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Opportunities and challenges in the emerging field of Learning Analytics

A literature review

ir. M.A. (Rianne) Conijn
prof.dr. C.C.P. (Chris) Snijders
dr. U. (Uwe) Matzat
dr.ir. P.A.M. (Ad) Kleingeld

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Management summary

Assessing information about students and their behaviour is traditionally conducted using questionnaires, interviews, and observations. However, with the introduction of ICT into learning and teaching, data are now easily collected from Learning Management Systems (LMSs). LMSs, also called Virtual Learning Environments (VLEs), are online systems which provide content online and allow for additional benefits such as presentations, quizzes, screen casts, assignments, and forums. As every click in these systems is recorded, students' (online) behaviour is measured, without an intervention needed. It is therefore not surprising researchers started to use these data. Interpreting and contextualizing data about students, to improve learning and teaching, is also known as learning analytics.

As learning management systems are a relatively new development, the field of learning analytics is rather new, with its first conference held in 2010. The field has attracted a variety of researchers with different backgrounds, including computer science, statistics, (educational) psychology, psychometrics, and several other fields. Hence, already a wide variety of research can be found. Therefore, this literature review provides an overview of the interdisciplinary field of learning analytics. Three categories of studies were found in the literature: predicting student performance, analytics and visualization tools, and implementing learning analytics. This report is the first one of the project "EXCTRA - EXploiting the Click-TRAil. Assessing the benefits of Learning Analytics". The main objective of the project is to figure out how Learning Analytics can be better used to predict student performance. We therefore explicitly identify gaps in research predicting student performance that we address in later phases of the project.

Predicting student performance: Gaps in the study of learning analytics data

Predicting student performance is by far the most common topic found in learning analytics. Learner data (such as demographics, characteristics, and dispositions), course data, and data from learning management systems can be used to predict student performance. Most studies only used data from learning management systems and have shown that LMS data, such as the amount of content views, forum posts, or quizzes passed, can be used to predict student performance to some extent within their specific context. However, within these studies, a wide variety can be found in the variables extracted from the LMS and the analytical methods used. Even when the same method and variables are used, differences are found in the outcomes. Thus, it has indeed been shown that within several courses it is possible to predict student performance based on LMS data, but it is hard or impossible to draw general (that is, cross-course) conclusions about which parts of LMS data will be of use in predicting student performance.

Gap: determine better which general (that is, cross-course) insights can be retrieved from learning analytics data.

To be able to draw more general conclusions and better compare the different studies, the link between educational theories and the included measurements should be made much more explicit. This could give a better motivation for which variables should be included to begin with and it would give clearer insight in how the results could be interpreted.

Gap: there is a lack of studies including educational theories explicitly in learning analytics applications.

A disadvantage of most current studies is that they estimate student performance based on LMS data available at the *end* of the course mainly. This is insightful, but of little use for teachers who might be interested in influencing students who are at risk of a poor course performance.
Gap: there is a lack of studies estimating (for instance) course performance soon after the course has started.

Many studies that model some kind of student behaviour (mostly study results) only report model fit statistics that are not obviously related to prediction error. As one example: a study reporting an R^2-value of 0.75, which is a very high value when compared to R^2-values in other social-scientific research, nevertheless has prediction confidence intervals that are so wide that using the model to actually predict future performance would be hazardous (consider: the future score of this student is likely to be a 6.75 plus or minus 2).
Gap: there is a lack of concern for the size of actual prediction intervals.

Lastly, it is a useful idea to combine LMS data with learner data and course data. This could give additional insight into which source is most useful for predicting student performance, could show more clearly how learner data are related to LMS data, and might improve the portability of the prediction models.
Gap: there is a lack of studies combining LMS data with other data (most importantly learner data and course data).

Learning analytics tools

As using and interpreting the raw LMS log data might be very complex, analytical tools have been made to help educators with interpreting this data. Moreover, visualization tools are implemented to help teachers with tracking students' behaviour. These visualization tools can often be used by students as well, to track their own study progress, compared to their peers. Although the tools can help the instructors, most tools are still found too complex. Hence, future work should make the tools less complex to use. Moreover, more evaluation of the tools is needed to assess the user experience and improve the tools. Lastly, as most tools are now used within only one institution, the tools should become open source and freely available so more institutions can use it. In this way, the tools can also be evaluated more generally.

Implementing learning analytics

An emerging theme in learning analytics is the actual implementation of the learning analytics, the actual use of the analyses of learner data to improve learning and teaching. For successful implementation several frameworks have been proposed. The implementation in turn can be evaluated, which is often referred to as action analytics, to determine whether the implementation actually improved learning and teaching. As this theme recently emerged in learning analytics, there are a lot of opportunities for future work. The frameworks for implementing action analytics should be used within other institutions as well. Moreover, action analytics should be extended, to get insight in the impact of learning analytics and which interventions are useful in which situations.

Thus, the field of learning analytics is rather new and offers many opportunities for future work. Especially, learning analytics should move outside the specific institutions, to be able to draw more general conclusions about the prediction models, to make the analytics and visualization tools more freely available, and to get a better insight in how and in what situations learning analytics can improve learning and teaching.

Contents

1 Introduction

In the last few decades, ICT has emerged more and more in learning and teaching. This resulted in the adoption of learning management systems (LMSs), also known as Virtual Learning Environments (VLEs), in a vast majority of educational institutions (Retalis, Papasalouros, Psaromiligkos, Siscos, & Kargidis, 2006). LMSs have the goal to support student learning by providing course content, and by allowing for additional benefits such as quizzes, presentations, assignments, and forums (Piña, 2012). These developments do not only change the way courses are taught and learned, but also provide opportunities to improve learning and teaching. As all clicks are monitored and stored in LMSs, this gives a lot of information about the behaviour of users in these systems. Interpreting and contextualizing this information to improve learning and teaching, increasing student success, and detecting at-risk students, i.e. students who have a high chance of failure, is also known as learning analytics (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014).

Although the term learning analytics is rather new, already a wide variety of research can be found within the field. This is mostly due to the wide variety of backgrounds of the researchers, including computer science, statistics, (educational) psychology, psychometrics, and several other fields (Clow, 2013). These backgrounds result in different goals of learning analytics, different methods used, and publications scattered amongst multiple journals. This variety and spread makes it hard to get a good overview of the field and which questions still need to be answered. Therefore, this literature review discusses current research and topics in the field of learning analytics with its challenges and opportunities. This review does not aim to provide a complete list of all studies conducted in the field, but it focuses on giving an overview of the range of literature available.

2 Scope

Literature on learning analytics can be found in the specific journal and conference on learning analytics: the *International Conference on Learning Analytics and Knowledge* and the *Journal of Learning Analytics*. However, using reference search, cited reference search, and keyword search in general search engines such as Google Scholar or Web of Knowledge, a lot more journals and conferences can be found where learning analytics is addressed. Useful keywords for these searches are: ‘learning analytics’, ‘academic analytics’, ‘educational data mining’, ‘action analytics’, ‘predicting student performance’, ‘predicting student success’, ‘predicting academic success’, ‘predicting academic achievement’, ‘student modelling’, ‘learning management systems’, ‘course management systems’, and ‘virtual learning environments’.

Based on these searches 87 papers were selected, scattered over more than 30 journals and conference proceedings. We found that learning analytics is closely related to the fields of educational data mining and academic analytics. Moreover, three central topics emerged: predicting student performance, analytics and visualization tools, and implementing learning analytics. In the current literature review we first define the field of learning analytics, and compare it to the adjacent fields. Thereafter the three central topics are discussed, with the main focus on predicting student performance, as this is the most common subject in the literature. These prediction studies are categorized on the different types of predictors used: learner data, course data, and data from learning management systems. Finally, a comprehensive overview for future work and research directions is given.

3 Defining the field

Learning analytics has emerged as an interdisciplinary research field over the last decade. Already in this short period of time, multiple definitions have been provided for learning analytics (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). In the current literature review, we define learning analytics as the measurement, collection, analysis, and reporting of behavioural data, contextual data, and learner data, for purposes of understanding and optimising learning and the environments in which it occurs (Siemens, 2011). The growing research community initiated the annual Learning Analytics and Knowledge (LAK) conference in 2010 and in 2011 the Society of Learning Analytics Research (SoLAR) was formed (Clow, 2013; Siemens & Baker, 2012). Although the field and the term learning analytics is rather new, analysing student data to understand how students learn and to improve learning and teaching has been a topic of research over decades. For example, for 80 years class attendance has been found to predict performance (Dollinger, Matyja, & Huber, 2008).

Formerly, analyses of student data was mostly done by researchers from the fields of social sciences, educational psychology, and pedagogy. These studies were often based on earlier research or frameworks, and were tested with validated questionnaires. For example, Jenson (1953) used standardized tests and grade point average (GPA) to predict student achievement. One often used theory in these studies is the constructivists learning theory, which proposes that learning is based on an active process of constructing knowledge rather than just acquiring it. Based on this theory Vermunt (1998) found that for realising constructive, high-quality learning, the control of the learning process should be transferred from the teacher to the students.

