

Hence, *cognitive* processes could be supported for example through features for repeating learning content, providing connections of new content to previous or enabling learners to create such connections, or by offering a feature for reading texts, that can be annotated, linked to other learning material, extracted for excerpts or concept maps. Based on the processes learners perform or on an initial knowledge test, the system could recommend additional suitable learning resources. Furthermore, text processing applications including a referencing functionality might be included and provide learners with feedback on their texts by comparing them to expert solutions or the learning materials (Marzouk et al., 2016; Schumacher, Tai, Boud, & Ifenthaler, 2019). Or learners can be supported in programming tasks by offering automated feedback prompting them to reflect on their code and showing the next line of a correct solution (Gross, Mokbel, Hammer, & Pinkwart, 2015). To gain detailed insights into operations students perform while interacting with information or peers, Winne et al. (2019) developed a browser extension that tracks learners' activities and produced artefacts such as highlighting a text, creating a bookmark or taking notes. To obtain additional information why students highlight a text, they can tag the highlight with "important", "follow up" or an individual tag.

With regard to *metacognitive* processes planning might be supported either by suggesting study plans for novices or by offering a function to set individual learning goals to which resources and deadlines can be assigned. Information about learners' goals could support the identification of self-regulated learning and whether learners reached not only the course objectives but their individual goals (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). In addition, clear learning objectives of the course and criteria for success should be provided to foster self-regulation (paper 4). For supporting monitoring processes learning analytics should offer sufficient self-assessments and feedback about learners' progress and on how to improve (study 1 and 2). Following the integrative assessment analytics framework (paper 4) these self-assessments might adapt to learners' current competencies. Furthermore, these data could inform the features which were identified in study 1 to support monitoring by offering learning recommendations for successful course completion or a timeline showing learners' progress towards learning goals. Moreover, the system might analyze strategies learners use and provide suggestions for improvement or recommend relevant trainings (e.g., how to set learning goals, use appropriate learning strategies or how to self-regulate). If the learners prefer or depending on their goal orientations and reference norms, they might receive information about their strategies and approaches used or their performance compared to those of their peers. For example, Bodily, Ikahihifo, Mackley, and Graham (2018) developed a content recommender that, based on assessment data, provides learners with recommendations of learning content (e.g., videos, practice problems) to increase mastery of the course concepts. In addition, they offer a skill recommender, that aims at inferring among others on learners' time management, knowledge awareness or persistence, results are visualized to the learners including recommendations on how to improve.

To consider and support the *motivational* component of self-regulated learning prompts can be used either to investigate current motivation, current goals or to provide "motivational" feedback on success or to persist in a task. This might further be enhanced with digital badges, which should encourage learners by certifying their achievements (Mah, 2016). Motivation might also be supported through the above-mentioned function enabling learners to set individual goals (Zimmerman, 1990), by providing learners with clear objectives, adaptive recommendations, and by offering autonomy through customization and voluntary use of the system. Also, by presenting a variety of functions, learners might perceive having the choice to use the features of which they benefit the most. To gain additional information about students' motivation several data could be included such as their overall interest in the course, the perceived difficulty of materials or value of learning tasks or the entire course. As revealed in study 1 learners fear too much guidance or surveillance which could affect motivation. Hence, even if learning analytics might "know it better", following theory on self-regulated learning still the learners should be considered as autonomous to decide what to do and which feedback to accept.

Related to all components of self-regulated learning would be functionalities for peer learning in the form of communication (e.g., video, chat, forum), co-production of learning products (e.g., cloud-based text processing, wikis) or help seeking (e.g., recommendation of learning partners). For example, to gain insights into discussions in forums they can be analyzed with regard to students' behavioral engagement patterns and emotional states and further related to course performance (Liu, Pinkwart, Liu, Liu, & Zhang, 2018)

As findings of study 4 suggest, prompts should be provided adaptively based on learners' current needs and preferences. Therefore, the implementation of the integrative assessment framework (paper 4) seems suitable as it facilitates the operationalization and integration of the data for generating comprehensive student models. Furthermore, offering well designed (self-) assessments to learners (as demanded in study 1) enhances learning and enables adaptive prompts or recommendations. Further scenarios of how the integrative assessment framework could be implemented are described in section 6.4.3. In addition, findings of study 3 indicate that students in undergraduate courses perceive more support from learning analytics. Hence, specific features might be offered to them such as preparatory resources or connecting them with advanced students.

