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ORIGINAL RESEARCH

Learning Analytics and Digital Badges: Potential Impact on Student Retention in Higher Education

Dana-Kristin Mah[1]

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Abstract Learning analytics and digital badges are emerging research fields in educational science. They both show promise for enhancing student retention in higher education, where withdrawals prior to degree completion remain at about 30 % in Organisation for Economic Cooperation and Development member countries. This integrative review provides an overview of the theoretical literature as well as current practices and experience with learning analytics and digital badges in higher education with regard to their potential impact on student retention to enhance students' first-year experience. Learning analytics involves measuring and analyzing dynamic student data in order to gain insight into students' learning processes and optimize learning and teaching. One purpose of learning analytics is to construct predictive models to identify students who risk failing a course and thus are more likely to drop out of higher education. Personalized feedback provides students with information about academic support services, helping them to improve their skills and therefore be successful in higher education. Digital badges are symbols for certifying knowledge, skills, and competencies on web-based platforms. The intention is to encourage student persistence by motivating them, recognizing their generic skills, signaling their achievements, and capturing their learning paths. This article proposes a model that synthesizes learning analytics, digital badges, and generic skills such as academic competencies. The main idea is that generic skills can be represented as digital badges, which can be used for learning analytics algorithms to predict student success and to provide students with personalized feedback for improvement. Moreover, this model may serve as a platform for discussion and further research on learning analytics and digital badges to increase student retention in higher education.

Keywords Learning analytics · Digital badges · Student retention · Generic skills · Academic competencies

✉ Dana-Kristin Mah
dana-kristin.mah@uni-potsdam.de

[1] Applied Teaching and Learning Research, University of Potsdam, Karl-Liebknecht-Straße 24–25, 14476 Potsdam, Germany

1 Introduction and Purpose of this Integrative Review

Student retention is an important issue for higher education institutions as withdrawals from higher education prior to degree completion remain at about 30 % in the member countries of the Organisation for Economic Cooperation and Development. The first year of higher education is considered particularly crucial, as students often decide to leave higher education within this period (Brinkworth et al. 2009; Reason et al. 2006; Tinto 1993). Several studies on student retention exist (Bean and Metzner 1985; Bowles et al. 2014; Kuh et al. 2005; OECD 2013a; Rovai 2003; Tinto 1975, 1993, 2012) and higher education institutions have been offering academic support programs, such as summer bridge programs, first-year seminars, mentoring programs, and learning communities in an effort to enhance student retention (Barefoot et al. 1998; Clark and Cundiff 2011; Keup 2005; Scott et al. 2008; Tinto 2012).

In recent years, educational technology for teaching and learning has become more established in everyday academic practices. Most higher education institutions in the U.S. and Australia already use a learning management system (LMS), a software application that integrates teaching, learning activities, and course administration tools (Dahlstrom et al. 2014). The number of higher education institutions that offer online courses, such as massive open online courses (MOOCs), has increased (Cormier and Siemens 2010). Students' digital trails are captured when they learn online and use LMSs, mobile devices, and social media (Long and Siemens 2011; Siemens 2013).

Thus, higher education institutions have recently gained interest in collecting and mining these dynamic student data with learning analytics to gain insight into learners' experiences and to predict and optimize learning processes (Ferguson 2012; Fiaidhi 2014; Ifenthaler 2015; Ifenthaler et al. 2014; Long and Siemens 2011). Furthermore, digital badges are a relatively new technology in educational settings for representing learners' achievements, knowledge, skills, and competencies in formal and informal learning environments (EDUCAUSE 2012; Gibson et al. 2013; Ifenthaler et al. 2016).

The purpose of this integrative review is to analyze the potential of learning analytics and digital badges in order to enhance student retention in the all-important first year of higher education. Hence, this review provides an overview of (1) student retention in higher education and the relevance of generic skills, such as academic competencies. Then, (2) learning analytics and (3) digital badges are described separately, including their main objectives, opportunities and challenges, as well as current research and practices in higher education, with a focus on student retention. Further, (4) a synthesis of learning analytics and digital badges with links to generic skills is proposed here. Digital badges may certify generic skills for a prediction of student success based on learning analytics, and increase student retention by providing personalized support. Early guidance in particular may contribute to first-year students' persistence, as they often describe the transition to higher education as challenging, for example with regard to coping with academic demands (Evans 2000; Hughes and Smail 2015; Yorke 2000; Yorke and Longden 2008). This synthesis is illustrated in a model that aims to contribute to further discussion and future research on the interconnectedness of learning analytics and digital badges in efforts to enhance student retention in higher education.