With the advancement of computers and internet, the field entered a whole new era. The adoption of learning management systems (LMSs) to assist courses resulted in new and more data available, as every action of a student in the LMS is stored. LMSs are used for online content creation, communication, assessment, and administration (Piña, 2012). A variety of commercial academic learning management systems are available, including Blackboard, Angel, Desire2Learn, and Pearson eCollege as well as open source LMSs, including Moodle and Sakai. All these systems record every click, resulting in a rich pool of (raw) data. LMSs are used for fully online as well as blended learning courses. Blended learning is a combination of a face-to-face course with e-learning, where a significant amount of the course is presented online (Hoic-Bozic, Mornar, & Boticki, 2009). Thus, with blended courses, not all behaviour is monitored in the LMS, as there is also offline behaviour, for example in lectures. However, even with fully online courses not all behaviour is monitored, as students can for example download materials and read them offline, or use other offline or online communication platforms to contact their peers.

Thus, data from LMSs cannot give a complete overview of all behaviour, but it can provide a significant amount of information about students and their learning processes without intervention. Additionally, LMS data show actual (online) behaviour of all students, compared to questionnaires which only consist of self-reports on behaviour, learner dispositions, and abilities, and of only students who participated in the questionnaire. Because of these advantages, more and more researchers started using LMS data. As LMSs were used more, the amount of data available increased extensively, which made it harder and more time consuming to analyse the data. Improvements in data mining techniques in other fields made it possible to deal with those large amounts of data and to conduct more advanced analyses (Clow, 2013). Both the adoption of LMS data and advancements in data mining techniques led to an increased interest in the field (Siemens & Baker, 2012). This lead to the advent of the term ‘learning analytics’ and the development of the subarea academic analytics and the adjacent field educational data mining (Clow, 2013).

3.1 Academic Analytics

Learning analytics is a subarea of academic analytics. Academic analytics not only focusses on the usage of LMS and student administration data for improving teaching and learning, but for improving all decision-making processes in educational institutions. Goldstein (2005) was the first to use the term academic analytics “to describe the intersection of technology, information, management culture, and the application of information to manage the academic enterprise” (p. 2). In the beginning most institutions used these analytics for recruitment strategies to improve the enrolment processes. Nowadays more and more institutions also use it to improve teaching, learning, and student success, i.e. for learning analytics (Agudo-Peregrina et al., 2014; Campbell, DeBlois, & Oblinger, 2007). An often mentioned challenge in academic analytics is privacy, because all actions of a student can be tracked (Campbell & Oblinger, 2007). Moreover, it is unsure what the obligations are of the students, faculty, and institutions to act on the received information from the analysis and what the consequences are of a false prediction (Campbell & Oblinger, 2007). Lastly, academic analytics is limited by the lack of skilled staff for analysis (Goldstein, 2005).

3.2 Educational Data Mining (EDM)

The field of learning analytics shows quite some overlap with educational data mining. The goal of educational data mining (EDM) is to better understand how students learn and identify the settings in which they learn, to improve educational outcomes and gain insight into and explain educational phenomena (Romero & Ventura, 2013). The first EDM workshop was held in 2005, followed by its first international conference in 2008 and the Journal of Educational Data Mining in 2009 (Siemens & Baker, 2012). The current topics of interest in EDM include the development of generic frameworks and methods for mining the data, to be able to obtain more general results across studies; educational process mining, based on the processes in LMSs; data-driven adaptation and personalization; and replication studies (Romero & Ventura, 2013).

Hence, both learning analytics and educational data mining focus on improving learning and teaching. Romero and Ventura (2013) describe EDM as a combination of the fields of computer science, education, and statistics, with the subareas computer-based education, data mining, and machine learning, and learning analytics (**Error! Reference source not found.**). However, other iterature shows that a distinction between learning analytics and educational data mining is not made that easy. Multiple papers try to compare and contrast the fields and come up with different comparisons (Romero & Ventura, 2013; Siemens & Baker, 2012). The most notable difference between researchers using the term 'educational data mining' and researchers who use the term 'learning analytics' is that EDM is mostly used by computer scientists. This results in more advanced data mining techniques used, and a focus on comparing these techniques, automated discovery, and automated adaption as intelligent tutoring systems in EDM (cf. Siemens & Baker, 2012). On the other hand, learning analytics is mostly conducted by researchers from social sciences, resulting in models which are primarily used for informing educators about their decision-making processes and improvements in their teaching, rather than about automated adaptations in teaching and student feedback (cf. Siemens & Baker, 2012).

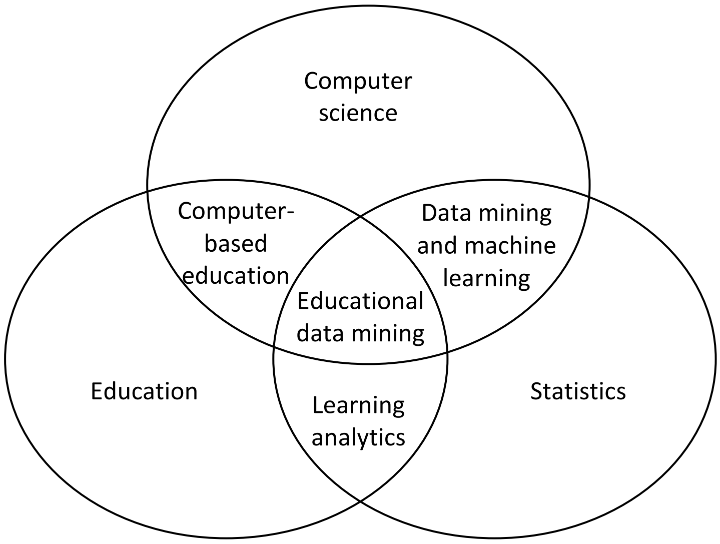

Figure 1: Overview of fields related to Educational Data Mining and Learning Analytics (Romero & Ventura, 2013, p. 13).

Thus, both learning analytics and educational data mining have similar goals, but somewhat different methods to achieve these goals. Even though the fields show quite some overlap, there is little communication and collaboration between the fields. Sharing findings and collaboration could benefit both fields, and therefore Siemens and Baker (2012) argue that more communication between the fields is necessary. Accordingly, in the current literature review, we will not only discuss current challenges and research goals in learning analytics, but also include some relevant studies from the field of educational data mining.

3.3 Overview of goals and methods in learning analytics

Research in the field of learning analytics can be categorized by a large amount of goals, methods, and tasks, but little consensus has been reached on these categorizations. Romero and Ventura (2007) analysed papers in educational data mining from 1995-2005 and grouped these papers based on task in two categories: 1) statistics and visualization, and 2) web mining. Three year later the same authors conducted a literature review on 304 papers and categorized these in eleven task categories: 1) analysis and visualization of data, 2) providing feedback for supporting instructors, 3) recommendations for students, 4) predicting student's performance, 5) student modelling, 6) detecting undesirable student behaviour, 7) grouping students, 8) social network analysis, 9) developing concept maps, 10) constructing courseware, and 11) planning and scheduling (Romero & Ventura, 2010). Baker (as cited in Baker & Yacef, 2009) classified the trends in EDM into five categories: 1) prediction, 2) clustering, 3) relationship mining, 4) distillation of data for human judgement, and 5) discovery with models. Literature reviews combining literature on educational data mining and learning analytics distinguished a somewhat different set of goals and methods. The goals found were: 1) student modelling, 2) predicting student's performance, 3) increasing students' self-reflection, 4) predicting student retention or drop-out, 5) improving feedback and assignments, and 6) recommendation of resources (Chatti et al., 2012). The methods found were: 1), classification, 2) prediction, 3) data mining, 4) visualization, 5) statistics, and 6) social network analysis.

Thus, most categorizations mention predictive models, visualization, and some way of actually using the findings for recommendations or human judgement. These are also the categories of studies we found in the consulted literature. Hence, the current literature review focuses on these three topics.

4 Predicting student performance

Most studies on learning analytics focus on predicting student performance. Student performance is often quantified by final grade or whether the student passed a course or not. Data used for predictive modelling can come from the learner itself, such as student characteristics, demographics, and dispositions, the course, and the learning management system used.

4.1 Learner data

Most analytics on learner data fall into the field of learning analytics, and only a small number of studies can be categorized as educational data mining. This is because data mining techniques are new, compared to the use of learner data for predicting student performance. Moreover, learner data often does not offer enough input for these complex data mining techniques in comparison to the vast amount of data available in learning management systems.

Studies on learner data influencing student success have resulted in a stable set of variables found influencing academic performance. The most important and robust predictors of student success are ability, measured by tests such as SAT and ACT, and past performance, quantified with past GPA (Bipp, Kleingeld, & Schinkel, 2013; Conard, 2006; Dollinger et al., 2008; Hattie, 2008; Superby, Vandamme, & Meskens, 2006). However, ability and GPA cannot account for all variability in student success. Especially in higher education these variables have less predictive power, as the range of intelligence scores get restricted. Therefore, researchers also tested other predictors, cited in literature as 'non-cognitive predictors' (O'Connor & Paunonen, 2007).