However, implementation of such holistic systems requires interdisciplinary integration of all stakeholders as it implies not only high technical expenses but also pedagogical design efforts in that sufficient learning resources need to be developed, intertwined, and assigned to learning objectives (paper 4).

With regard to LeAP some of the above proposed functions were developed and are predominantly implemented into a dashboard (see Figure 7-1 for the learner dashboard), showing learning objectives and related materials plus learners' progress of using the resources and performance in the self-assessments (left side). For each learning objective learners can rate the perceived difficulty and need for feedback. In addition, learners can set individual goals including a deadline, add materials and track their progress, which is displayed on the right side of the dashboard. Furthermore, various types of prompts can be provided to learners such as simple reminders or short questions. To account for students' privacy, they can choose if they want to be tracked anonymously (aggregated at course level), pseudonymously or not tracked at all. In addition, to increase anonymity by separating the trace data from the student identifier of the learning management system but still having the possibility to aggregate the data collected, the identifier is pseudonymized using a double-hash (Klasen & Ifenthaler, 2019).

Furthermore, a dashboard for teachers is implemented showing the use of resources aggregated for the course as well as learners' perceived difficulty and need for feedback, which could be used to adapt teaching or to offer additional support.

LeAP was developed by integrating expertise from educational science and computer science which should be further enhanced with expertise from data science. Even though the functionalities of LeAP are currently still limited and not near the proposed holistic learning analytics system, they are at least perceived as learning support (Schumacher, Klasen, & Ifenthaler, 2019).