2 Student Retention and Generic Skills in Higher Education

There are numerous approaches to investigating students' experiences in their first year of studies. They often concentrate on conceptual models for student retention (Bean and Metzner 1985; Tinto 1975, 1993), measurements for readiness and success (ACT 2008;

Conley 2011; Jansen et al. 2013), the transition to higher education (Bowles et al. 2014; Hughes and Smail 2015; Kantanis 2000), expectations (Brinkworth et al. 2009; Crisp et al. 2009; Nadelson et al. 2013), and reasons for dropout decisions (Krause 2005; Yorke and Longden 2008). Consistent factors for discontinuing higher education found in studies include wrong choice of course, lack of motivation, personal factors such as financial problems, health, and family circumstances, an unsatisfactory first-year experience, lack of university support services, and academic unpreparedness (Heublein 2014; Nadelson et al. 2013; Thomas 2002; Tinto 1993, 2012; Willcoxson et al. 2011; Yorke and Longden 2008). Yorke and Longden (2008), for example, surveyed 462 students in the UK and found seven factors that accounted for 60.9 % of variance for leaving higher education prior to degree completion, with poor quality of learning experience (16.6 %), not coping with academic demands (9.6 %), and wrong choice of field of study (8.7 %) being the most important aspects. The inability to cope with academic demands is associated with insufficient study skills for higher education, for example academic writing and note taking (Goldfinch and Hughes 2007; Tinto 1993; Wingate 2006). Research shows that university teachers often expect first-year students to enter with certain study skills. However, studies reveal that not all students are academically prepared for higher education requirements, for instance independent studying, time management, and digital literacy (Brinkworth et al. 2009; Jansen and Suhre 2011; Jansen and van der Meer 2007; Prensky 2001; Taylor and Bedford 2004; Waters 2003). Students' digital literacy is often taken for granted by higher education institutions based on the myth of the net generation (Margaryan et al. 2011; Murray and Pérez 2014; Selwyn 2009). However, research has shown that even people with sophisticated technology skills for leisure activities are not automatically competent in using technologies for learning (Lai and Hong 2014; Schulmeister 2010). Thus, students are often unprepared to transfer their skills for personal digital use to an educational context.

This academic unpreparedness can be linked to the concept of generic skills, which, in contrast to subject-specific skills, focus on interdisciplinary aspects, such as critical thinking, independent learning, time management, and problem solving (Bennett et al. 1999; Clanchy and Ballard 1995; Griffin et al. 2012; Leggett et al. 2004). Generic skills, often also labeled as soft skills or 21st century skills, have been examined and internationally assessed by large-scale studies focusing on learning outcomes and competencies carried out by the OECD, such as the Program for International Student Assessment (PISA) (OECD 2014), the Assessment of Higher Education Learning Outcomes (AHELO) (Tremblay et al. 2012), and the Programme for the International Assessment for Adult Competencies (PIAAC) (OECD 2013b). Binkley et al. (2012), for instance, provide a broad overview and analysis of 21st century skills and organize these skills into four groups: ways of thinking (creativity and innovation, critical thinking, problem solving, decision making, learning to learn, metacognition), ways of working (communication, collaboration), tools for working (information literacy, ICT literacy), and living in the world (citizenship, life and career, personal and social responsibility).

While these studies indicate the relevance for generic skills for all levels of education, traditional degrees normally do not certify them. Reasons for this may include discussions about generic skills' complexity and interactiveness with different contexts, instruments for assessment, standards for certification, trust and validation. Digital badges may function as an alternative form of recognition and validation in competency-based education and assessment (Gibson et al. 2013; Hickey 2014; Sullivan 2013). Furthermore, learning analytics may contribute to student retention by using learners' data for prediction and by providing meaningful real-time feedback on students' learning status, strengths, and areas for improvement (Ifenthaler 2015; Lauría et al. 2012).

3 Learning Analytics in Higher Education

Learning analytics uses dynamic information about learners and learning environments to assess, elicit, and analyze them for modeling, prediction, and optimization of learning processes (Ifenthaler 2015; Ifenthaler et al. 2014). Campbell and Oblinger (2007) postulate five steps of the analytic process: capture, report, predict, act, and refine. Student data for analytics is captured on the basis of multiple resources, such as student information systems (SIS), LMSs, financial systems, and several online devices students use for learning. The SIS, for example, provides student data, such as demographics, academic ability, and academic performance. The LMS provides information about academic effort, such as student engagement in the LMS, and the financial system provides information such as student aid usage (Campbell and Oblinger 2007). In using these student data, however, it is necessary to discuss topics like data quality, ethics of use, data privacy, and learner rights (Campbell et al. 2007; Long and Siemens 2011; Siemens 2012; Siemens et al. 2013; Slade and Galpin 2012). Reports requested by educators on demand provide insight into learning progress. Therefore, data from the SIS, LMS, and financial system is used to generate a statistical algorithm for predictions, for instance about students' likelihood of passing a course. On the basis of the model's result, the institution can provide feedback and support services (Bach 2010; de Freitas et al. 2015).

