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REPORT THREE

Predicting student performance:
LMS data versus learner data

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

This report is the third one of the project "EXCTRA - EXploiting the Click-TRAil. Assessing the benefits of Learning Analytics". The main objective of the project covering three reports is to figure out how learning management system (LMS) data can be better used to predict student performance in order to facilitate educational interventions. In the first report, we gave an overview of the academic literature on learning analytics. In the second report, we offered a template to convert the raw LMS data to an analysable data set. In this third report we use the LMS data from seventeen blended courses with 4,989 students taught at Eindhoven university of Technology, combined with data from a test for prospective students (the "TU/e Study Choice Check"). With these data we answer the following questions:

1. *What are the characteristics of the blended courses taught at Eindhoven University of Technology using the learning management system Moodle?*
2. *What is the portability of the models predicting student performance using data from learning management systems across courses?*
3. *What is the value of using data from a learning management system compared to learner data and performance data for the (early) prediction of student performance?*
4. *What is the relationship between data from learning management systems and learner characteristics that are known to be good predictors of student performance?*

Scientific problem background

Given the increased use of learning management systems (that track all online behaviour), learning analytics has recently focused more and more on the interpretation of students' online behaviour. The aim is to obtain insight into students' online learning behaviour and through that to improve the study materials, support students' learning in better ways, and in general get a better understanding of which kinds of teaching is most appropriate under which conditions. One of the major topics in learning analytics is the prediction of student performance. Previous studies have shown a large diversity in the methods and variables used for the predictive modelling of student performance. This results in different outcomes that are hard to compare. Even when the same methods are used, different results are found. Hence, the portability of the models across courses might be low. Additionally, most studies focus on data from learning management systems only, while ignoring learner characteristics such as ability, personality, and motivation. These variables have been found significant and robust predictors of student performance. However, the prediction models using learner data and LMS data have rarely been combined or compared. This is the main reason why in the current study we aim to determine the value of using LMS data and learner data for predicting student performance and the portability of these models across courses.

Course characteristics

The data from the learning management system Moodle were used to determine the characteristics of the courses taught using Moodle. In total seventeen courses were analysed, mostly first-year courses in the fields of Mathematics or Physics. The courses were quite similar and varied only somewhat in the level, type, assessments, and course design. Almost all courses could be classified as sharing and submission courses, with the most activity found in the resources and quizzes. Activities which foster collaboration and communications such as a discussion forum, peer-reviewed assignments, or a wiki were rarely used.

Portability of models predicting student performance using LMS data

Correlational analyses, ordinary least squares regressions, multi-variate analyses, and multiple linear regressions were used to determine the portability of the models predicting student performance across the seventeen courses. While in-between assessment grade and the total number of sessions correlated significantly in most courses, all other predictors correlated significantly only in 30-60% of the courses. Moreover, the regression analyses showed differences among the effects of the predictors of the courses. The irregularity of study time per session was the least present in the models (6 out of 17), while total time online and the irregularity of study interval were most often present (12 out of 17). However, the sign of the predictors sometimes varied. Only in-between assessment grade and the number of online sessions showed consistently positive effects and the time until the first activity consistently showed a negative effect.

Thus, LMS data from different courses cannot be simply combined, hence the portability across courses is low. This makes it hard to draw general conclusions about which LMS predictors are useful for the prediction of student performance, and general conclusions should be restricted to the more robust variables (in-between assessment grade, total number of sessions, and time until first activity). Nevertheless, the regressions per course showed that LMS data could explain 10% to 37% of the variance in final exam grade, indicating that these data are still useful for the prediction of student success in a single course.

Predictability of student performance using LMS data, learner data, and performance data

In the second study, learner data and in-between performance data were added to the LMS data. As learner data were not available for all students, this resulted in a subsample of five courses with 888 students. Multi-variate analyses and multiple linear regressions showed that learner data had a higher accuracy in predicting student performance compared to LMS data: learner data explained 31% of the variance in final exam grade (cross-validated $R^2 = 0.12$), while LMS data explained 19% of the variance (cross-validated $R^2 = 0.06$). However, when in-between assessment grades were added to LMS data (39% of the variance explained, cross-validated $R^2 = 0.16$), learner data had a lower accuracy. Moreover, when LMS data was added to learner data and performance data, it had limited added value for the prediction of student performance.