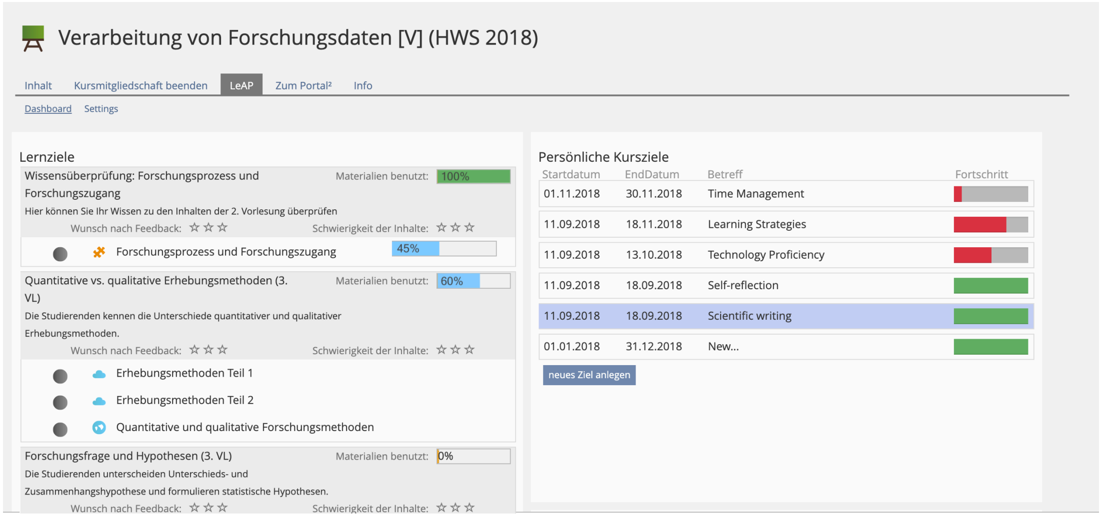

Figure 7-1. Overview about the LeAP dashboard presented to learners

7.3 Limitations and future research

The present thesis shows several limitations as discussed in each previous chapter in detail. In the following the limitations will be discussed in general and further research needs will be outlined. With regard to the sampling, this thesis is limited as all studies use samples from a single German university. In addition, study 1, 2, and 3 use self-report data and focus on a hypothetical learning analytics system. Study 4 integrates self-report data and trace data however, not in an authentic learning setting but in an experimental environment, and results did not meet the associated hopes of predicting learning performance. Hence, generalizations based on the findings of the studies conducted are limited. The theoretical model developed in paper 4 shows limitations as the theoretical foundation focuses on one specific framework of principle-based assessment design and one learning analytics framework. Furthermore, the focus of this thesis was on the individual learner with regard to learning analytics, not particularly considering collaborative learning processes (e.g., Gašević, Joksimović, Eagan, & Shaffer, 2019; Järvelä, Malmberg, Haataja, Sobocinski, & Kirschner, in press; Noroozi et al., 2019). Limitations of the thesis are presented in the subsequent sections and will be discussed with regard to future research needs.

7.3.1 Integrating stakeholders when developing learning analytics

In study 1 learners' expectations with regard to learning analytics features were investigated. Furthermore, in study 2 learners' willingness to use these features and their perceived learning support through these features was examined. However, even though participants received an introduction on learning analytics, which might have increased participants' understanding (Roberts, Howell, Seaman, & Gibson, 2016), these results might be limited as the participants have never used such systems. Study 2 focused on one of the major expected benefits of learning analytics, supporting learning but future research should investigate this after learners have used learning analytics or a feature for a certain time. Moreover, not the perceived learning support is relevant but most notably the actual impact learning analytics have on learning processes and performance, as discussed further in section 7.3.4.

This thesis focuses on the learners' perspective on learning analytics without investigating other stakeholders' perceptions. But as Dollinger and Lodge (2018) postulate, learning analytics systems should be co-created by all stakeholders. This might positively impact the design of learning analytics (e.g., flexibility, diversity, consider needs and context, shift from performance to other assessments), increase the sensemaking of the data, which in turn would increase adoption by decreasing concerns, considering needs and goals of stakeholders and thus their agency (Dollinger & Lodge, 2018). Hence, even though current studies already investigated other stakeholders' perspectives (Howell, Roberts, Seaman, & Gibson, 2018; Ifenthaler & Yau, 2019) further research is needed including IT developers or the management level and considering the institutional context. For example, with regard to LeAP, teachers' perspectives as well as students' actual use of the implemented learning analytics features will be investigated further (e.g., accessing the dashboard, using the function to rate the materials), and enhanced with self-report data on perceived benefits of learning analytics. Investigating the use of learning analytics is relevant because if learners do not use the interventions this might bias results on the potential or absent impact on learning (Bodily et al., 2018) and requires further research investigating why learning analytics are not used (e.g., usability, design, accessibility, value, not meeting users' needs). However, to actively integrate stakeholders in learning analytics processes their educational data literacy needs to be developed. As this is a major area for future research and training the project Learn2Analyse[2], founded through the Erasmus+ Program was launched in 2018. The project focuses on educational data literacy and first developed a framework including the relevant competencies required for working with educational data such as analyzing, interpreting, and applying data and results. Based on these identified relevant competencies the project committee developed a massive open online course for interested stakeholders using educational data. To prepare future staff in the education sector accordingly, study programs need to develop relevant competencies as identified in the Learn2Analyze framework.

In summary, future research integrating stakeholders when developing learning analytics should investigate:

1. Which learning analytics features are actually used and by whom?
2. Do the perceptions with regard to learning support of implemented learning analytics features differ from those in study 2? Will the learning analytics features demanded by learners be used and do they impact learning?
3. Which learning analytics features do stakeholders consider as valuable and beneficiary with regard to supporting students, teaching or institutions?
4. How do stakeholders perceive implemented learning analytics with regard to ethics, privacy, workload, or ease of use?