Since learning analytics is an emerging field of study in the area of education, numerous frameworks have been proposed which focus on objectives, potentials, and challenges (Chatti et al. 2012; Ferguson 2012; Greller and Drachsler 2012; Ifenthaler and Widanapathirana 2014; Scheffel et al. 2015). Greller and Drachsler (2012) propose a learning analytics framework considering six critical dimensions, including stakeholders, objectives, data, instruments, external constraints, and internal limitations. Regarding objectives, they make a fundamental distinction between reflection and prediction. Reflection is seen as critical self-evaluation, while learning analytics can support reflection by suggesting interventions or activities designed to enhance the learning process. Predicting and modeling learners' activities can be used for early interventions to prevent dropouts, as well as to adapt services and curricula. Scheffel et al. (2014) introduce a framework of five quality indicators for learning analytics, including objectives (awareness, reflection, motivation, behavioral change), learning support (perceived usefulness, recommendation, activity classification, detection of students at risk), learning measures and output (comparability, effectiveness, efficiency, helpfulness), data aspects (transparency, data standards, data ownership, privacy), and organizational aspects (availability, implementation, training of educational stakeholders, organizational change). Ifenthaler and Widanapathirana (2014) propose a holistic learning analytics framework that combines various types of educational information in a meaningful way. Components include users' individual characteristics and physical data, their interactions within social networks and online learning environments, as well as curricular elements, stakeholder groups (institutions, governance), a learning analytics engine, a personalization and adaptive engine, and a reporting engine. Papamitsiou and Economides (2014) examined the literature on experimental case studies conducted within the domains of learning analytics and educational data mining from 2008 to 2013. They classified 40 core case studies with regard to learning settings, analysis methods, research objectives, algorithmic-oriented findings, and pedagogy-oriented findings. Focusing on research objectives, they classified the case studies into six categories, with the majority exploring student behavior modeling and predictions of performance, followed by students' and teachers' increased reflection and awareness, predictions of dropout and retention, improvement of assessment services and feedback, as well as recommendations for resources.

These frameworks describe aspects of learning analytics that should be considered as guidelines for developing learning analytics projects and for designing and implementing learning analytics applications. In order to contribute to student retention in the first year of higher education, three common aspects derived from the presented frameworks are crucial, including (1) predictive models and algorithms, (2) learning support recommendations and feedback, and (3) data privacy and ethical issues.

(1) One objective of learning analytics is the prediction of which students are at risk of failing a course. In this regard, learning analytics is used as an early warning system, which may be particularly relevant for the crucial first year of higher education (Brinkworth et al. 2009; Jayaprakash et al. 2014; Reason et al. 2006; Tinto 1993). Data used for the predictive algorithms is usually derived from LMS and SIS, including such variables as high school grades, course grades, activities in the learning environment, socio-economic status, gender, and citizenship (Campbell and Oblinger 2007; Chatti et al. 2012). Predictive models enable institutions to forecast learner processes and to model student success rates. The institution can use this information in a proactive approach to intervene at an early stage of risk, and create and adapt appropriate support services in order to enhance teaching quality, students' first-year experience, and thus student retention in higher education (Arnold and Pistilli 2012; Colvin et al. 2015; Gašević et al. 2016). For educators, learning analytics provides real-time insight into students' performance and progress (Corrin et al. 2013) and therefore the opportunity to refine their practice, plan teaching activities, and create a learning environment that is highly adaptive for students as well as to intervene early enough by providing appropriate support to improve students' chances of success and prevent them from failing a course (Arnold and Pistilli 2012; Barber and Sharkey 2012; Greller et al. 2014). Hence, teachers need to be competent in interpreting the data (Papamitsiou and Economides 2014; Romero et al. 2008). While some educators may appreciate this support and view the student information as beneficial for their teaching (Arnold and Pistilli 2012), concerns may arise with regard to objectivity and fairness in dealing with students (Slade and Galpin 2012). Moreover, learning analytics tools provided by researchers may be too complex for practitioners, and a lack of acceptance and knowledge of learning analytics can make it challenging to implement in educational settings (Siemens 2012; Siemens et al. 2013). As learners receive notifications concerning their chances of failing or passing a course, they can reflect on their learning progress. Personalized recommendations are provided and expected to support students in achieving their learning outcomes, ultimately increasing student retention (Colvin et al. 2015; de Freitas et al. 2015).

(2) Learning analytics provides automated real-time feedback and suggestions for academic guidance through multiple sources (e.g., learning analytics dashboard, LMS visualization, email) that can contribute to learners' self-regulated learning, motivation, goal achievement, and success (Corrin and de Barba 2014; Hattie and Timperley 2007; Long and Siemens 2011; Siemens et al. 2011). Corrin and de Barba

(2014) analyzed 28 students to gain insights into how students interpret and act upon the feedback delivered through learning analytics dashboards. Their findings indicate that the majority of participants reported increased motivation after seeing the feedback, which was mainly associated with the regulation of effort and the awareness of progress. Arnold and Pistilli (2012) reported a positive impact of the learning analytics application Course Signals on students' learning and motivation. Tanes et al. (2011) examined the content and nature of the feedback given in Course Signals and found, for example, that student success was associated with instructional rather than motivational feedback. These results are promising for student retention, and especially first-year students may benefit from early feedback and guidance. Further research is needed to verify the impact of feedback on students' engagement, performance, and retention in higher education (Verbert et al. 2013). Moreover, it should be considered that detailed information about progress and support services may motivate some students, continuous feedback and guidance may disempower students from becoming independent learners and developing competencies, such as critical thinking, metacognition, reflection, learning-to-learn skills, and autonomous learning (Shum and Crick 2012; Ifenthaler et al. 2014; Long and Siemens 2011).