The predictions over time showed that LMS data and learner data are especially useful for early prediction of student performance, before in-between assessments are available. Especially week 3 appeared to be the best compromise between accuracy and early feedback. However, the predictions were still far away from an accurate prediction (typically more than 1.35 points on scale of 0 to 10), indicating that these predictions are not suitable for targeted early interventions.

Relationship between LMS data and learner data

Lastly, the relationship between LMS data and learner characteristics was determined. It was found that there was only a limited relationship between those variables. Conscientiousness and time management did show significant correlations with most of the LMS variables, but the effect sizes were low, with correlations between 0.07 and 0.15. In-between assessment grade showed significant correlations with all LMS variables, with small to moderate effect sizes (*r*'s = 0.07 - 0.32). This indicates that LMS data may still be used to predict in-between assessment grades. As in-between assessment grades are a part of the final exam grade, this can also give an indication of whether a student is at risk of failing the course.

To conclude, this study provided insight in how LMS data, produced as a by-product of online learning, can be used to predict student performance to improve learning and teaching. The results showed that only a limited number of LMS features are used in the TU/e courses. Moreover, LMS data can be used for the prediction of student performance. Although the prediction models of final exam grade vary across the courses, and hence the portability is low, we showed that in-between assessment grades, the number of sessions, and the time until the first activity were pretty robust predictors across courses. Additionally, LMS data are still useful for the prediction of student performance in a single course. When learner data or in-between assessment data are added to LMS data, the accuracy of the prediction and especially the early prediction improves, but the prediction accuracy is currently too low for targeted early intervention. Lastly, LMS data showed to have some relation with in-between assessment grades, conscientiousness, and time management as well.

Future work should include course characteristics or incorporate theoretical concepts and arguments about students' learning behavior and learning processes to improve the accuracy and portability of LMS data and to get a better understanding of how LMS data can be used to predict student performance. With a better understanding of LMS data, this rich amount of data may be better used to its full potential. With this study we hope to have contributed to facilitating this endeavor.

Contents

1 Introduction

Improving learning and teaching is a key topic in educational context. Learning analytics is defined as the contextualization and interpretation of behavioural data, contextual data, and learner data to improve learning and teaching (Siemens & Baker, 2012). Although the field and the term learning analytics are rather new, analysing student data to understand how students learn and to improve learning and teaching has been a topic of research for over decades. Formerly, analyses on student data were mostly conducted using student characteristics, also known as learner data, measured with validated questionnaires. With the advancement of computers and internet, the field entered a whole new era.

For example, nowadays a vast majority of educational institutions make use of Learning Management Systems (LMSs) (Retalis, Papasalouros, Psaromiligkos, Siscos, & Kargidis, 2006). LMSs support student learning by providing content online and by allowing for additional benefits such as presentations, quizzes, assignments, and forums (Piña, 2012). LMSs support teachers by enabling them to provide such content in a relatively easy and integrated way. Moreover, as every action is recorded and stored in an LMS, insight can be gained in students' online behaviour. These data are produced as a by-product of their learning, and no intervention is needed. Accordingly, researchers started using LMS data instead of learner data to improve learning and teaching.

Currently, much research in the field of learning analytics is focussed on predictive modelling of student performance (Baker & Yacef, 2009; Buckingham Shum & Ferguson, 2012; Romero & Ventura, 2010). Specifically, these studies try to predict students' grades and students who are at risk of failing a course (Gašević, Dawson, Rogers, & Gasevic, 2016). Predictive modelling of student performance is an important step in learning analytics, as it informs the implementation of intervention, such as personalized feedback. Contrary to student characteristics questionnaires, LMSs provide raw log data, not concrete measurements. Thus, the question is how LMS data can be used to predict student performance. To date, most studies use different methodologies with various sets of predictors, generated from the raw log data (Conijn, Snijders, Matzat, & Kleingeld, 2016). Because of these differences, the studies are hard to compare and the best way to predict student performance remains unknown.