[2] http://www.learn2analyze.eu

5. How can the proposed implementation frameworks (e.g., Sclater & Bailey, 2015; West, Heath, & Huijser, 2016) for learning analytics be set into practice for example with regard to cultural change or institution-wide adoption?
6. How can the required competencies with regard to learning analytics of the current and future stakeholders be developed?
    a. With regard to developing and implementing learning analytics systems (IT developers and administrators).
    b. With regard to deriving meaningful interventions (e.g., adapt teaching, learning, and institutional strategies).
    c. With regard to embedding the competence development into study programs and postgraduate training.

7.3.2 Investigating the development of adaptive learning support and feedback through learning analytics

In study 4 the provided learning support through prompts did not entail the expected impact on learning performance. One reason might be that the prompts were not adaptive to the learners, and thus, depending on learners' characteristics might have been more or less effective (Backhaus, Jeske, Pointstingl, & Koenig, 2017; Cronbach & Snow, 1977; Ifenthaler, 2012; Prieger & Bannert, 2018). Furthermore, findings of study 3 suggest that depending on academic characteristics anticipated support from learning analytics differs. In addition, learners demand feedback from learning analytics on where and how to improve (study 1 and 2). As discussed in paper 4 such feedback needs to be provided considering learners' personal, academic, social, emotional, and cognitive characteristics, their preferences, current needs and goals to support learning. Therefore, learning analytics need to include comprehensive learner profiles. With this regard the research on adaptive learning (e.g., Graf & Kinshuk, 2014; Xie, Chu, Hwang, & Wang, 2019) might be considered as a fruitful foundation (Mavroudi, Giannakos, & Krogstie, 2018). However, an extended adaptivity of learning analytics requires additional personal information of learners across contexts emphasizing the consideration of ethics and privacy (West et al., 2020).

Within this thesis no feedback based on learning analytics was provided to learners. Currently, if any, learning analytics feedback is provided to learners predominantly through dashboards or visualizations (Kitto et al., 2017). However, these dashboards are often not designed based on learning theory (Jivet, Scheffel, Specht, & Drachsler, 2018) or students' needs (Roberts et al., 2017), and feedback provided might even hamper learning (Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018), or the dashboards are seldomly used by learners (Bodily et al., 2018). In addition, the feedback provided through the dashboards might not be easy to understand without guidance (Park & Jo, 2015) or not used by the learners as intended. Presenting comparisons of students related to the cohort are not considered to support reflection and metacognition (Kitto et al., 2017) and are perceived differently by the learners (Bennett & Folley, in press; Roberts et al., 2017). Furthermore, presenting performance indicators to students is not sufficient for learners to deduce how to improve their learning (Sedrakyan et al., 2018). Following Lockyer, Heathcote, and Dawson (2013), such checkpoint analytics focus on representing learners' access of content but do not provide insights into learning processes.

As research on feedback through learning analytics is limited further studies should investigate timing, content, and instructional character of the feedback plus its impact on learners' emotions, motivation, learning behavior and achievement. In this regard, experimental studies are required to investigate learners' perceptions of (automated) feedback and how this affects them (Howell, Roberts, & Mancini, 2018) for example by using a combination of electrodermal measures and self-report inventories plus trace data. Furthermore, it needs to be investigated how feedback for improvement based on learning analytics can be offered.

To investigate the use of prompts further, another quasi-experimental study was conducted providing learners with generic, specific, and adaptive specific prompts while interacting with a digital learning environment (Schumacher, Schultheis, Aprea, & Ifenthaler, 2019). Preliminary results indicate that predefined support (generic and specific) was less effective with regard to achievement in a transfer test than the adaptive support or no support. However, the adaptive support was provided based on learners' digital learning behavior only and not with regard to their prior domain knowledge or other characteristics, which is the aim of an upcoming study. To further investigate learners' reactions to the prompts screencast and think-aloud methods plus trace data will be used to gather more fine-grained data (e.g., Engelmann & Bannert, in press).