First of all, several trait variables have been found to be important in predicting student success. Trait variables are non-controllable and relatively stable in a person over time. Personality is a trait variable known to be a robust predictor of student success. Personality is frequently tested with the Big Five traits of personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Especially conscientiousness is found to be a stable predictor. A meta-analysis of papers using the Big Five traits as predictors showed that the mean correlation between performance and conscientiousness was $r = 0.24$ (O'Connor & Paunonen, 2007). The mean correlations of the other factors were considerably lower: openness to experience $r = 0.06$, extraversion $r = -0.05$, agreeableness $r = 0.06$, and neuroticism $r = -0.03$.

Contrary to personality, sex is found to be an unstable predictor of academic success, with women being more successful than men in some cases (Bipp et al., 2013; Kotsiantis, Pierrakeas, & Pinteas, 2004; Van den Berg & Hofman, 2005), and no significant effects in other (Bipp et al., 2013; Superby et al., 2006). Being older than average as well as having children is found to have a negative effect on performance (Kotsiantis et al., 2004; Superby et al., 2006). Additionally, educational level of one's parents is found relevant for study success, but only for immigrants (Kaufman, Agars, & Lopez-Wagner, 2008). For natives, educational level of parents does not have a significant effect (Superby et al., 2006; Van den Berg & Hofman, 2005).

Next to trait variables, also state variables have been identified as important predictors of student success. As state variables are under the control of the student, they can change over time due to practice, training, or different contexts. Even though trait variables can often explain large amount of variance in students' results, researchers emphasize the importance of the state variables as these can actually be changed by students to improve their success. State variables such as motivation and time management have been found positively correlated with student success (Bipp et al., 2013; Britton & Tesser, 1991; Hattie, 2008; Kaufman et al., 2008). Kaufman et al. (2008) found that intrinsic and extrinsic motivation could explain an additional 6% of variance in student success next to GPA and parental educational level. Britton and Tesser (1991) found that time attitudes, i.e. the feeling that you are in charge of how your time is spent, could account for 15% of the variance in GPA, and short-range planning for an additional 6%. Long-range planning was not found to have a significant influence. Superby et al. (2006) found that perceptions of the environment and the academic context did not have a significant influence on academic success. However, students who felt they had made a thorough decision for what university they wanted to go to did receive a higher average grade ($r = 0.18$).

Lastly, behaviour such as class attendance is shown to be significantly correlated with exam scores ($r = 0.38$) (Dollinger et al., 2008). Class attendance also increased the amount of variance explained in exam scores when added as an explanatory variable next to next to the uncontrollable factors GPA and verbal ability. Superby et al. (2006) also found that class attendance was positively related to academic success ($r = 0.25$). Conard (2006) found that attendance, partly mediated by conscientiousness, was positively related to GPA.

Overall, research showed that state variables, trait variables, and behaviour combined could account for 16% (Kaufman et al., 2008), 20-30% (Bipp et al., 2013), 36% (Britton & Tesser, 1991), 43% (Dollinger et al., 2008) of the variance in student success.

4.2 Course data

Next to learner data, course design and scheduling characteristics have also been pointed as possible predictors for student success (Van den Berg & Hofman, 2005). In a large scale synthesis of meta-analyses, Hattie (2008) found that positive predictors of achievement next to learner data consisted of: teaching approaches, such as providing formative evaluation of the programs (r = 0.90); teacher, such as teaching for a small group (r = 0.88); teaching strategies, such as cooperative and competitive learning (r = 0.59); classroom, such as classroom cohesion (r = 0.53); and teaching practices, such as questioning (r = 0.46). Providing feedback on performance is also found to be positively related to performance (Hattie & Timperley, 2007; Kluger & DeNisi, 1996).

Compared to learner data, course data might be easier to change to improve overall performance, as they are not controllable at the student level, but at the institutional or teacher level. However, Van den Berg and Hofman (2005) found that most variance is explained at the student level: course and scheduling characteristics had almost no influence on student performance. Only passive education (e.g. lectures) resulted in a significantly lower study progress compared to active education (e.g. seminars, workshops). Rienties, Toetenel, and Bryan (2015) tested data of 87 courses and showed that course design does have some impact on performance. Modules with a high proportion of assimilative learning activities, such as reading content, had a negative influence on completion and pass rates. Positive relations were found between pass rates and productive activities (actively constructing an artefact) and assessment activities, however these were not found statistically significant. All other learning activities did not have a significant relation with performance.

4.3 LMS data

LMS data are analysed in a variety of studies, using different types of LMSs, blended or fully online courses, and different techniques. LMS data are often gathered from courses at the university where the researchers work, but an increasing amount of open LMS datasets become available as well (Verbert, Manouselis, Drachsler, & Duval, 2012). As LMSs provide raw data, the data are pre-processed to produce (predictor) variables. A variety of variables are used in the literature. For example, Calvert (2014) examined approximately 200 variables for predicting course completion. The analyses range from relatively simple multiple linear and logistic regression models to more complex and advanced data mining techniques. An overview of the studies, techniques, and LMSs used to predict student success can be found in Table 1.

Table 1: Overview of studies using LMS data to predict student performance

	LMS	Number of students	Number of courses	Techniques used	Regression Accuracy (R^2) [1)]
(Agudo-Peregrina et al., 2014)	Moodle	356	8	Classification of predictors, Multiple Regression	
(Arbaugh, 2014)	Blackboard + Desire2Learn	1,118 (total)	6 + 42	Hierarchical Multiple Regression	13%
(Beer et al., 2010)	Moodle + Blackboard	91,284 + 1,515	2,674 + 40	Correlation	
(Davies & Graff, 2005)	Blackboard	122	6	Kruskal-Wallis test	
(Dawson et al., 2008)	Blackboard	1,026	1	*t*-Test	
(Gašević et al., 2016)	Moodle	4,134	9	ANOVA, Chi-squared test, Multiple Regression, Logistic Regression	21%
(Hu et al., 2014)	*N/A*	300	1	Classification (3 techniques)	
(Iglesias-Pradas et al., 2015)	Moodle	39	10	Multiple Regression	- %[2)]
(Jayaprakash et al., 2014)	Sakai	15,150	*N/A*	Classification (4 techniques)	
(Joksimović et al., 2015)	Moodle	352	204	Hierarchical Multiple Regression	
(Kovanović et al., 2015)	Moodle	81 + 4,049	1 + 9	Multiple Regression	
(Lauría et al., 2012)	Sakai	3,877	4	Correlation, Classification (3 techniques)	
(Macfadyen & Dawson, 2010)	Blackboard	118	1	Correlation, Multiple Regression, Logistic Regression, Network Analysis	33%
(Milne et al., 2012)	*N/A*	658	9	Chi-squared test	
(Minaei-Bidgoli & Punch, 2003)	LON-CAPA	227	1	Classification (6 techniques)	
(Morris et al., 2005)	eCore	284	3	Correlation, Multiple Regression	31%
(Munoz-Organero et al., 2010)	Moodle	180	3	Correlation	
(Nandi et al., 2011)	Blackboard	645	2	Graph (visualization)	
(Rafaeli & Ravid, 1997)	OnLine	178	3	Multiple Regression	22%
(Rienties et al., 2015)	Moodle	21,803	87	Clustering (3 techniques)	
(Romero et al., 2013)	Moodle	438	7	Classification (21 techniques)	
(Tempelaar et al., 2015a)	Blackboard	873	2	Correlation, Hierarchical Multiple Regression	4%
(You, 2016)	*N/A*	530	1	Hierarchical Multiple Regression	37%/58%
(Yu & Jo, 2014)	Moodle	84	1	Multiple Regression	34%
(Zacharis, 2015)	Moodle	134	1	Correlation, Multiple Regression, Logistic Regression	52%

[1)] Accuracy for predicting pass/fail probabilities is not reported, as a lot of different accuracy measures are used.
[2)] All variables were removed from the model as no significant relations were found.

4.3.1 Statistical analyses

Rafaeli and Ravid (1997) were one of the first to use LMS data for learning analytics. They evaluated the implementation of an LMS, based on the usage of the online environment and performance in the course. Data from 178 undergraduate and graduate students in three blended classes were analysed. Students who were inexperienced in using online systems tended to stick to a page-by-page reading order, whereas more experienced students adopted a much more non-linear style. Linear regression analyses showed that 22% of the variance in final grade could be explained by the amount of pages read and the grades for online questions posted during the course. This is quite far away from an accurate prediction, but is still a high amount when taken into account that a large proportion of students read the materials offline, about one third of the students used usernames and passwords from other students on occasion, and about half of the students did not use internet prior to the course. This all restricts the reliability of the predictor variables.