(3) As learning analytics uses student data collection to measure and analyze learning processes, it also necessitates a discussion of privacy and ethical issues. Pardo and Siemens (2014) define privacy as "the regulation of how personal digital information is being observed by the self or distributed to other observers" and ethics as "the systematization of correct and incorrect behavior in virtual spaces according to all stakeholders" (p. 438). Several privacy and ethical issues have emerged, and frameworks and guidelines have been proposed (Drachsler and Greller 2016; Ferguson et al. 2016; Sclater and Bailey 2015; Prinsloo and Slade 2013; Slade and Galpin 2012; Willis et al. 2013). Pardo and Siemens (2014) identified four principles with which to categorize the numerous issues concerning data privacy and ethics of learning analytics: transparency, student control over the data, security, and accountability and assessment. Transparency means that all stakeholder groups should be informed about when, how, and what type of data is collected, stored, and processed. Student control over the data empathizes with users' right to access and correct the data obtained about them. Institutions should ensure data security to avoid users' highly sensitive data being exposed. Accountability refers to the identification of responsible entities, and assessment refers to the constant evaluation, revision, and refinement of data collection, security, transparency, and accountability. Slade and Prinsloo (2013) classify issues for learning analytics into three categories (location and interpretation of data; informed consent, privacy, and the de identification of data; and classification and management of data) and introduce an ethical framework featuring six principles. For example, they argue that student identity and performance are temporal and dynamic constructs, and that student data may be incomplete and analyses misinterpreted and biased. Thus, student success should be seen as a complex and multidimensional phenomenon. While students' control over their data is emphasized in most guidelines, ethics and data protection affects teachers as well. For instance, institutions also use learning analytics to assure the quality of teaching performance (Greller and Drachsler 2012). With the focus on student retention, further research and discussion should address questions such as how long the institution will keep students' data, whether the institution will use students' data after graduation (e.g. for longitudinal studies over

several years and cohorts), and whether instructors can still remain objective toward students when they have access to this data and know which of them are at risk of failing (Pardo and Siemens 2014; Slade and Galpin 2012).

Some higher education institutions have already implemented learning analytics. Sclater et al. (2016) present ten prominent examples in the U.S., Australia, and the UK. These and other examples of universities that utilize learning analytics to identify at-risk students include Purdue University (Arnold 2010; Arnold and Pistilli 2012; Pistilli and Arnold 2010), the University of Phoenix (Barber and Sharkey 2012), the Open University UK (Wolff et al. 2014, 2013), and the University of Wisconsin (Shehata and Arnold 2015).

Employed since 2007, Purdue's application Course Signals indicates students' status of failing a course using an algorithm of four components: students' performance as indicated by grades in the course; students' effort as measured by interactions with the university's LMS in comparison to peers; students' past academic history, such as GPA and scores on standardized tests; and demographic variables, such as age, attempted credits, and residency (Arnold 2010; Arnold and Pistilli 2012). Real-time feedback in the LMS is provided and displayed by a traffic light that signals whether students are likely to be successful in the course (green), have potential problems (yellow), or are at high risk to fail (red), as well as via personalized emails from instructors, text messages, reminders, referral to academic advisors, and face-to-face meetings. According to Arnold and Pistilli (2012), nearly 24,000 students and more than 145 instructors used Course Signals in 2012. Quantitative research revealed a positive impact on students' academic performance in courses that implemented Course Signals, with increased A/B grades (12 %) and less D/F grades (9 %) than the control group. Furthermore, the authors reported a significantly higher retention rate for the 2007, 2008 and 2009 cohorts that used Course Signals compared to students who had no Course Signals classes. For example, in 2007 the retention rate of 5134 students with no Course Signals courses was 83.4 % in the first year and decreased to 69.4 % in the fourth year, compared to the experimental group of 1518 students with at least one Course Signals course, which had a retention rate of 96.7 % in the first year and 87.4 % in the fourth year. To gain insight into students' perspective on Course Signals, more than 1500 students who used Course Signals participated in surveys, focus groups, and interviews across five semesters. According to quantitative data, 89 % reported positive experiences with Course Signals and 74 % stated that their motivation to change their learning behavior was positively affected by Course Signals (Arnold and Pistilli 2012).

The University of Phoenix developed several prediction models and discussed variables on the basis of a literature review in order to create a valid model to predict students' likelihood of failing a course (Barber and Sharkey 2012). To create the algorithms, the university aimed to use only existing data from the SIS, LMS, and the financial aid system, therefore not considering unavailable variables, such as self-discipline, motivation, locus of control, and self-efficacy. In a test of different models, the percentage of cumulative points students earned was found to be the strongest predictor for potential problems for undergraduate students enrolled in online courses, followed by the students' financial status. The model, constructed using a tenfold cross-validation procedure, was reported to be highly accurate for predicting whether students would pass or fail a course, with 85 % accuracy at week 0 and 95 % by week 3 of 5.

Predictive models of student success in courses are promising and already feature good accuracy. To further increase accuracy, generic skills should be included in predictive models, as they have been identified as one of the contributing factors to student retention (Thomas 2002; Tinto 1993; Yorke and Longden 2008). Ifenthaler (2015) identified the missing connection between learner characteristics, learning behavior and curricular requirements as a limitation of learning analytics frameworks and proposed linking various types of education information, including competencies such as digital literacy, in a meaningful way. One reason for the exclusion of generic skills thus far may be because data about students' generic skills is usually not available in the SIS or LMS. Digital badges provide the opportunity to assess and certify generic skills, which could then be included as a variable in predictive models.