Research with regard to the provision of adaptive support and feedback through learning analytics might investigate:

1. How can the theoretical and empirical contribution in the area of adaptive learning and learning analytics be synthesized?
2. How can student models be integrated and updated in learning analytics systems to increase adaptation? How can learners' characteristics (e.g., preferences, prior knowledge, goals) be considered for providing adaptive feedback through learning analytics?
3. How do students with different characteristics benefit from learning analytics? Does the perceived support from certain implemented learning analytics features (study 2) differ depending on students' personal, academic, social, emotional or cognitive characteristics (e.g., capacity to self-regulated)?
4. How do students perceive (automated) feedback or interventions through learning analytics with regard to emotions, motivation, autonomy, distraction, and usefulness?
5. Which feedback and presentation modes (e.g., dashboards, prompts, feedback button, e-mail) are suitable for which content and learner?
6. How can learners' understanding of learning analytics results be supported that they are able to scrutinize the analyses and results, and if appropriate adapt their learning accordingly?
7. How do students react to feedback provided as indicated through trace data?

7.3.3 Using trace data to investigate (self-regulated) learning processes

Within this thesis participants' self-regulation was only limitedly analyzed, in study 3 with regard to motivation and in study 4 with regard to metacognitive awareness. Furthermore, the digital learning behavior in study 4 was not analyzed with regard to processes of self-regulated learning due to limitations of the data available. Still tracking of indicators in digital learning environments which are related to learning is limited (Bodily et al., 2018; Corrin & de Barba, 2014; Wilson, Watson, Thompson, Drew, & Doyle, 2017; Winne et al., 2019) . Learning processes in digital learning environments are difficult to separate from “noise” and particularly cognitive processes such as thinking might not be captured (Lerche & Kiel, 2018). Hadwin, Nesbit, Jamieson-Noel, Code, and Winne (2007) state that furthermore little evidence and information is given about how to use the data to identify self-regulated learning activities or patterns. Comparable, Prieger and Bannert (2018) argue that it is difficult to determine which behavioral pattern is more preferable compared to others. Further, what beneficial navigation patterns are, depends on the design of the learning environment. To gain better understanding of self-regulated learning McCardle and Hadwin (2015) propose assessing it in authentic learning scenarios to analyze how learners’ cope within different situations by integrating their perceptions, experiences and challenges. Hence, additional research is required to validly identify self-regulated learning by integrating trace data and additional measures.

In study 4 trace data were recorded in an experimental setting and investigated with regard to learning performance (study 4). However, even when controlling for learning behavior outside the digital learning environment findings suggest reservedness regarding relying on trace data for predicting learning performance. By focusing solely on trace data, the attention is particularly on quantifying learners’ actions and relating them to learning performance. Hence, the underlying assumption would be that the number of actions within trackable learning environments is related to the quality of learning and performance (Gašević et al., 2015; Lodge & Lewis, 2012; Wise & Shaffer, 2015). Likewise, results of study 4 indicate that the prompts impacted learners’ note-taking behavior (length of notes) but this was not related to learning performance. Thus, the analysis of the quality of learners’ artefacts or behavior should to be emphasized. Furthermore, the impact of the design of the digital learning environment on learning processes and achievement was not investigated in study 4. Hence, learning analytics including indicators and algorithms need to be adapted to the course design as developed by the instructors, guided by their pedagogical intentions (Aljohani et al., 2019) or discipline standards. The course design influences digital learning behavior (Rienties & Toetenel, 2016) and thus determines which indicators are available and relevant for the analyses within a particular course (Aljohani et al., 2019). Hence, behavioral indicators should not be overstated and enhanced with other relevant variables as indicated by educational research (e.g., contextual, individual) (Wilson et al., 2017). In addition, the limitations of trace data suggest integrating self-assessments which learners demand from learning analytics (study 1 and 2) as they might be a valid source for integrating quality indicators of learning (paper 4). For example, Strang (2017) found that typical engagement indicators within digital learning environments were not sufficiently predicting learning performance, but quiz activity and scores as well as course login and lesson reading. Furthermore, to define the relation of data on behavior and on performance with valuable learning processes the proposed framework in paper 4 might be useful.