Likewise, Morris, Finnegan, and Wu (2005) found that the number of content pages viewed was a significant predictor in three fully online courses (‘English Composition II’, ‘Introduction to Geology’, and ‘U.S. history to 1865’) in eCore (n= 354) as well. Contrary to Rafaeli and Ravid (1997), they used a total of eight duration and frequency variables, and no in-between measurements of performance. Multiple regression analyses with these predictors on final grade of the 284 completers showed that 31% of the variability in final grade was accounted for by the number of discussion posts viewed, the number of content pages viewed, and the time spent on viewing discussion posts. Moreover, they found that withdrawers had a significantly lower frequency of activities and spent less time online, compared to completers.

Macfadyen and Dawson (2010) also found that the amount of links and files viewed had a positive correlation with final grade. However, these variables did not turn out to be significant predictors in their final model. As in Morris et al. (2005), a fully online course was analysed, but using another LMS: Blackboard. In total, 13 of the 22 variables examined had a significant positive correlation with final grade. Multiple regression analyses showed that 33% of the variance in final grade of 118 completers could be explained by three variables: the total number of discussion messages posted, mail messages sent, and assessments completed. A binary logistic regression resulted in a classification accuracy of 74%, where 38 out of 63 students who failed were accurately predicted as at risk, and 49 out of 65 successful students could be accurately predicted as not at risk.

Only the number of discussion posts was found in both final prediction models of Macfadyen and Dawson (2010) and Morris et al. (2005). The usage of the discussion forum was important for predicting student performance in several other studies as well. In an analysis of discussion forum usage in Blackboard in a course of 1,026 students, Dawson, McWilliam, and Tan (2008) found a significant effect of discussion forum usage on final grade. Students who made at least one post in the forum scored on average 8% higher than students who did not post at all. Moreover, they found that low and high performing students did not differ in the time spent per session, but low performing students attended fewer online sessions than high performing students.

Discussion posts and interactions with peers were also found significantly correlated with final grade in blended courses in Moodle. Yu and Jo (2014) analysed data of 84 students in the course ‘Understanding of science and public administration’. Six variables were tested: total log in frequency, total time online, regularity of study interval, number of downloads, number of interactions with peers, and number of interactions with the instructor. Total time online and interaction with peers correlated significantly with final grade. All predictor variables combined accounted for 34% of the variance in final grade. Using the same LMS with 134 students in one course, Zacharis (2015) could explain 52% of the variance in student performance, using three predictors. Contrary to Yu and Jo (2014), 29 variables were analysed of which 14 correlated significantly with final grade. Total time online, the amount of files viewed, and the amount of links viewed were found to have a significant correlation with final grade, but as in Macfadyen and Dawson (2010), these were not retained in the final model for predicting student performance. Only four predictors were included: the number of files viewed and three broader variables measuring various interactions, contributions to content, and quiz engagement. Binary logistic regression resulted in an overall accuracy of 81%: 30 out of 43 students who failed were correctly predicted, and 79 out of 91 students who passed were correctly predicted.

Although You (2016) also found that the number of discussion posts was related to final grade, this variable was not found a significant predictor in the final model. You (2016) used data from 530 students in an online course. Next to the number of discussion messages posted, the other variables extracted were more related to time management. Using hierarchical multiple regression it was found that regularity of studying, number of sessions, number of late submissions, and proof of reading the course information package could explain 58% of the variance in final course grade and 37% of the variance in course exam grade.

Nandi, Hamilton, Harland, and Warburton (2011) did not obtain a significant effect of forum usage on student performance at all, with data from 645 students using Blackboard in two courses. They did find a trend that high-achieving students participated more in the forum than other students. However, only 40% of the students participated in the forum, indicating that forum participation might be a more useful predictor when it is used by a high proportion of the students. Likewise, Davies and Graff (2005) also only found a trend of the effect of forum usage, with Blackboard data from 122 students in six courses. Students who failed a course showed a consistently lower proportion of forum usage compared to whole LMS usage. A higher proportion of forum usage increased the likelihood of better performance. A Kruskal-Wallis test showed a significant difference in only one of the courses for the proportion of forum usage between students who passed the course and students who failed.

Network analysis in Netdraw showed the importance of the forum relationships next to the measures of forum usage. Data of one fully online course on Blackboard with 118 students showed that low performing students had a small student interaction network, mainly consisting of low-performing peers, while high performing students had a dense network, comprised of more high-performing peers (Macfadyen & Dawson, 2010).

As could be seen, most studies analyse only one or a few courses, in one or a few institutions. A few studies offered more general results. For example, a large scale study on 2,674 Blackboard courses with 91,284 students and 40 Moodle courses with 1,515 students showed that there was a positive correlation between the number of clicks and final grade in both learning management systems (Beer, Clark, & Jones, 2010). A literature review on 34 studies describing the use of an LMS, showed that students differed in the usage of the LMS (Lust, Juarez Collazo, Elen, & Clarebout, 2012). Most students use the required tools for the course, such as the content pages. Quizzes are used less. Only a few students post messages on the forums, while many read the posts.

Although all these studies report how well the regression or classification model performs, this is not always a useful metric. The model fit statistics as R^2-values are not obviously related to prediction error. It might be more insightful to know how far away the prediction is from the true value, on average, or how the classification accuracy is away from a baseline, such as just predicting that everyone will pass. This could for example give more insight in whether the model could be used for automated assessment. It would therefore be useful if future work would include more metrics to get a better understanding of the outcomes, such as prediction confidence intervals.

4.3.2 Data mining techniques

Other studies used more complex methods to classify students, based on whether they are likely to pass the course or not. Minaei-Bidgoli and Punch (2003) compared six classification techniques for classifying students in 2, 3, or 9 classes based on their final grade. Data was collected from 227 completers in one course in LON-CAPA LMS and included the variables: number of correct answers, getting problem right on the first try, number of tries, time spent on problem until solved, time spent on the problem regardless of it was solved, and participating in communication. In total 72% of the students passed the course. The maximum prediction accuracy was 82% for 2-class prediction, thus 10% higher than when they would just predict that everyone would pass. The accuracy was 60% for 3-class prediction and 43% for 9-class prediction. A combination of the classification techniques yielded better prediction accuracy (87%, 71% and 51%, for 2, 3 and 9 classes, respectively).

Romero, Espejo, Zafra, Romero, and Ventura (2013) compared 21 classification techniques with 10-fold cross-validation with 438 students in seven courses. To classify whether a student passed the course or not, they used nine variables: course, number of assignments submitted, quizzes passed, quizzes failed, discussions posted, and discussions read, time spent on assignments, quizzes, and forum. The highest percentage of correctly classified students as pass or fail found was 65%.

Thus, more complex classification techniques will not always result in higher accuracy in the classification. Also, most complex techniques are not easy interpretable, which makes it harder to use the results for improving learning and teaching. When more complex techniques are desired, Romero et al. (2013) suggest to use decision trees, rule indication and fuzzy rule algorithms, as these provide the best interpretable results.

4.3.3 Investigating early predictors

Most studies that have tried to predict student performance analysed the behaviour of students in the LMS during the whole course, after the course has finished. This indicates whether it is possible to infer study success from LMS data, but at a point in time where interventions are no longer meaningful (Campbell & Oblinger, 2007). Several but not many researchers have acknowledged this issue and decided to analyse potentially predictive data from early stages in a course.

For instance, Milne, Jeffrey, Suddaby, and Higgins (2012) have analysed LMS data of the first week of a course for 658 students in 9 blended courses. Students were grouped in no LMS usage, 1-5 page views, 6-20 page views, and more than 20 page views. They found that usage of the LMS in the first week of the course was significantly higher for successful students than for students who failed the course. Hu, Lo, and Shih (2014) predicted student performance of 300 students at three points in time during the course. In total fourteen different LMS variables were extracted, which were grouped for the first four, eight, and thirteen weeks of the course. Using three different classification techniques, it was found that prediction accuracy increased as the course progressed. The most significant predictors were the total time online, the number of course materials viewed, the average time per session, and the total time used for viewing materials.

Schell, Lukoff, and Alvarado (2014) have also found that prediction accuracy increases over time, while analysing performance data (entry test, midterms, and quiz grades) and self-efficacy. Multiple linear regression on 89 students in a blended course showed that 29% of the variance in final grade could be explained by the entry test. The explained variance increased to 34% when self-efficacy was included. The addition of midterm grades over time led to a substantial increase in prediction (partly because midterm scores were a significant part of students' final grades), and to a decrease in the predictive power of self-efficacy. Tempelaar et al. (2015a) also found that the prediction accuracy increases over time and that performance data are especially important. The number of clicks in the week before the course had started (week 0) was found to have the highest predictive power. As the course progressed, the prediction of student performance gradually improved. Assessment data from the quizzes were shown to be the best predictor, but these data are typically only available after a couple of weeks. Indeed, a notable improvement in predictive power was found in the week where the first assessment data became available. The authors therefore argued that the best time to predict student performance is as soon as possible after the first assessment, as this would be the best compromise between early feedback and sufficient predictive power.