Moreover, the question is whether there is actually one best way to predict student performance. When similar methods and predictors are used, studies still found different results in the correlational analyses and prediction models. Thus, the effects of LMS behaviour on student performance might differ per institution or even per course. Gašević et al. (2016) indeed found differences between models predicting final grade in nine courses within one institution. Hence, the portability of prediction models across courses might not be that high. However, Gašević et al. (2016) used predictors which were related to specific modules in the LMS, which were not available in all courses. Moreover, the courses differed to a great extent (from biology to graphical design and accountancy) with different types of students and different features used in Moodle. Thus, the differences in the prediction models could be explained by the differences in students and courses and the fact that not the same set of predictors was used in every course.

Therefore, in our first study we determine the portability of the prediction models across courses within one institution, with a more homogeneous group of students (all technical students) and a more homogeneous set of courses, while using only predictors which are available in all courses. To determine this, data are used from seventeen blended courses taught at Eindhoven University of Technology using Moodle LMS. We first explore the course characteristics to determine the differences between the courses using Moodle LMS at this university. Thereafter the prediction models for student performance using LMS data are analysed. This results in the following research questions:

1. *What are the characteristics of the blended courses taught at Eindhoven University of Technology using the learning management system Moodle?*
2. *What is the portability of the models predicting student performance using data from learning management systems across courses?*

In our second study we add learner data and performance data to the LMS data. Contrary to LMS data, learner data such as past performance, personality, and motivation have been found significant and robust predictors across courses (e.g., Britton & Tesser, 1991; Conard, 2006; Dollinger, Matyja, & Huber, 2008; O'Connor & Paunonen, 2007; Superby, Vandamme, & Meskens, 2006). Learner data might even be a better predictor for student performance, as it can provide more detailed and timely information (Buckingham Shum & Crick, 2012). However, the prediction models using learner data and LMS data have rarely been compared, except for Tempelaar, Rienties, and Giesbers (2015) who indeed found that LMS data are of limited value compared to learner dispositions and performance data. Therefore, our second study aims to compare the value of the different data sources (learner data, performance data, or LMS data) for the prediction of student performance. This is done both at the end of the course as well as during the course, at a point in time were interventions are still meaningful (Campbell & Oblinger, 2007):

3. *What is the value of using data from a learning management system compared to learner data and performance data for the (early) prediction of student performance?*

Currently, LMS data are mostly used to predict student performance. However, LMS data might also be used as a 'live' way of measuring student characteristics, or the other way around, student characteristics might influence the behaviour of students in the LMS. Commitment and teamwork are found not significantly related to LMS behaviour (Iglesias-Pradas, Ruiz-de-Azcárate, & Agudo-Peregrina, 2015). However, other characteristics might influence LMS behaviour, such as for example motivation, time management, conscientiousness, or in-between assessment grades. Therefore, our last research question is:

4. *What are the relationships between data from learning management systems and learner data?*

2 Study 1 – LMS data: Method

The aim of the first study is to determine the portability of the prediction models using LMS data across courses. This study is in the review process for the special issue on learning analytics of the IEEE Transactions on Learning Technologies journal (Conijn, Snijders, Kleingeld, & Matzat, under review).

2.1 Participants and study context

For this study, data were used from courses using Moodle LMS taught at Eindhoven University of Technology in the first two quarters (fall and winter) of cohort 2014-2015. Data were used from courses with at least 50 students, which resulted in a sample of seventeen courses with 6,601 students. Data from students who did not take the final exam, or who did not take the final exam for the first time directly after the lecture period, were excluded from the analyses. This resulted in the final sample of 4,989 students in these seventeen courses. The amount of students per course ranged from 62 to 1,121 (M = 293, SD = 324). Some students were enrolled in multiple courses: 1,445 students were enrolled in 1 course, 1,121 students in 2 courses, 143 students in 3 courses, 147 in 4 courses, and 57 in 5 courses. Hence, the sample consisted of 2,913 unique students. More information about the courses can be found in section 3.1.

Data of the courses in the fall quarter were collected from August 25th 2014 (1 week before the lectures started) until November 9th 2014 (end of the exam week) and grouped per week, which resulted in 11 weeks of data. Data of the courses in the winter quarter were collected likewise from November 3rd 2014 (1 week before lectures started) until February 1st 2015 (end of the exam week). As the two-week Christmas break fell into the winter quarter, this resulted in a total of 13 weeks of LMS data.