However, results of study 4 should not be overinterpreted as they only refer to a short learning period under experimental conditions influenced by contextual factors (e.g., the design of the learning environment and prompts). Hence, upcoming research should consider contextual variables, investigate trace data in both authentic and experimental settings, and over a longer period of time. The following research questions might guide future investigations:

1. How does self-regulated digital learning behavior look like?
2. How could the focus on quantifying behavior be enhanced with quality of learning processes and outcomes?
3. How can valid indicators be identified and aggregated using the proposed framework of integrative assessment analytics (paper 4)?
4. How can the limitedness of trace data within learning analytics be considered in the analyses (e.g., weighting using the proposed framework of integrative assessment analytics)?
5. How can trace data and self-report data be validly enhanced to identify (self-regulated) learning?

6. How are contextual factors (e.g., learning environment, design of interventions) related to learners' digital learning behavior and how can they be integrated into the analyses?
7. How informative are traces of digital learning behavior to identify learning processes and indicators for predicting learning performance?

Identification of valid learning behavior and related performance is a prerequisite for providing support to foster self-regulated learning and achievement.

7.3.4 Investigating if learning analytics are capable of supporting self-regulated learning and achievement

Within this thesis the investigation of the potential support learning analytics might provide to foster self-regulated learning was limited to a theoretical contribution. In study 2 the perceived learning support through learning analytics was investigated and study 1 reveals concerns of a potential loss of autonomy and motivation, which are crucial for self-regulation. Hence, additional research is required to investigate how and if learning analytics are capable of supporting self-regulated learning, and who requires which support (study 3 and 4) and how this could be adapted (section 7.3.2). The use of the support provided could be analyzed by investigating learners' reactions as indicated by trace data (Thillmann, Künsting, Wirth, & Leutner, 2009; Winne & Baker, 2013). Furthermore, even if learning analytics interventions potentially impact digital learning behavior further research needs to investigate if this relates to achievement (study 4). However, as proposed in paper 4 extending the validity of learning analytics and offering holistic systems (study 1) might increase the likelihood of providing support that is aligned with the course goals and meeting learners' knowledge and competencies. Findings of study 3 indicate that learning analytics may be particularly beneficiary for students which are at the beginning of their studies which possibly face difficulties. Hence, referring to Mah (2016) learning analytics can be suitable for supporting first-year students. However, to avoid that less self-regulated learners develop dependency on such support systems, the support needs to be adaptive or fade out. This highlights the need to develop learning analytics that foster learners' own monitoring and judgement processes for example by supporting reflection or using peer feedback as discussed in the fourth paper.

Likewise, Kitto et al. (2017) propose that due to limitations of using algorithms in educational contexts, learners should be encouraged to reflect on their learning analytics results and if they perceive being represented correctly. This might increase learners' reflection and monitoring but also requires high skills and data literacy as discussed in section 7.3.1.