4.4 Challenges and future work in predicting student performance using LMS data

The studies above show that there is a wide variety in the studies on LMS data. Especially the predictor variables used show a great diversity (see Table 2). Also, the regression models show a high variety in explained variance in final grade, including 4% (Tempelaar et al., 2015a), 22% (Rafaeli & Ravid, 1997), 31% (Morris et al., 2005), 33% (Macfadyen & Dawson, 2010), 34% (Yu & Jo, 2014), 52% (Zacharis, 2015), and 58% (You, 2016), see Table 1, page 13. Thus, there is no consistency in the methods and predictors used, but also the findings show a vast diversity.

Table 2: Predictor variables used in studies predicting student performance

		(Agudo-Peregrina et al., 2014)	(Arbaugh, 2014)	(Beer et al., 2010)	(Davies & Graff, 2005)	(Dawson et al., 2008)	(Gašević et al., 2016)	(Hu et al., 2014)	(Iglesias-Pradas et al., 2015)	(Jayaprakash et al., 2014)	(Joksimović et al., 2015)	(Kovanović et al., 2015)	(Lauría et al., 2012)	(Macfadyen & Dawson, 2010)	(Milne et al., 2012)	(Minaei-Bidgoli & Punch,	(Morris et al., 2005)	(Munoz-Organero et al., 2010)	(Nandi et al., 2011)	(Rafaeli & Ravid, 1997)	(Rienties et al., 2015)	(Romero et al., 2013)	(Tempelaar et al., 2015a)	(You, 2016)	(Yu & Jo, 2014)	(Zacharis, 2015)
Total	Number of online sessions					X				X			X	X										X		X
	Number of logins		X				X	X				X													X	
	Regularity of study interval																	X						X	X	
	Number of LMS hits/interactions	X[1)]		X					X[1)]		X[1)]							X			X[2)]		X[2)]			X
	Number of LMS hits first week														X								X			
	Time per session					X		X																		
	Time per interaction										X[1)]															
	Total time online							X						X							X[2)]		X[2)]		X	X
General	Number of course page views											X														X
	Number of announcement views													X												
	Course information read [Y/N]																							X		
Content	Number of downloads																								X	
	Number of files viewed							X						X												X
	Number of resources viewed						X					X														X
	Numbers of links viewed													X												X
	Number of content page views						X			X		X	X				X	X		X						
	Time spent viewing content pages							X				X[3)]					X									
	Time spent on viewing videos																							X		
Forum	Number of clicks in the forum						X					X						X								
	Number of discussion posts views				X							X	X	X			X		X			X				X
	Total number of discussion posts					X							X	X		X			X			X		X		X
	Number of original posts											X		X			X									
	Number of follow-up posts							X				X		X			X									
	Number of follow-up posts to peers																								X	
	Number of follow-up posts to instructor																								X	
	REPO messages (email, chat, discussion forum)																									X
	Time spent on forum											X[3)]					X					X				
	Time spent creating original posts											X[3)]					X									
	Time spent creating follow-up posts											X[3)]					X									

Mail	Mail messages read													X												X
	Mail messages sent													X												
Chat	Use of chat function						X					X														
	Number of chat posts											X														X
	Number of chat views													X												X
	Time spent on chat											X[3)]														
Quiz / Assessment	Number of clicks in the quizzes						X					X														X
	Number of quizzes started											X	X	X		X										X
	Number of quizzes continued																									X
	Number of quizzes passed													X		X						X				X
	Number of quizzes failed																					X				
	Number of quizzes right at first try															X										
	Number of quiz views											X														X
	Number of quiz reviews											X														X
	Quiz grades																			X						
	Time spent on quizzes until solved															X						X				
	Time spent on (un)solved quizzes											X[3)]		X		X										
Assignment	Number of clicks in the assignments						X					X														
	Number of assignments read											X		X												X
	Number of assignments submitted							X				X	X	X								X				X
	Number of late assignments submitted							X																X		
	Time spent on assignments											X[3)]		X								X				
LMS tool	Uses of 'compile' tool													X												
	Uses of 'search' function													X												
	Use of ‘map’ tool						X					X														
	Visits to MyGrades tool													X												X
	Visits to MyProgress tool													X												
	Upload of photo to profile																	X								
	Uses of the 'who is online' viewer													X												
Wiki	Number of wiki edits																									X
	Number of wiki views																									X
	Number of wiki add pages																									X
Blogs	Number of blog updates																									X
	Number of blog views																									X

1) Categorized on interaction type: learner-learner, learner-instructor, learner-content, and learner-system

2) Grouped per week

3) Calculated with 15 different calculation strategies

The differences in predictor variables used can be explained by the fact that not all researchers have access to all variables in the LMS. Also, different courses and institutions can use different tools in the LMS. The differences in the findings can be explained by the multiple predictors used, but even when similar predictor variables are used, they are not always robust. For example, Morris et al. (2005) and Macfadyen and Dawson (2010) found a significant positive correlation between discussion forum posts and final grade, while Zacharis (2015) did not find a significant correlation. Moreover, Kovanović et al. (2015) showed that even when the same variable is used, just calculated differently, differences are found in the resulting prediction models. They analysed LMS data of ten courses in Moodle and used fifteen different methods to estimate the time on task (grouped in: no outlier processing, different processing of the last action, threshold the outliers and last action, threshold outliers and estimate the last action, and estimate outliers and last action). Especially when count measures (such as the total amount of clicks) were omitted, substantial differences were found between the effects of the fifteen time-on-task measures in the same courses.

Another explanation for the different outcomes is that most studies only describe special cases, where the outcomes apply to a specific institution, course, or group of students. For example when in a specific course the discussion forum is rarely used, it will be highly likely that it is a bad predictor, as there will be low variance in this predictor. On the other hand, in courses which regularly use the forum, it can be a very good predictor.

The case studies are useful for the institution or course itself, but of less value for other institutions and no general conclusions for the field of learning analytics can be drawn. Hence, it indicates that models predicting student performance used within one institution or course cannot simply be used in another institution or course. This is also referred to as the low portability of the prediction models (Lauría, Baron, Devireddy, Sundararaju, & Jayaprakash, 2012). Given the current results in the literature, we feel that future work should include research into the portability of models predicting student performance.

Moreover, to be able to compare the different models from different studies and to draw more general conclusions, it is useful to better connect learning analytics with educational theories (Gašević, Dawson, & Siemens, 2014). Most current studies are more data-driven and not explicitly based on theory (Clow, 2013). Including theory would provide better motivation for which predictors from the LMS data should be included. The count measures currently used cannot simply be related to the quality of learning (Gašević et al., 2014). For example, a high amount of clicks in an LMS does not have to mean that a student has a higher motivation or is more engaged. Theory would provide better arguments to ground learning analytics and the methodological choices made (Richardson, Abraham, & Bond, 2012). Additionally, including theory would also give more insight in how analytical results could be interpreted.

Lastly, it is useful to combine learner data, LMS data, and course data. The studies above showed that these three sources separately can be used to predict student performance. Data in learning management systems is collected real-time and each click is recorded, hence it might be more extensive and accurate than learner data (Campbell & Oblinger, 2007). On the other hand, self-reports provide a higher order of information about someone's state or intentions, compared to raw LMS event logs (Shum & Crick, 2012). Interestingly, after the introduction of LMSs most researchers started from scratch and only focused on online behavioural data, while ignoring the previous findings from learner data. Comparing LMS data with learner data might give insight about the usefulness of both predictors and might give more in which learner characteristics are related to LMS data. Additionally, combining research on LMS data with social sciences might result in more accurate predictions, as learner data can give more detailed and timely information (Shum & Crick, 2012). Combining course data with LMS data could improve the portability of the prediction models. Therefore, future work should not only focus on LMS data, but also take course data and learner data into account.

Thus, there are three challenges in prediction student performance using LMS data: the portability of the prediction models, the use of theory and frameworks, and the combination of LMS data with course data and learner data. Already a few studies have addressed these problems and their preliminary results are discussed below.

4.4.1 Examine the portability of the prediction models

The issue of the portability of the prediction models has been recognized at least from 2011, when the Open Academic Analytics Initiative (OAAI) was initiated. OAAI has the goal to advance the field of learning analytics by exploring the challenges in scaling learning analytics across all higher education institutions (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). The first two subgoals of this initiative specifically focus on the scaling of prediction models and on developing an open source model for predicting student performance (Lauría et al., 2012). Unfortunately, only a few researchers have started to investigate the portability of the prediction models.

Lauría et al. (2012) did test the portability of a prediction model for final grade between two institutions: Purdue University and Marist College (n = 18,968 and n = 27,276, respectively). Although these institutions differ in institutional type, size, approaches, and type of LMS used (Blackboard versus Sakai), similarities were found based on correlational analysis and the prediction models for final grade (Lauría et al., 2012). All variables analysed (the number of sessions, content viewed, discussions read, discussions posted, assignments submitted, and assessments submitted) correlated significantly with final grade in both institutions and had a similar effect size. A follow-up study found that the prediction model used at Marist College for classifying students as pass or fail, had a 10% lower accuracy when applied to data from three partner institutions (Jayaprakash et al., 2014). Hence, the authors argued that the portability of prediction models for student performance might be higher than expected.