2.2 Data pre-processing

As the LMS provides raw log data, the data needs to be pre-processed first. The pre-processing is done in R, based on the method for pre-processing LMS data described in more detail in our previous report (Nij Bijvank, Conijn, Snijders, Matzat, & Kleingeld, 2016). Four basic aggregated predictors were used per course, as these are often used in the literature (Conijn et al., 2016): the total number of clicks, the number of online sessions, the total time online, and the total number of views. A session was defined similarly as in Zacharis (2015), as the sequence of behaviour from the first click after the login to the LMS until the last click before logging out, or the last click before staying inactive for at least 40 minutes. Additionally, each session had to consist of at least two clicks. The time between the first and the last click of a session was used to compute the total time online. Next to the basic predictors, more complex predictors based on study patterns were included: the irregularity of study time (SD of the time per session), the irregularity of study interval (SD of the time between sessions), the largest period of inactivity (time between two sessions), the time until first activity, and the average time per session. Next to LMS data, the final exam grade was collected and used as outcome variable. The final exam grades are on a scale from 0 to 10, where grades $\geq$ 5.5 indicate a pass and grades < 5.5 indicate a fail. The descriptive values of the predictors and outcome variable can be found in Table 1.

Table 1: Descriptive statistics LMS variables and outcome variable

Variable	N	Min	Max	*M*	*SD*
Total number of clicks	4989	1	5435	605	630
Number of online sessions	4989	0	127	30.3	21.2
Total time online (min)	4989	0	6167	815	678
Number of course page views	4989	1	1665	208	144
Irregularity of study time	4989	0	16374	1926	993
Irregularity of study interval	4989	0	24666278	309000	252000
Largest period of inactivity (min)	4989	0	110591	20500	13100
Time until first activity (min)	4989	786	116195	17167	11250
Average time per session (min)	4989	0	256	27.2	15
Final exam grade	4989	0	10	5.44	2.34

2.3 Data analyses

After data pre-processing in R, all analyses were run with Stata 14. First of all, some explorative analyses were done to determine the course characteristics. Thereafter, correlational analyses and ordinary least squares regressions, multi-level analyses, and multiple linear regressions were run to determine the portability of the prediction models using LMS data across courses. As some students followed multiple courses, there was overlap between the students. Moreover, as the data was clustered by course, multi-level analyses were run with crossed-random effects for student and course. Additionally, multiple linear regressions were run on all courses separately, using stepwise backward regression, where all predictors with a p-value > .2 were removed from the model. As the assumption of homoscedasticity was often not met, robust regressions were used.

3 Study 1 – LMS data: Results

3.1 Course characteristics

In the fall and winter quarter of 2014-2015 a total of 28 courses of Eindhoven University of Technology used Moodle LMS. In this study we only use data from courses which had at least 50 students, which resulted in a total of seventeen courses. An overview of the courses and course characteristics can be found in Table 2. Most of the courses were first-year courses, but also three second-year, one third-year, and to prerequisite courses for entering the graduate programs were included (pre M). The courses included of basic courses which every undergraduate student at the university has to take, to specific courses in the fields of mathematics, physics, and psychology.

All courses were blended courses, as part of the course was presented online in Moodle LMS combined with three to six hours of face-to-face lectures per week. Sixteen courses made use of the quizzes and for fifteen of these courses most activity in the LMS can be found in the quizzes (47% - 94% of the clicks). Fourteen courses provided additional content or resources online, two courses provided an assignment online, one course a peer-reviewed assignment, and one course a wiki. A discussion forum was provided in all courses, but the usage was really low in most courses with on average 0 to 5.6 clicks per student. In only one course (Behavioural Research Methods) students showed somewhat more activity in the forum (average of 23.5 clicks per student). Some modules were used even less, such as the attendance and the poll function. The chat function and virtual classroom were not used at all.

The counts of online activities show that the courses are similar in the implementation of blended learning, according to the classification of blended learning made by Park, Yu, and Jo (2016). Most courses could be classified as sharing and submission courses, as they provided content, assignments, and quizzes. Two courses were somewhat different and could be classified differently. Behavioural research methods could also be classified as a delivery or discussion course, as this course made use of a wiki and the discussion forum more extensively. Linear algebra 1 could also be considered as a communication or collaboration course, as the course included peer-reviewed assignments.