Still learning analytics are predominantly focusing on instructors rather than learners (Kitto et al., 2017; Schwendimann et al., 2017) and a recent literature review found only little evidence that learning analytics support learning processes and outcomes (Viberg et al., 2018). Hence, further research is required to investigate if learning analytics are capable of identifying and supporting learning. However, researching the impact of an intervention is difficult as changes in learning performance could also dependent on contextual, situational or intra-personal factors which are difficult to control for. Likewise, experimental research enables to control for such factors but creates artificial learning situations which potentially impact participants' motivation and learning processes, and may have been a major limitation of study 4. Thus, upcoming research on learning analytics should integrate a variety of methodological approaches to increase empirical evidence. For example, experimental studies including think-aloud methods could be used to investigate the perceived support and the use of learning analytics features and analyses. Another potential approach within authentic learning scenarios would be to invite learners to perform their common course-related learning processes and to think aloud about what they are doing and why, as well as how they perceive the learning analytics interventions if used. In addition, learning performance of cohorts which have not used learning analytics could be compared to cohorts having used learning analytics. Furthermore, students in a course could receive different support by randomly assigning them to the learning analytics treatment or the control group to investigate their digital learning behavior and achievement plus changes over time. However, such approaches are difficult with regard to ethics of equal treatment of students and controlling for other influencing variables. Even more difficult would be to identify which features of learning analytics are most beneficial and for which learners. However, most important might not be to know if learning analytics can identify and support learning but if they at least do not impair learning. Furthermore, rather than developing "perfect" learning analytics, future research might focus on how humans and learning analytics approaches can enhance each other (Baker, 2016; Kitto et al., 2018; Rosé et al., in press), and which capabilities humans as well as what techniques learning analytics need for that. In line with this, results of learning analytics should be useful for learners who should further be encouraged to scrutinize them (Bennett & Folley, in press) instead of relying on potential incorrect learning analytics feedback. Hence, learning analytics feedback should rather encourage self-regulated learning processes for example by providing personalized prompts instead of taking on all tasks for students (Lodge, Panadero, Broadbent, & de Barba, 2018).

Future research might investigate the following aspects further:

1. Do learning analytics actually support self-regulated learning or hinder it by providing too much or incorrect support, reducing learners' agency or motivation?
2. How can support provided through learning analytics be faded out to increase learners' responsibility?
3. How can learning analytics be used to foster learners' own evaluative judgement and learning processes?
4. How can first-year students in particular be supported through learning analytics?
5. Does the feedback provided through learning analytics enable learners to react to it, and how does this relate to their learning processes, self-regulation and achievement?
6. Are learning analytics interventions related to digital learning behavior and is digital learning behavior related to achievement?
8. How can humans and learning analytics enhance each other? How can teachers (data literacy premised) be integrated to mediate between learning analytics results and learners?

Referring to LeAP, students' digital behavior (e.g., use of the different resources, use of the dashboard) was tracked over three semesters, enhanced with self-report data on learning strategies, study interest or perceptions about learning analytics, as well as data from self-assessments plus the final course grade. Hence, these data could be used to identify typical patterns and to investigate which variables are most likely related to achievement.

7.3.5 Developing theory-driven learning analytics

The underlying theory within this thesis is self-regulated learning which might be the predominant learning theory for researching learning analytics (Wong et al., 2019). In addition, motivation theory was investigated with regard to learning analytics however, the focus was only on two concepts, goal-orientations and academic self-concept. In the integrative review (paper 4) theory on assessment, assessment design and feedback including the perspective on self-regulated learning were linked to learning analytics. However, even though several theoretical approaches were considered within this thesis other approaches should be investigated with regard to learning analytics and used as foundation for research. For example, self-determination theory might be useful to investigate and support learners' autonomy perceptions and motivation when using learning analytics (Marzouk et al., 2016). Due to the ambiguous findings with regard to the reference norms of the academic self-concept and the perceived benefits of learning analytics it might be reasonable to further investigate the related concept of self-efficacy beliefs. The integrative assessment analytics framework in paper 4 considered merely one principle-based assessment design, hence, other approaches might be investigated in upcoming treatises. Moreover, to implement the proposed assessment analytics framework the underlying models needs to be aligned with the curricula of all study programs, with the modules, courses, the potential learning paths, all learning objectives, learning materials and assessments. In addition, further research needs to investigate the effectiveness of the proposed model.