However, Gašević et al. (2016) found that the portability across courses in an Australian university was not that high at all. They analysed and compared prediction models of nine first-year courses with a total of 4,134 students. The predictor variables consisted of the number of actions in the different modules in Moodle, with courses differing in the modules used. To control for individual characteristics, some student characteristics were included: age, gender, domestic versus international student, full versus part time program, and first course versus later course. Multiple linear regression showed that student characteristics accounted for 5% of the variance in final grade. The addition of LMS data led to an increase of 16% of explained variance. The models for all courses separately differed from each other and from the generalized model that included all courses. The authors argued that analysing the whole sample might underestimate or overestimate the effects of the predictors. Thus, it might not be a good idea to use a single model for multiple courses, questioning the portability of the models between courses. These contradicting results show that there is a need for further studies that enlarge the empirical base of the issue of portability of prediction models.

4.4.2 Use theory and frameworks

Thus far, few studies on learning analytics have explicitly connected theoretical arguments to the selection of prediction variables (Shaffer et al., 2009). Studies which do use theory often select their predictor variables based on the interaction theory of Moore (1989). This theory describes three kinds of interactions in a networked learning environment: learner–content interactions, learner–instructor interactions, and learner–learner interactions (Moore, 1989). Later, Hillman, Willis, and Gunawardena (1994) added a fourth type of interaction: learner-interface (or learner-system) interaction. Based on these types of interaction, Petropoulou, Retalis, Siassiakos, Karamouzis, and Kargidis (2008) proposed a framework of interaction including 1) outcomes: quantitative and qualitative, 2) types of interaction: learner-content, instructor-learner, and learner-learner, and 3) the effectiveness of the applied pedagogical model for building and maintaining a collaborating community. Based on this framework, a tool was created to analyse the interactions.

Agudo-Peregrina and colleagues (2014) used the types of interaction in their model for analysing Moodle data. LMS data were classified on type of interaction, frequency of use (most, moderately, or rarely used), and participation mode (passive or active). The classification was tested on data of eight courses, of which six fully online, with 20 to 30 students per course. The number of learner-learner interactions and learner-instructor interactions were found to be significant positive predictors of final course grade in fully online courses, but not in the blended courses. The number of learner-system interactions and learner-content interactions were not found to be significant predictors in both the blended and fully online courses.

Contrary, using the same classification, Joksimović, Gašević, Loughin, and Kovanović (2015) did find significant effects for learner-system and learner-content interactions. They analysed Moodle data of 352 unique students in 29 fully online courses with 204 offerings over six years. Hierarchical linear mixed models showed that the number of learner-content interactions had a negative relation with final grade, while the time spent on learner-system interactions had a positive relation. The number of learner-learner interactions only had a significant positive effect in the core and pre-master courses (not in the electives). Time spent on learner-instructor interactions even had a significant negative effect, but only in the core courses.

Other researchers based their framework on the different components in LMSs (Rankine, Stevenson, Malfroy, & Ashford-Rowe, 2009). The different components identified were content, communication, collaboration, assessment, and explicit learner support. This classification was shown useful for benchmarking activity in LMSs across two universities in Australia, using different versions of Blackboard LMS, with a sample of 10% of the courses. With the framework, the authors were able to find that in each component a similar amount of activity was found across both universities. The framework is however not (yet) used for grouping predictor variables for predicting student success.

Thus, there is not much empirical evidence yet showing whether predictors grounded in theory lead to more robust models for predicting student performance. Actually, the little amount of studies already show differences in the results, when the predictors resulting from the same theory are used. This emphasizes the need for more studies using theories, compared over multiple courses and institutions. Recently, the lack of educational theory in learning analytics already has received more attention, partly because the Journal of Learning Analytics has devoted a special section to this problem in 2015 (Dawson, Mirriahi, & Gasevic, 2015), including several papers in which the grounding of learning analytics in theoretical argumentation was at stake.

4.4.3 Combine LMS data with learner data and course data

By including instructional conditions and cognitive conditions, including beliefs, motivation, and prior knowledge, we can control for the effects of these conditions on the learning behaviour in the LMS. Additionally, comparing LMS data with learner data and course data might give insight in the usefulness of these predictors. Lastly, combining LMS data with learner data and course data might result in a higher portability and predictability, as the models also account for differences in the student and the courses. Indeed, a study using 29 courses with 204 offerings, with a total of 352 unique students, has found that the variance in students' performance (final grade), was accounted for a large extent by individual differences (18%) as well as by course offerings (22%) (Joksimović et al., 2015).

Some studies did supplement LMS data with basic background information about the student, such as age, gender, and prior education or prior GPA to control for these variables (Tempelaar, Heck, Cuypers, van der Kooij, & van de Vrie, 2013). However, most studies do not state any statistics about the influence of these variables (Arnold & Pistilli, 2012; Beer et al., 2010). Hence, it cannot be determined whether background variables are of any added value next to the LMS data. Others supplemented LMS data with some course characteristics, such as type of course (elective versus required) and the amount of students per course (Arbaugh, 2014; Joksimović et al., 2015). It could be reasoned that the type of course, prior academic data, and demographics, cannot be controlled by the student or teacher and are therefore not useful as indicators for students and teachers on how to improve student success (Yu & Jo, 2014). Other learner data, such as motivation and time management might be of more value, as these could be influenced.

However, the combination and comparison of behavioural data with learner data to predict student success is rare. To stimulate research in this area, Shum and Crick (2012) proposed a theoretical framework for combining learning dispositions, values, and attitudes with online behavioural data. Based on this framework, Tempelaar et al. (2013) combined online data from two test-directed environments with demographics, entry test data, self-reports on culture, learning style, and emotions. Regressions were done on data of 1832 students in two courses. Tempelaar et al. (2013) showed that prior education and entry test were significant predictors and therefore these variables were controlled for in later analyses. The most important predictor of academic performance was the level reached in the online test environment. Culture was found to have an impact on the amount of practice: masculinity and hedonism had a stronger influence on the intensity of practising, than on the outcomes of practising. Students with the stepwise learning style practised more often and had a better performance than other students. External regulated students benefitted most from practising while students with behavioural lacking regulation practised longer and more, but achieved less. Lastly, positive emotions had a positive influence on performance, while negative emotions had a negative impact. Unfortunately no statistics were mentioned, so the effects cannot be compared.

Tempelaar and colleagues (2015a) replicated the study from Tempelaar et al. (2013), and added data from Blackboard LMS and motivation and engagement questionnaires. The predictive power of all sources was analysed and compared. Linear hierarchical regression on 873 Mathematics and Statistics students showed that behaviour in the two test-directed environments could best predict performance (R = 0.51-0.66). Especially behaviour in the week before the course started had the highest predictive power, and week 3 seemed to be the best compromise between early feedback and high predictive power. Furthermore, entry test could predict performance (R = 0.41-0.45), followed by motivation and engagement (R = 0.27-0.34), and learning styles (R = 0.21-0.25). Interestingly, LMS data played just a minor role: only the number of clicks was a significant predictor, and all LMS data combined could explain a marginal 4% of the variance in performance. This low percentage of variance explained could be due the fact that most behaviour occurred in the e-tutorials, while the LMS was marginally used. Thus, which such rich data available, LMS data might not be of an added value.

Arbaugh (2014) added self-reported data from students and teachers to LMS data. He used data from 634 students and 18 instructors in 48 fully online courses (42 in Desire2Learn, 6 in Blackboard). They included four variables, based on both LMS data and self-reported data from instructor and learner surveys: instructor presence, social presence, perceived usefulness, and perceived ease of use. He controlled for which semester the course took place, how many times a student participated, the amount of students per course, required versus elective course, gender, age, and experience with online courses. Hierarchical regression on final course grade and perceived learning showed that the predictors could only explain an additional 2% of the variance in final grade over the control variables and an additional 40% of the variance in perceived learning. Students' social presence was the strongest predictor for final grade, while teacher presence had the highest effect size for perceived learning. Thus, reported teacher and student social presence had a higher influence on (perceived) learning than LMS data.

Lastly, a few studies combined course data and learner data could to predict LMS behaviour, to get a better insight in what LMS data represents. It can be argued that LMS behaviour mediates the relation between learner data and student success. For example, students who have a higher motivation might make more use of the LMS and therefore receive higher grades. Because of this, learner data are also used to predict LMS behaviour (Iglesias-Pradas, Ruiz-de-Azcárate, & Agudo-Peregrina, 2015). Indeed, Munoz-Organero, Munoz-Merino, and Kloos (2010) found positive correlations between motivation and LMS behaviour. They analysed learner data, which consisted of three types of motivation (intrinsic motivation, extrinsic motivation, and e-learning motivation) and LMS data of three offerings of a fully online course with 180 unique students. A correlation was found between uploading a photo to the students' profile page and intrinsic and e-learning motivation. The number of clicks in the content pages, the number of clicks in the forum, and the regularity of studying correlated with all three types of motivation.