4 Digital Badges in Higher Education

Described as a "new way to capture and communicate what an individual knows and can demonstrate" (Finkelstein et al. 2013, p. 1), digital badges are symbols or indicators of learning achievements, skills, competencies, and interests across educational contexts use (EDUCAUSE 2012; Gibson et al. 2013; Ifenthaler et al. 2016). Learners can collect the digital images in their personal badge system, such as Mozilla's freely available Open Badges framework, and display them on other social media platforms and professional networks like LinkedIn (Glover and Latif 2013; Põldoja and Laanpere 2014).

In 2012, the Mozilla Foundation and Peer 2 Peer University introduced digital badges as a valuable technology for educational settings. Since then, digital badges have been implemented in various educational institutions. Oliver (2016) gives an overview of 19 higher education institutions that utilize digital badges, including examples such as Coursera by Stanford University, Open2Study backed up by Open Universities Australia, and Passport by Purdue University.

The concept of awarding badges for achievements has a long tradition. For instance, earning badges is a concept scouting programs use to certify the acquisition of knowledge or skills (Halavais 2012; Wu et al. 2015). Moreover, badges have been used in games with features such as scores and levels to encourage players to continue the game (Ahn et al. 2014). Thus, digital badges in education are related to the concept of gamification, the use of game design elements, such as scores and levels, in non-game contexts (Deterding et al. 2011).

Transparency is an important aspect of digital badges and aims to validate and justify the badges. Thus, the badge image file includes information about the issuing organization, for example a higher education institution, the criteria for obtaining the badge, the date of issue, and evidence of the accomplishment, such as an artifact or document (Gibson et al. 2013; Grant 2014; Jovanovic and Devedžic 2015). Wright and O'Shea (2014) documented these criteria in a worksheet that should be completed by the badge developer prior to badge creation in a badge platform. Newby et al. (2016) introduce guidelines for designing digital badges in the Passport platform. For instance, students' digital literacy can be presented in a digital badge such as "Being Digitally Literate in the 21st Century", which is one of multiple digital badges designed to achieve the key competencies for the course "Intro to Educational Technology". Examples of potential learning activities include ones in which students have to "review how current teachers are modeling digital literacy and the teaching of 21st century skills", activities where they "create ways to effectively teach digital literacy and 21st century skills to other teachers", and those which stipulate that required evidence and assessment criteria consist of a "clear written summary of what it means to be digitally literate". In terms of learners' orientation and motivation, the purpose and objectives of digital badges, key questions, case scenarios, requirements, and the value of the skills and knowledge when accomplishing the badge are all described in the platform as well as any prerequisite badges (e.g., basic badges for 21st century skills, and learning and technology).

As discussed by Mozilla Foundation and Peer 2 Peer University (2012), Hickey (2012), Gibson et al. (2013), and Jovanovic and Devedžic (2015), for example, digital badges can play four main roles in education: (1) motivation, (2) recognition of learning, (3) signaling of achievements, and (4) capturing of learning paths. These functions of digital badges have the potential to contribute to student retention in higher education (5).

(1) Motivation is perhaps the aspect of digital badges that has been discussed most. Motivation is a crucial aspect of learning and performance and has been broadly researched in motivation theories, for example with respect to intrinsic and extrinsic motivation (e.g., Bandura and Cervone 1983; Bandura and Schunk 1981; Deci et al. 1991; Försterling 2001; Heckhausen et al. 1985; Malone and Lepper 1987; Schuster et al. 1989; Weiner 1986). In this perspective, digital badges can be recognized as rewards and thus may impact learners' motivation (Moon et al. 2011). Existing research on analogue programs aimed at earning points, such as sticker charts or reading points, may provide valuable insight into how the digital version may affect learner motivation and engagement (Deci 1971; Lepper et al. 1973). The motivational aspect has received attention in many studies. For example, Abramovich et al. (2013) found that the motivational effects of digital badges depend on learners' prior knowledge and that different types of badges (e.g., participatory badges and skill badges) have different effects on student motivation as well as on learning performance. Resnick (2012) argues that the collection of badges itself could become the motivational focus for students instead of the learning content. Badge designers should consider motivation theories when developing digital badges, for example by asking questions concerning target group, purpose, and relevance (Newby et al. 2016), as well as instructional design considerations such as Keller's (1987) ARCD model that describes four aspects of motivation: attention, relevance, confidence, and satisfaction. Furthermore, Tran et al. (2014) analyzed 30 digital badge projects and extracted eleven design principles for motivating learning, such as displaying badges to the public, setting goals, collaborating, and providing privileges.