The courses varied in the types and the weights of the assessments. Most courses used multiple assessments to calculate the final course grade. One course (Linear Algebra) used only the final exam grade to calculate the final course grade. For the other courses, the final course grade consisted for 50% to 80% of the final exam grade. The other part of the final course grade consisted of entry test grade (for the four Calculus courses), online homework (seven courses), offline homework (seven courses), and a midterm exam (fourteen courses).

Table 2: Course characteristics courses using Moodle LMS

							Online activities (% of clicks)						Assessment weights						
	Course name	Quarter	Level (year)	Type	F2F hours per week	Clicks per student	Content	Forum	Quiz	Assignment	Peer-review assignment	Wiki	Entry test	Homework online	Homework offline	Midterm	Final exam	N study 1	N study 2
1	Calculus A	1	1	Basic	4.5	889	2.9%	.4%	80%				10%	10%		10%	70%	438	122
2	Calculus B	1	1	Basic	5.3	1164	.6%	.5%	85%				10%	10%		10%	70%	1121	297
3	Calculus C	1	1	Basic	5.3	742	.9%	.5%	75%				10%	10%		10%	70%	227	
4	Calculus pre M Architecture	1	Pre M	Basic	3.0	815	1.8%	.0%	94%				10%	10%			80%	135	
5	Set theory and Algebra	1	1	Mathematics	6.0	587	8.3%	.1%	71%						15%	15%	70%	73	
6	Linear Algebra and Vector Calculus	2	2	Mathematics	6.0	673	1.0%	.1%	90%						10%	30%	60%	120	
7	Linear Algebra	1	Pre M	Mathematics	4.5	279		.2%	89%								100%	76	
8	Experimental Physics 1	1	1	Physics	5.3	302	4.1%	.2%	77%							40%	60%	168	
9	Experimental Physics 2	2	1	Physics	6.0	94	4.7%	.0%	75%							40%	60%	155	
10	Behavioural Research Methods	2	2	Psychology	4.5	620	14.1%	3.1%	58%			5%			30%		70%	136	
11	Applied Physical Sciences formal	2	1	Basic	6.0	234	1.4%	.1%	79%					10%		20%	70%	836	45
12	Applied Physical Sciences conceptual	2	1	Basic	6.0	227	1.1%	.1%	81%					10%		20%	70%	822	350
13	Condensed Matter	2	3	Physics	3.0	189	4.1%	.1%	78%							30%	70%	74	
14	Intro to Psychology & Technology	1	1	Psychology	4.5	189	13.2%	.2%	47%	6%				10%	20%	20%	50%	154	74
15	Linear Algebra 1	1	1	Mathematics	6.0	61		.5%	29%		30%				15%	15%	70%	66	
16	Statistics	2	2	Mathematics	6.0	164		.0%	89%						15%	15%	70%	326	
17	The Effectiveness of Mathematics	2	1	Mathematics	6.0	198	18.5%	.1%		37%					50%		50%	62	

Thus, the courses vary somewhat in type, level, course design, and assessment weight. Interestingly, most courses did not exploit the full potential of LMSs, as many interactive features such as wikis, virtual classrooms, and peer-reviewed assignments are hardly utilized. However, as all courses implemented blended learning in a similar way and use more similar features in Moodle, the courses are more similar compared to Gašević et al. (2016). Moreover, all courses are mostly first-year courses and are from a technical university, which attracts a more homogeneous group of students. Therefore, in the following we analyse whether the portability of the prediction models is low, as in Gašević et al. (2016), using more similar courses and a more homogeneous group of students, and thereby controlling more for student and course effects.

3.2 Portability of LMS data

To determine the portability of the LMS data several analyses were conducted: correlational analyses, ordinary least squares regressions, multi-level analysis, and multiple linear regressions.

3.2.1 Correlational analyses

To determine the portability of the LMS data across courses, first of all Pearson correlation analyses were conducted between final exam grade and the predictor variables on both the whole sample and the courses separately. The results can be found in Table 3 (p. 14). The correlational analyses on the whole sample showed that only the irregularity of study time did not significantly correlate with final exam grade. The total number of clicks, the number of online sessions, the total time online, and the number of course page views were all positively related with final exam grade. A higher SD of the study interval, a longer period of inactivity, a longer time until the first activity, and a longer average time per session were all related with a lower final exam grade. However, all effect sizes were below .21.