However, as Lodge, Alhadad, Lewis, and Gašević (2017, p. 386) emphasize, before learning can be supported it first of all needs to be "consider[ed] what exactly learning is and how best to infer it from large datasets". Comparably, Kitto et al. (2018) summarize that the focus should not be on the data which are available or easy to capture and analyze, but on the data which are considered to be meaningful for supporting learning. In addition, learning analytics methods are considered to support the understanding of current theoretical assumptions on learning (Lodge et al., 2018) and enhancing educational research. Hence, future research in learning analytics should focus on theory-based approaches and investigate:

1. Which theories can enhance learning analytics research, development, and models to gain valid insights and derive meaningful support?
2. How can the proposed assessment analytics framework be implemented and how does it enhance understanding and supporting learning?
3. How can learning analytics approaches be applied for educational research?

7.4 Conclusion

Learning analytics are associated with high hopes with regard to current challenges in the education system (Dollinger & Lodge, 2018). They are considered to support learning, reduce drop-out by applying early interventions, predict academic success, and enhance educational decision-making. However, learning analytics are still at an initial stage facing several challenges for example with regard to deriving valid indicators, lacking theoretical foundation and empirical evidence, supporting learning and providing feedback, considering stakeholders, integrating data across systems without violating privacy, or identifying algorithms considering the specifics of education and contextual factors. To consider stakeholders and thus increase usefulness and adoption of learning analytics this thesis contributes by investigating students' perceptions of learning analytics systems and related learning support. Furthermore, theoretical foundation was promoted further by integrating theory on self-regulated learning, assessment and feedback which might serve as a useful guidance for developing learning analytics systems supporting learning. Furthermore, studies within this thesis emphasize the need to include learners' characteristics within learning analytics. By investigating the use of trace data for predicting learning performance in a quasi-experimental study design this thesis contributes to the need for empirical evidence of learning analytics. To forward research on learning analytics suggestions for future research were presented.

However, learning analytics should not encourage the design of learning environments that can be analyzed easily (e.g., using multiple choice tasks, offering learning resources that are trackable but not useful), but rather support learning processes. Or as Lodge et al. (2017, p. 389) state, “simplified output measures become the goal of education rather than the earlier focus on teaching for quality learning”. Therefore, as findings of this thesis indicate, learning analytics should be holistic systems comprising several functions, meeting students’ needs and preferences, integrate more than mere trace data, grounded in learning theory, and enhanced with additional measures and information on the context. If focusing only on learners’ actions instead of on the quality, Long and Siemens (2011) consider learning analytics to be reminiscent of behaviorism. Learning analytics on their own as currently applied are not a valid and reliable approach for analyzing and supporting learning processes, and should rather be considered to be an addition. With regard to theory on self-regulated learning, learners, especially in higher education, need to be considered as the agents of their learning, and as Knox (2017) states not be reduced to just *reacting* to learning analytics results. Hence, considering learners’ autonomy is important and support should be provided depending on their characteristics or upon request. Due to the current limitations of learning analytics feedback needs to be provided with care and investigated further to avoid harm. When learning theory is sufficiently considered and the attempts to go beyond the sole use of algorithms for detecting potential learning are advanced to increase validity, learning analytics can serve as a valuable approach to investigate and support (self-regulated) learning as well as offering benefits for all stakeholders.

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Curriculum Vitae

Appointments

since 2015	Research Assistant, Economic and Business Education – Learning, Design and Technology, Business School, University of Mannheim, GER Project Assignments: Evidence-based implementation of learning analytics in higher education (LeAP) Development process of integrating media in schools (MEP BW) Preparing International Students Online (PRESTO) Research stay (02-03/2019): Center for Learning and Teaching, Curtin University, Perth, Australia

Professional Preparation

2014	Diploma with Distinction in Educational Science (Major: Psychology, Minor: Work Psychology), University of Koblenz-Landau, GER Internships and working student positions: Allianz Deutschland AG (05/2011-04/2012), Allianz SE (05/2012-10/2012), Siemens AG (11/2012-03/2014), BMW Brilliance Automotive Ltd. (06/2014-12/2014)

Teaching activities

Since 2015	Statistical Methods (Undergraduate level – German, fall) Educational Management (Undergraduate level – German, spring) Supervising bachelor theses

Memberships

AERA, AECT, EARLI-JURE