Iglesias-Pradas and colleagues (2015) compared the competencies commitment and teamwork of 39 students with LMS data collected from Moodle. They showed that commitment and teamwork could not significantly predict LMS usage. This could be due to the low variety in the scores on these competencies, as commitment and teamwork were measured with six questions on a four point scale. As all participants also worked as teachers, they probably already had acquired these skills. It is thus likely that (almost) all scored on the upper half of the scale. Future research with a larger sample size and a less experienced group needs to be conducted to find out whether learner data can predict LMS behaviour.

Course design and participation of the teacher did have been shown to influence LMS behaviour. Rienties et al. (2015) used correlation and three different clustering techniques to compare the learning design and its impact on LMS behaviour and performance of 87 courses in Moodle. Four learning design clusters were distinguished: constructivist, assessment-driven, balanced-variety, and social constructivist. Of 32 courses with a total of 19,322 students, the number of visits to the LMS and the average time spent in the LMS were measured and aggregated per week. Rienties et al. (2015) found that communication activities had a positive effect on LMS visits and time spent in the LMS, while assessment activities had a negative effect. In a large scale study with 2,674 Blackboard courses with 91,284 students and 40 Moodle courses with 1,515 students, Beer et al. (2010) found that participation of the instructor in the discussion forum increased the amount of clicks in the LMS.

5 Learning analytics tools

As LMS log data can be large, relatively information poor, and can have a lot of irrelevant entries, and as most educators lack extensive statistical background, learning analytics tools are made to help educators with processing the raw LMS log data (Zaïane & Luo, 2001). Additionally, visualization tools are developed to help instructors with interpreting this data. These visualization tools can also be used for teacher to track students and for students to track their own behaviour (sometimes compared to their peers). A selection of the available tools is described below.

5.1 Analytics tools

The Academic Analytics Tool (AAT) performs complex analytical queries with the use of an SQL editor on data of any LMS (Graf, Ives, Rahman, & Ferri, 2011). The tool focusses mainly on behaviour of students in relation to a learning object, such as the discussion forum, quizzes, or learning material. Teachers can specify what information they want from which courses (or group of courses), learning objects, and time span. In this manner, educators can more easily extract useful information out of the log data and analyse the relation between students' behaviour and learning objects.

AnalyticsTool also helps educators to extract useful information out of the log data, but is especially focussed on interaction patterns in Moodle (Petropoulou et al., 2008). The tool stores the interaction patterns in case-by-case matrices. The interaction patterns are based on the interaction framework described in section 4.4.2. The tool can report the following indicators: actor's degree centrality, work amount, argumentation, collaboration, average number of contributions, participation, and number of messages. With these indicators instructors can easily analyse interaction patterns in statistical programs. The Multidimensional Interaction Analytics Tool (MIAT) provides even more insight in users' interaction patterns (Kim & Lee, 2012). Next to quantitative analysis and social network analysis, MIAT can be used for qualitative or content analysis of the messages.

CosyLMSanalytics focuses on learning paths of students in Moodle (Retalis et al., 2006). The tool uses input from web analytics tools, automatically gathers this data and analyses the learning patterns. It provides correlations among students' learning paths and the data can be used to cluster the learners using SPSS. The tool also provides ways to analyse discussion forum usage qualitatively, as the teacher can annotate the messages based on the content and use these annotations in their analyses.

Zaïane and Luo (2001) made a tool which implemented several data mining algorithms. These algorithms included association rule mining to discover correlations between online activities; sequential pattern mining for analysing the sequences of activities; and clustering for grouping learners with similar behaviour. Educators can set constraints and use the algorithms, without knowledge of the algorithms needed. Zaïane and Luo (2001) tested the tool with association rule mining algorithm in two experiments using data from 100 students in two courses. It was shown that the tool was useful to extract which pages are often visited together, which can provide useful insight for the educators in terms of recommending activities or structuring the content.

5.2 Visualization tools

Next to analytics tools, visualization tools have been used to support educators with interpreting the data and results. An often cited visualization tool is Netdraw, which is used for analysing the social network and relationships in discussion fora (Dawson et al., 2008; Macfadyen & Dawson, 2010; Retalis et al., 2006). CourseVis is a graphical student monitoring tool, used in web-based courses

(Mazza & Dimitrova, 2007). The tool provides graphical representations of data in three aspects: social (interactions), cognitive (performance), and behavioural (attendance, progress). The effectiveness of the tool was tested with a focus group (N=5), experiments (N=6), and a questionnaire (N=6). It was found that teachers could gain information faster and with a higher accuracy using the CourseVis tool than with textual explanations only. However, the participants were a bit confused when graphs were rotated, variables were missing, or too many variables were displayed. In these cases visualizations were difficult to understand and not really useful.

The exploratory learning analytics toolkit (eLAT) also provides graphical information about students' behaviour, including the access count, forum usage, top ten resource usage, and the adoption rate (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). According to the authors, eLAT is more flexible than CourseVis, as teachers can choose between the different indicators and filter the data, for example on gender. Experience with the user interface was tested with eight semi-structured interviews, heuristic evaluation, and four think-aloud studies. These evaluations showed that especially the possibility to filter the data was important. Expert users requested more personalization and advanced analytical functionality.

Visualization tools are also made for students to inform them about their study progress. These tools are often referred to as dashboards. According to Clow (2013), one of the most prominent dashboards used is Course Signals. Course Signals is a plugin on Blackboard which provides feedback to the students (and educators) in the form of a traffic light on the homepage, which indicates whether students are at risk (Arnold & Pistilli, 2012). The feedback is calculated by a student success algorithm, which is based on performance (available to date), interaction compared to peers, prior academic history, and student characteristics. Next to the feedback, educators can send personalized emails to encourage students. Although it is not reported whether the algorithm accurately predicts student success, the tool is shown to be successful in providing feedback. An evaluation of this application on nearly 24,000 students showed that students who used Course Signals got higher grades and the earlier students used the application in their academic career, the better their performance. Moreover, it was shown that their motivation was positively influenced, but the students were negative about the number of messages received and would like to have more specific information about their progress.

Another dashboard is Moodog, which is a special plug-in for Moodle (Zhang & Almeroth, 2010). Moodog provides progress bars for every student, showing the amount course materials viewed, the number of sessions, the amount of time spent, the number of resources accessed, the number of initial posts, and the number of follow-up posts. Students can compare their progress with their peers and automatic reminders are sent. The impact of the tool on students' performance has not been evaluated (yet). Another dashboard, ALAS-KA, is an add-in which extends the functionality of the learning analytics provided by Khan Academy (Ruipérez-Valiente, Muñoz-Merino, Leony, & Delgado Kloos, 2015). Charts provide insight in 21 variables compared to the class mean, categorized in: total platform use, correct progress on the platform, time distribution, gamification habits, exercise solving habits, and affective state.

The student activity meter (SAM) provides some more extended visualizations compared to Moodog and ALAS-KA (Govaerts, Verbert, Duval, & Pardo, 2012). SAM consists of a line chart which shows students' effort; parallel coordinates which show the time spent and resources used; a bar chart for the total time spent and resources used; statistics; and a recommendation pane for resources. The system was evaluated with structured interviews and surveys with teachers and students. Teachers indicated that the most important function of the dashboard was to inform for providing feedback. Overall, visualizations were found clear. To improve SAM, teachers indicated that metrics over groups could be included, as well as lines for expected students.

5.3 Challenges and future work in learning analytics tools

Thus, there are a variety of analytics and visualization tools available to inform students and teachers about students' behaviour in the LMS. These tools are useful for learning analytics, but the tools are still considered too complex, are often not evaluated, and are generally only used within one institution. Hence, there are a lot of opportunities for future work.

5.3.1 Make tools less complex

Although the tools help teachers and students for evaluating students' behaviour, they are often still too complex to use for educators and non-experts (Romero & Ventura, 2007). For teachers, the tools need to be more flexible and user friendly (Romero, Ventura, & García, 2008; Zaïane & Luo, 2001). It is useful to integrate the tools into the e-learning environment (Romero & Ventura, 2010), and thereby contextualize the data to help interpretations (Macfadyen & Dawson, 2012). The integration should also support decisions or give recommendations (Retalis et al., 2006; Romero et al., 2013). The dashboards for students must have better features to monitor progress (Hoic-Bozic et al., 2009), be more customizable (Macfadyen & Dawson, 2010), and motivate behavioural change (Graf et al., 2011; Macfadyen & Dawson, 2012). This makes the dashboards more useful for the students. To determine the complexity, ease of use, and perceived usefulness of the tools more evaluations are needed.