The correlational analyses on all courses separately showed different results across the courses. None of the predictors correlated significantly in all of the courses. The number of online sessions was the most stable predictor, as it correlated significantly in the most courses (14 out of 17). All other predictors correlated significantly in only 30% to 60% of the courses. Moreover, some of the variables showed even substantial differences in the direction and the effect size of the correlation across courses. This indicates that the effects of the variables as predictors might differ across courses.

3.2.2 Ordinary least squares regressions

To determine to what extent the effects of the variables on final exam grade differ across courses, ordinary least squares regressions were run on all courses with the courses coded as dummies and interaction effects for each course with the predictors. As there was overlap in the students, student clustered standard errors were used. All nine basic and study pattern predictors varied significantly and substantially between the courses (all p's < .001). However, these standard regressions are an obvious simplification of the structure of the data. The data shows a hierarchical structure and is clustered by course and student (as not all cases represent unique students. To take this structure into account, a multi-level regression analysis is conducted.

3.2.3 Multi-level analyses

A multi-level analysis on final exam grade with crossed-random effects for course and student was run to check whether there is indeed some variance in student performance that resides at course level. The analysis showed that 8% of the variance resides at course level and 48% resides at student level, leaving 44% of the variance unexplained. This means that the clustering at course and student level cannot simply be ignored and that the highest gain in explaining the variance can be found on the student level. Combined, these results show that we cannot simply combine the LMS data of all courses into one analysis without using a large number of interaction effects. Therefore, in the following all courses are analysed separately, to investigate the differences between the prediction models per course.

3.2.4 Multiple linear regressions

Multiple linear regressions were run with final exam grade as outcome variable and all nine basic and study pattern variables as predictors. All predictors with a significance level below .2 were removed from the models. The results of the final models with standardized coefficients for the predictor variables are shown in Table 4. The results show that for each course LMS data can explain some of the variance in final exam grade. However, the amount of explained variance differs to a great extent: from 8% for course 9 (Experimental Physics 2), where none of the predictors were significant, to 37% in course 7 (Linear Algebra).

Additionally, the predictor variables included in the final models differ to a great extent as well. None of the predictors is present in all of the models. The total time online and the irregularity of study interval are most often present in the models (12 out of 17), whereas the irregularity of study time per session is the least present (6 out of 17). Some predictors even differ in the direction of the coefficient across courses. Two exceptions are the number of sessions which always shows a positive coefficient and the time until the first activity which always shows a negative coefficient. This implies that more general conclusions based on our current dataset should be restricted to these two variables; more online sessions and less time until the first session (i.e. starting early) go with a higher grade.

3.2.5 Conclusion

To conclude, the results showed differences in the correlational analyses of final exam grade with the predictors over the different courses. Moreover, substantial differences were found in the regression analyses between the sign and the size of the predictors across courses. This shows that we cannot simply run analyses on the data of multiple courses combined without including a large number of interaction effects. Hence, the portability of the models for predicting student performance appears to be low. For individual courses the prediction models still provide useful information for the instructor to improve learning and teaching, but it cannot simply be assumed that the models can be used for other courses as well.

Table 3: Correlations between final exam grade and LMS variables for all courses (Pearson's r)