(2) Digital badges can serve to recognize and verify learning. Different types of badges, such as smaller badges for motivational aspects or feedback and larger badges for certification purposes, also allow a greater granularity of skills, knowledge, competencies, as well as capacity for work (Ahn et al. 2014; Mozilla Foundation and Peer 2 Peer University 2012; Põldoja and Laanpere 2014). Hence, digital badges can display informal skills, such as collaboration, entrepreneurial thinking, and social skills, as well as 21st century skills like digital literacy skills, which are usually not recognized in university degrees (Gibson et al. 2013). As traditional tests focus mainly on knowledge assessment, digital badges may represent generic competencies and soft skills or newer skills such as digital literacies (Jovanovic and Devedžic 2015; Mozilla Foundation and Peer 2 Peer University 2012). Grading Soft Skills (GRASS) (European Commission 2014) is a research project carried out by the European Union (EU) that focuses on the development of pedagogical, technological, and administrative solutions for grading learners' soft skills at different levels of education as well as in formal and informal learning settings. The aim is to create digital badges as credentials, and gradual recognition for the development of soft

skills by educational institutions and employers in a quantitative and measurable way. From this perspective, digital badges are not intended to replace traditional certificates and degrees, but to complement traditional assessment approaches and mechanisms of recognition. Moreover, frameworks for generic skills and key competencies such as the Programme for the International Assessment for Adult Competencies (PIAAC) (OECD 2013b) may function as an orientation for creating standardized digital badges (Finkelstein et al. 2013).

(3) Digital badges can signal achievements to relevant stakeholders, such as university teachers or potential employers (EDUCAUSE 2012; Foster 2013). Glover (2016) conducted a survey containing both quantitative and qualitative elements and found that 19 of 26 respondents used digital badges to show their experience in professional profiles to target potential employers. Research needs to be undertaken to investigate whether employers view digital badges as valuable for seeking employees and whether they trust and accept digital badges as symbols of skills and competencies (EDUCAUSE 2012), even though employability might not be the most crucial aspect of students' first-year retention in higher education. When shared publicly in social networks or placed on user profiles (e.g., via Carney Labs' MARI: https://www.mari.com/, ADL's CASS: https://www.adlnet.gov/introducing-the-next-big-thing-cass/), digital badges also contain a social context, including such aspects as reputation and group identification (Antin and Churchill 2011; Mozilla Foundation and Peer 2 Peer University 2012). Moreover, open access to digital badges on web-based platforms raises questions about how to design technical and social systems for badge production (Ahn et al. 2014), as well as issues about data privacy such as whether badge data can be used against individuals if it exposes intellectual weaknesses (Willis et al. 2015).

(4) Digital badges may support learners in capturing and planning their learning paths (Ahn et al. 2014). Digital badges represent skills earned in various contexts, such as vocational education and professional experience (West and Lockley 2016). Thus, they may connect learning pathways from different educational and professional backgrounds. As signposts, they can function as a means of guidance for learners and thus enhance their self-regulation (Jovanovic and Devedžic 2015). In a quantitative study with 155 students participating in a MOOC, participants reported that digital badges were helpful for tracking their learning progress (Dona et al. 2014).

(5) Digital badges can contribute to students' first-year experience and enhance student retention. First-year students can feel motivated to achieve digital badges that recognize and verify their learning within the higher education institution, as well as in informal settings and from previous experiences. The signaling of learners' achievements and the capturing of learning paths can assist first-year students in the transition to higher education by providing structure, as well as targeting short-term and long-term goals. Glover and Latif (2013) believe that digital badges have the potential to assess less obvious learning and thus support retention and employability, and the Mozilla Foundation and Peer 2 Peer University (2012, p. 5) argue that digital badges can "encourage continued engagement and retention". Kelley and Hickey (2014) reported "high retention rates" in a big open online course (BOOC) on educational assessment in which digital badges were issued. Out of 460 registrants who started the course, over 160 (35 %) completed the first assignment and 60 (37 %) completed the course. Moreover, learning motivation is a crucial factor for student retention (Atkinson 1957; Baik et al. 2015; Tinto 1975; Weiner

1985, 1986). On account of their gamification elements, digital badges may encourage students to keep on track with their studies or make learners aware of their skills and therefore motivate them to either extend those skills or explore new learning paths (Gibson et al. 2013; Jovanovic and Devedžic 2015). In a study by Põldoja and Laanpere (2014, p. 176) one participant revealed that “if there is a possibility to collect something, I want to achieve all the possible badges.”

In addition to the open questions concerning the main roles of digital badges in education and student retention stated above, potential challenges to implementing digital badges in higher education institutions include stakeholders’ understanding and acceptance of them (EDUCAUSE 2012; Grant 2014), technological frameworks (Dimitrijević et al. 2016; Mozilla Foundation and Peer 2 Peer University 2012), and learning and instructional design considerations (McDaniel and Fanfarelli 2016; Randall et al. 2013). Moreover, digital badges’ validity, transparency, and trust should be discussed in depth.

5 Synthesis: Interconnectedness of Learning Analytics, Digital Badges, and Generic Skills in Enhancing Student Retention

So far, this integrative review provides a separate overview of learning analytics and digital badges. However, similarities and intersections exist, such as their motivational aspect and issues surrounding data privacy and ethics. Furthermore, learning analytics may be used to analyze digital badge data and to provide recommendations on which digital badges are appropriate to achieve next.