5.3.2 Evaluate the tools with students and teachers

To improve the tools, it is useful to empirically test the tools with educators and students (Govaerts et al., 2012; Ruipérez-Valiente et al., 2015; Zhang & Almeroth, 2010). These evaluations should not only be conducted after the course, but also during the course (Govaerts et al., 2012). These evaluations can help improving the user interface and further development of the tool, by indicating which additional variables and visualizations are useful. Some tools were already extensively evaluated (e.g. Arnold & Pistilli, 2012; Dyckhoff et al., 2012; Govaerts et al., 2012; Ruipérez-Valiente et al., 2015). However, most other evaluations are often small and not generalizable (Dyckhoff, Lukarov, Muslim, Chatti, & Schroeder, 2013). Often, the evaluations are focussed on the outcomes of the tools and analyses. Thus, more empirical tests especially focussing on the user experience are needed, also within different departments, institutions and with data from different LMSs (Dyckhoff et al., 2013; Macfadyen & Dawson, 2010; Retalis et al., 2006).

5.3.3 Extend usage of the tools

To stimulate the development of the tools, the tools must move outside the universities and become open source and freely available (Romero et al., 2013). Now tools are often only used within one institution. When more institutions use the tool, it can be evaluated more generally and therefore might be more useful to improve the tool and finally to improve learning and teaching. In this way, tools can eventually be used to automatically intervene to enhance student retention, motivation, and learning success (Graf et al., 2011).

6 Implementing learning analytics

Increasingly, adaptive hypermedia systems, adaptive LMSs, and recommendation systems are used to improve the learning environment based on the data of the student, i.e. learning analytics (Hoic-Bozic et al., 2009; Romero & Ventura, 2010). Action analytics focuses on the reflective process of testing whether learning analytics is actually successfully implemented and indeed improved learning and teaching (Dyckhoff et al., 2013). Recently the field of learning analytics also started to focus more on action analytics. This development is stimulated by a special issue on action analytics in the journal of Computers in Human Behavior (Conde & Hernández-García, 2015). The editors stated that it is not only needed to gain knowledge about learning processes to optimize learning and teaching, but this information should also be transformed to be able to act upon it (Conde & Hernández-García, 2015). The small amount of literature on action analytics mostly focuses on frameworks of how to implement learning analytics. A few also describe empirical results on whether the use of learning analytics actually improved learning and teaching.

6.1 Frameworks for implementing learning analytics

To successfully implement learning analytics, some challenges should be taken into account. Successful implementation of learning analytics should lead to improvement in learning and teaching. According to Greller and Drachsler (2012), six dimensions need to be covered in the design to successfully implement learning analytics. First of all, stakeholders need to be identified. Campbell and Oblinger (2007) identified five stakeholders: faculty, students, executive officers, student affairs, and IT. Secondly, it is important to identify their objectives, as these could differ between the stakeholders. Next to that, educational data are needed in useful data formats with instruments for analysing this data. Lastly, there are external constraints such as ethics and privacy, and internal limitations such as competences and acceptance. Additionally, it is important to be open about learning analytics being conducted, without giving students the feeling that they are monitored all the time (Clow, 2013). When these dimensions are considered, the data could be analysed.

Lockyer, Heathcote, & Dawson (2013) distinguished three types of analytics for aligning learning design with learning analytics. These include: checkpoint analytics, to analyse whether a student accessed the relevant resources; process analytics, to give more insight in how students are learning; and content analysis, to deepen the insight in what students learn. These analyses can be used to intervene when students' behaviour does not match the learning design, to gain more insight in the engagement of the students, and to redesign the course.

Based on a review on the definitions, processes, and frameworks, Lias and Elias (2011) came up with an overall framework for evaluating the implementations, i.e. the action analytics. They distinguished seven related processes for learning analytics: select, capture, aggregate and report, predict, use, refine, and share. A similar framework has been proposed by Rienties et al. (2016), which defined how teachers can use learning analytics to make successful interventions, called the Analytics4Action Evaluation Framework (A4AEF). This framework is based on analysis of data from 18 large scale courses over two years. The framework consisted of six key steps. First, key stakeholders should be brought together. Second, a list should be made of possible response actions for the intervention, categorized in three types of presence: social, cognitive, and teaching. Third, a protocol should be determined for evaluating the impact of the strategy. For example, whether everyone gets the intervention or if there are randomized control groups. Fourth, the actual impact should be determined. Fifth, the evidence should be shared to compare the results with previous interventions. Last, a deep analysis is needed on all the results to gain insight in which interventions are useful in which situations.

6.2 Action analytics

Although there are quite some frameworks for implementing learning analytics and evaluating the implementations, descriptions and evaluations of actual implementations are rare in the literature. The evaluation of visualization tools is one example of action analytics, which is already discussed in sections 5.2 and 5.3.2. Other examples of action analytics include the use of learning analytics to make decisions about the usage of technology in educational institutions (Macfadyen & Dawson, 2012), to answer teachers' questions (Dyckhoff et al., 2013), and to make and evaluate an intervention (Rahal & Zainuba, 2016).

Macfadyen and Dawson (2012) showed that learning analytics will not always be able to lead to pedagogical changes. They analysed LMS data of 3,905 course sections and found that LMSs had a positive value in supporting student learning. The number of discussion messages posted, discussion messages read, discussion messages replied, course content read, and 'my grade' tool visited were positively related to final grade. However, these findings did not lead to more discussion in order to extend the usage of technology in the educational institution. Thus, although learning analytics can be very informative and provides a lot of opportunities, implementation will not always improve learning and teaching.

Dyckhoff et al. (2013) conducted meta-analysis on case studies of the German eLearning conference. They argued that the questions from teachers need to be included in learning analytics, as this can inform whether these questions are actually answered and if it had an impact on learning and teaching. Teachers' questions were grouped into qualitative evaluation, quantitative measures of use and attendance, differentiation between groups or course offerings, data correlations, and effects on performance. The meta-analysis showed that many of these questions still remain unanswered, especially the qualitative questions. To answer all questions, more data sources are needed to identify the whole learning process. Especially teacher data can be useful to identify whether teacher activities have an influence on learning and teaching.

Rahal and Zainuba (2016) implemented an intervention in a quantitative business course, where students played an active role in the prediction of their own performance. After the first exam, students had to predict their own grade, based on a database of graded activities. A spreadsheet continuously provided updated feedback. Based on their performance, students could self-regulate their engagement and seek intervention. Final grades were compared between students who got the intervention (n=147) and students who did not get the intervention (n=511, measured over four previous course offerings). The group who got the intervention received a 4.7% higher final grade than their first exam grade. Also, the group who got the intervention received more high grades and less low grades, compared to the group who did not get an intervention. However, the rate of the at-risk students stayed similar between the two groups.

6.3 Challenges and future work in implementing learning analytics

As implementing and evaluating learning analytics is a new and emerging topic in learning analytics, a lot of opportunities are available for future work. Especially the use of frameworks for implementing learning analytics is valuable, combined with the evaluation of the evaluation, i.e. action analytics. This would be a good step to actually improve learning and teaching.

6.3.1 Use frameworks for implementing learning analytics

Several frameworks are developed for implementing learning analytics. However, these frameworks are often not used outside a specific institution. Future work should focus more on the actual usage of these frameworks. For example, the stakeholders should be taken into account. Especially the input of the teacher is of importance for the improvement of pedagogical practice (Dyckhoff et al., 2013), as this is currently often omitted (Dawson et al., 2008).

6.3.2 *Extend action analytics*

Future work should include more action research, to evaluate the implementations of learning analytics. Theories and methodologies should be included that are oriented to educational decision making and improvement of learning and teaching (Conde & Hernández-García, 2015). In this way, it could be analysed if learning analytics lead to pedagogical changes and whether it indeed improved learning and teaching (Zhang & Almeroth, 2010). Moreover, evaluating the impact can provide more insight in which interventions are useful in which situations. Different formats and types of learner feedback should be tested to determine the preferences and sensitivities of the students to these types of feedback (Tempelaar, Rienties, & Giesbers, 2015b). Feedback could have a negative effect on for example self-efficacy (Gašević et al., 2014), and students might feel bullied when they get a lot of interventions (Rienties et al., 2016). Also, resources should not only be directed to students who have a high chance of failure, as strong students might feel treated unfairly (Clow, 2013).

7 General conclusion

In the current paper we provided a literature review on learning analytics. Learning analytics mainly focuses on predicting student success, the development of analytics and visualization tools, and the implementation of learning analytics. These three topics offer enough interesting venues and opportunities for extending research in the field of learning analytics. Within these topics, a wide variety can be found in the tools, techniques, and data used. The different studies found that LMS data, such as the amount of content views, forum posts, or quizzes passed, can be used to predict student success to some extent in different context. Moreover, it is shown that these data can be used develop analytics and visualization tools and to actual implement the learning analytics. Standardization of data and methods is needed to be able to compare the results more easily (Romero & Ventura, 2007). The emergence of public directories is a step into the right direction, as this makes it easier to externally validate data (Baker & Yacef, 2009). However, replication studies and further developments of frameworks are still needed to draw more general conclusion about improving learning and teaching. Moreover, analytics and visualization tools should be made more freely available. In this way, learning analytics can be more generally evaluated. This will eventually lead to better insight in how learning analytics can be used to improve learning and teaching.

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