	Course																	
	All	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Total number of clicks	.04**	.16***	.01	.03	.11	.05	.10	-.16	.15	-.07	.41***	.41***	.32***	.29*	.17*	.08	.15**	.36**
Number of online sessions	.21***	.37***	.32***	.29***	.31***	.20	.22*	-.04	.20**	.04	.53***	.41***	.30***	.26*	.26***	.36**	.16**	.44***
Total time online (min)	.12***	.24***	.18***	.09	.33***	-.04	.22*	-.04	.12	-.06	.49***	.37***	.29***	.40***	.11	-.04	.04	.20
Number of course page views	.19***	.32***	.23***	.20**	.18*	.22	.15	-.03	.09	-.09	.39***	.41***	.31***	.25*	.15	.27*	.14*	.37**
Irregularity of study time	.03	-.03	-.04	-.06	.06	-.19	.18*	-.10	-.01	-.09	.05	.31***	.20***	.30*	-.21**	-.17	-.08	-.15
Irregularity of study interval	-.11***	-.33***	-.29***	-.28***	-.19*	-.17	.00	.09	.07	.01	-.33***	-.05	-.02	-.12	-.13	-.27*	-.07	-.35**
Largest period of inactivity (min)	-.06***	-.16***	-.17***	-.32***	-.12	-.12	.06	-.01	.13	-.04	-.31***	.10**	.06	.02	.02	-.25*	.00	-.17
Time until first activity (min)	-.13***	-.15**	-.16***	-.08	-.32***	-.13	-.19*	-.36**	-.29***	-.20*	-.05	-.13***	-.13***	-.25*	-.04	-.06	-.18**	.04
Average time per session (min)	-.05***	-.06	-.05	-.14*	.02	-.17	-.05	.07	-.04	-.07	.05	.16***	.15***	.06	-.20*	-.22	-.10	-.27*
N	4989	438	1121	227	135	73	120	76	168	155	136	836	822	74	154	66	326	62

a) * p < .05, ** p < .01, *** p < .001

Table 4: Final models multiple linear regression on all courses

	Course																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Total number of clicks	-0.20**	-0.39***	-0.36***		- 0.31	- 0.14	-0.30*	1.30**			0.14*	0.21*	1.91**				
Number of online sessions		0.24**	0.12						0.14	0.55***	0.44***	0.24*		0.60***	0.46**		0.27
Total time online		-0.19*		0.17	- 0.23	0.25*	0.29			0.34**	-0.34***	-0.18*	0.76***	0.16	-0.23*	0.19	
Total number of views	0.31***	0.33***	0.35**		0.63***			-1.38**	-0.17	-0.42**			-2.28**	-0.52**			
Irregularity of study time		-0.09				0.26*	-0.57**				0.17***			-0.40*		-0.16	
Irregularity of study interval	-0.37***	-0.32***		-0.19**			0.38	-0.52*	0.27	-0.10	-0.22**	-0.12		-0.34		-0.53***	-0.77
Largest period of inactivity	0.16*	0.15**	-0.25**				-0.56*	0.56*	-0.24		0.32***	0.19**		0.33*		0.50**	0.72*
Time until first activity	-0.08	-0.10***		-0.27**		- 0.17	-0.58***	-0.27***	-0.21							-0.12*	
Average time per session		0.22**				- 0.22	0.35**				0.14	0.13**	-0.15	0.20		-0.18*	-0.20
R^2	.17	.19	.18	.18	.13	.13	.37	.18	.08	.32	.23	.12	.29	.19	.17	.10	.32
N	438	1121	227	135	73	120	76	168	155	136	836	822	74	154	66	326	62

a) Standardized betas for all variables

b) * p < .05, ** p < .01, *** p < .001

c) Constants omitted from the table

3.2.6 Discussion

The differences in the prediction models might be explained by differences in course characteristics and student characteristics across courses. Winne and Hadwin (1998) stated that learning is not only affected by task conditions (such as course characteristics), but also by internal factors, such as student dispositions and motivational factors. Hence, student and course characteristics could also influence the behaviour in the LMS and explain the differences in the prediction models. However, the current sample of seventeen courses is too small to determine if and which course characteristics have an effect on the prediction models. Therefore, we only focus on the student characteristics here. In our second study we include these student characteristics, also known as learner data, to find out whether these data can explain the differences between the models. Moreover, we determine which data source, LMS data or learner data, has the highest power in predicting final grade at the end of the course and during the course. Lastly, we determine how LMS data and learner data are related.

4 Study 2 – LMS data and learner data: Method

4.1 Participants and study context

For the second study, LMS data from study 1 were combined with learner data and performance data (in-between assessment grade). Learner data came from a survey among prospective students of Eindhoven University of Technology. In total 426 students both participated in the survey and completed at least one course that employed Moodle LMS. The survey data (learner data) of these students were combined with LMS data and performance data available per course using R. Only courses where at least 45 students had taken the test were included, which resulted in a sample of 5 courses with 426 unique students. As some students followed multiple courses (32 students followed 1 course, 326 followed 2, and 68 followed 3), this resulted in a total of 888 students in five courses. As the whole sample consisted of 3,371 cases in these five courses, these 888 cases were a subsample in these courses (26.3%). The five courses included were: Calculus A, Calculus B, Applied Physical Sciences formal, Applied Physical Sciences conceptual, and Introduction to Psychology & Technology (see Table 2, p. 11).