Figure 1 depicts a model that aims to synthesize learning analytics, digital badges, and generic skills with a focus on student retention. All three aspects may have an individual impact on student retention (dotted arrows) as described above; however, the model focuses on their interconnectedness (loops). Two loops can be distinguished. First, (1A) generic skills can be represented as digital badges, (1B) which can be used in algorithms to predict student success in courses and (1C) to provide students with personalized feedback about their strengths and weaknesses as well as guidance regarding support services. Second, (2A) when generic skills are considered as a variable for the predictive algorithm to identify students’ status quo for higher education demands, (2B) learning analytics may directly suggest digital badges that can be earned to meet these requirements, and (3B) students may feel motivated to develop their skills on the basis of the gamification elements of digital badges and the visualization of their learning paths and learning progress.

(1A) Generic skills with regard to students’ preparedness for higher education can be represented as digital badges. For example digital literacy, which higher education institutions often expect from incoming students. In a competence-based approach, digital badges offer a new opportunity to signal 21st century skills (Binkley et al. 2012; Gibson et al. 2013; Sullivan 2013). Digital badges visualize students’ skills and competencies, allowing students to identify their achievements as well as share their digital badges with relevant stakeholders, such as university teachers and potential employers, via social networks. In this regard, Glover and Latif (2013, p. 1398) emphasize the potential to support employability as well as retention “by surfacing the less-obvious learning that is often hidden due to the focus on grades and transcripts”. For example, digital literacy can be certified with digital badges.

(1B) While the student data is available in the form of digital badges in the badge ecosystem, it can be used for learning analytics to improve the predictive model for student

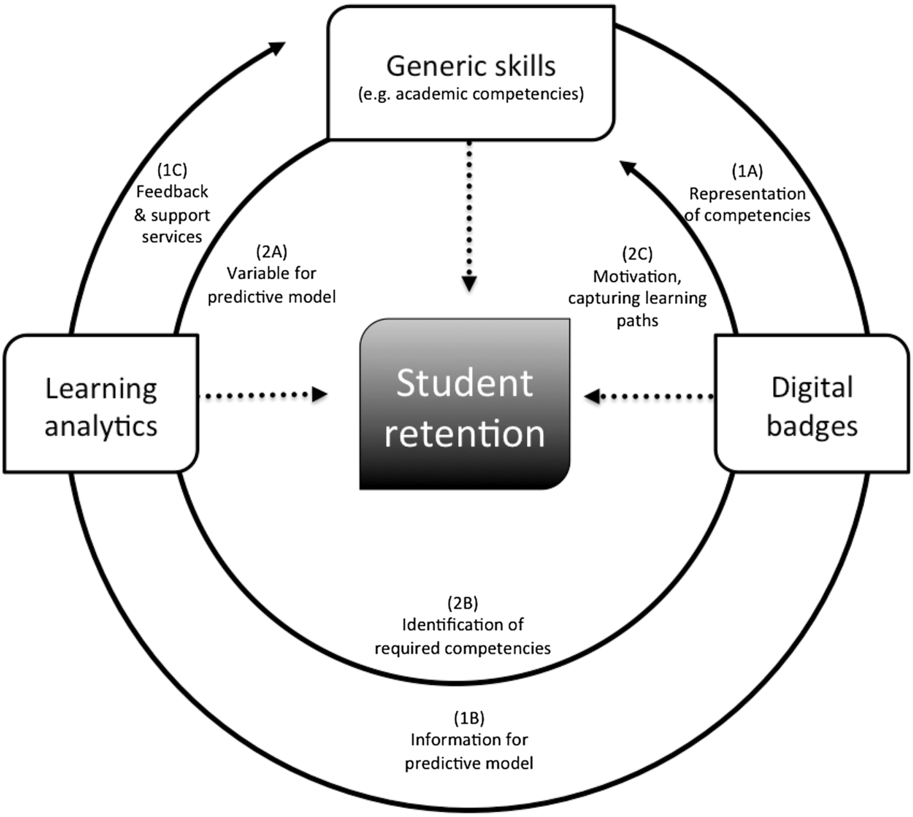

Fig. 1 Model of learning analytics, digital badges, and generic skills

success in courses. For predictive models, the numbers and types of digital badges can be weighted and scored, such as academic performance measured by GPA or standardized test results. Ifenthaler and Widanapathirana (2014) introduce a learning analytics framework including individual characteristics and physical data, learners' interaction with the social web and online learning environments, and curricular requirements. In this regard, digital badges are assigned to individual characteristics, including sociodemographic information, interests, prior knowledge, and demonstrated skills and competencies, such as computer literacy. Universities have been developing different models to predict student success more precisely (Barber and Sharkey 2012; Wolff et al. 2013). However, generic skills concerning academic demands and preparedness have been excluded in predictive models, although research has identified study skills as one of the contributing factors to student retention (Thomas 2002; Tinto 1993; Yorke and Longden 2008).

(1C) On the basis of the results of the predictive model, students receive personalized feedback about their strengths and weaknesses as well as guidance for support services. Examples for support services to enhance student retention include tutoring and mentoring programs, first-year seminars, and learning communities (Barefoot et al. 1998; Chatti et al. 2012; Clark and Cundiff 2011; Keup 2005; Scott et al. 2008; Tinto 2012).

Second, (2A) generic skills should be considered as a variable for the predictive algorithm identifying students' status quo for higher education demands. The inability to cope with academic demands is identified as one of the main reasons for withdrawals prior to degree completion (Tinto 1993; Yorke and Longden 2008). Some generic skills needed in higher education, such as time management and collaboration, are included in assessments of academic behavior and college readiness for incoming students [e.g. the Learning and Study Strategies Inventory (LASSI) (Weinstein and Palmer 1990), the Readiness and Expectations Questionnaire (REQ) (Jansen et al. 2013)]. These test results may be used in the algorithm to predict first-year students' likelihood of being successful in a course; however, the instruments' validity and type (e.g. self-report, measurement of competencies) needs to be considered. Furthermore, generic skills and competencies, such as learning strategies and digital skills, are dynamic parameters that can change over time (Ifenthaler and Widanapathirana 2014; Slade and Prinsloo 2013). Certified as digital badges, learners' progress and achieved competencies need to be regularly adapted for adequate predictions.

(2B) The predictive model recommends areas in which students need to improve and may directly suggest digital badges that can be earned in order to meet higher education demands. Thus, digital badges may make institutions' expectations of generic skills more transparent for students. Research has shown that students' adjustment to universities' expectations is an important factor in their successful transition to higher education and may contribute to enhancing student retention (Jackson et al. 2000; Smith and Wertlieb 2005; Yorke 2000). For instance, the Assessment of Higher Education Learning Outcomes (AHELO) framework provides examples of generic skills that may be important for students in higher education and thus valuable to obtain as digital badges. Moreover, Berge and Muilenburg (2016) argue that digital badges have relative or perceived value depending on the stakeholders' perspective.

(2C) Students may feel motivated to develop their skills on the basis of the gamification elements of digital badges and the visualization of their learning paths and learning progress. West and Lockley (2016) indicate that digital badges can build learning pathways between vocational education, higher education, and other training providers. In this perspective, digital badges can signal both subject-specific skills for courses as well as generic skills earned in various settings. Universities can provide guidance for learning pathways and support students in developing the competencies needed for higher education. Thus, these early interventions can enhance students' first year experience and thus contribute to student retention.

6 Discussion and Further Research

This integrative review provides an overview of learning analytics and digital badges in higher education with a focus on student retention. Research has shown that learning analytics has the potential to impact student success at universities (Arnold and Pistilli 2012; Barber and Sharkey 2012; Gibson and de Freitas 2015; Slade and Galpin 2012). Further empirical evidence and longitudinal research, however, are required to analyze whether learning analytics has a significant impact on first-year student progress and overall retention during their studies. Furthermore, Siemens (2012) suggests widening learning analytics research from its recent focus on identifying students at risk to include strategies for significantly optimizing the learning process. While learning analytics in higher education is still an emerging field, little empirical evidence on the sustainability of feedback and recommended guidance is available. With focus on student retention, studies that examine the quality of suggested academic support are needed, also with regard to feedback on generic skills for higher education. Further, criteria for measuring and operationalizing generic skills and academic preparedness have to be defined in order to integrate them into predictive algorithms. In this respect, digital badges may function as a means of defining achievements that can be used for predictive models.

As the use of digital badges in higher education is relatively new, there is a large research field to explore. There are already some studies available that focus on different aspects of digital badges, especially on their motivational impact. There have been fewer studies on how digital badges can influence student retention in higher education. When implementing digital badges, higher education institutions should provide information in the form of an introduction to this technology. Digital literacy is a prerequisite for understanding the concept of digital badges and using them adequately. Although students are assumed to be digital natives with sophisticated digital skills, research indicates that this label is a myth and not a reality for all students (Margaryan et al. 2011; Schulmeister 2010). Additionally, it will be necessary to collect empirical evidence to gain insight into how students view, experience and value digital badges, for instance with regard to their learning process and academic success. Furthermore, research on digital badges should address whether educators are competent enough to create meaningful badges that certify the acquisition of generic skills, explore strategies for enhancing student retention, and focus on their potential impact on the first-year experience, as this period is crucial for student retention.

To provide an initial synthesis of learning analytics, digital badges, and generic skills for enhancing student retention in higher education, a model (Fig. 1) was developed to serve as a platform for discussion, further research, and development. It will be necessary to conduct research to provide empirical evidence for the proposed model. For example, research needs to address the development of digital badges that aim to certify generic skills and how these digital badges may contribute to the predictive algorithm of learning analytics. In this light, studies observing the motivational impact of provided feedback and recommended digital badges are suggested in order to provide valuable practical insight into the theoretical model presented here.

Moreover, there are various fields of education that will benefit from learning analytics and digital badges, for example within the context of higher education such as MOOCs (Fournier et al. 2011; Dona et al. 2014; Pursel et al. 2016), and outside of higher education such as K-12 (Elkordy 2016) and professional development (Gamrat and Zimmerman 2016; Metzger et al. 2016). Future studies on learning analytics and digital badges, qualitative as well as quantitative, need to be conducted to obtain in-depth insight into these emerging research fields. In addition, studies should provide and report empirical evidence to enrich the discussion about the potential and limitations of learning analytics and digital badges. Many authors have predicted that learning analytics and digital badges will play a significant role in the future of higher education (Johnson et al. 2013; Johnson et al. 2014; Long and Siemens 2011), and indeed, both show promise as means of impacting student learning and thus enhancing student retention in higher education.

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