4.2 Learner data

The learner data were extracted from an online questionnaire, which was part of the TU/e Study Choice Check for prospective students of bachelor programs at Eindhoven University of Technology, which was distributed in the first half of 2014. Since 2014, all Dutch higher education institutions are required to offer some form of study choice check (ranging from just an online questionnaire to extensive on-site orientation programs), resulting in a study advice. The objective is to provide students the opportunity to make a well-considered decision with respect to their further education, to prevent drop-out and unnecessary switching between programs. The study choice check at Eindhoven University of Technology consists of an online questionnaire, an interview with a staff member, and an orientation activity at the university (e.g., a lecture, group work, a sample exam). The orientation activity takes place between three to six months before the start of the academic year.

Data used in the current study came from a pilot of the online questionnaire, which only included prospective bachelor students of the departments of Industrial Engineering & Innovation Sciences and Built Environment, resulting in a strong selectivity of students. An invitation to complete the questionnaires was sent three weeks before the prospective students took part in the on-site orientation activity. When students did not complete the questionnaire before the orientation activity, extra time was provided to complete the questionnaire during the activity. This resulted in a response rate of nearly 100% of the students who participated in the orientation activity. Based on the online questionnaire, an advice concerning the study choice was given to the prospective students, categorized in 'abilities & skills' and 'motivation for study choice'.

The questionnaire measured demographics and a total of nine factors related to abilities & skills (5) and motivation for the study choice (4). The demographical measures were gender, chosen Bachelor program (Industrial Engineering (IE), Psychology & Technology (P&T), Sustainable Innovation (SI), or Built Environment (BE)), and profile in prior education (science-oriented or society-oriented). Most of the ability/skills and motivation factors were adapted from validated questionnaires. The factors had been shown to be significant predictors in a previous longitudinal study on student performance and study continuation at the department of Industrial Engineering & Innovations Sciences (Bipp, Kleingeld, & Schinkel, 2013). The items for these factors (in Dutch) can be found in Appendix A.

Skills and capacities consisted of: GPA prior education, conscientiousness, time management, lack of study strategy, and self-efficacy. GPA was calculated using the average final grade for all courses in prior education, with a higher weight for the courses that are required to enter the study program (Mathematics for all four Bachelor programs, and in addition Physics for Built Environment). Conscientiousness was measured using the validated Dutch translation of the nine-item conscientiousness scale of the Big Five Inventory (Denissen, Geenen, van Aken, Gosling, & Potter, 2008). A sample item is 'Perseveres until the task is finished'. Time management was measured using four items from Kleijn, Topman, and Ploeg (1994). A sample item is 'I start on time to prepare for an exam'. Lack of study strategy was measured using the lack of strategy scale developed by Harackiewicz, Barron, Tauer, Carter, and Elliot (2000). This scale consists of three questions (e.g. 'I often find that I don't know what to study or where to start') and was translated into Dutch. Self-efficacy was measured using a slightly adapted version of the self-efficacy scale of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & De Groot, 1990). This scale consisted of nine questions related to students' perceived competence and confidence in their performance in the program (e.g. 'Compared to other students in this class I expect to do well') and was translated to Dutch. Conscientiousness and time management were measured using a five-point scale, ranging from 1 (almost never) to 5 (almost always). Lack of study strategy and self-efficacy were measured using a seven-point scale, ranging from 1 (completely disagree) to 7 (completely agree).

Motivation for study choice consisted of: connection with study program, confidence study choice, amotivation study choice, and external regulation. The connection with the study program was measured via six questions that were selected and adapted from the Dutch 'Startmonitor', a national annual survey among students who start with their higher education (e.g. 'This program fits well with my interests') (Warps, Hogeling, Pass, & Brukx, 2009). The confidence with study choice items were developed specifically for the Study Choice Check at TU/e. This scale consists of four questions (e.g. 'I hesitate between the TU/e and other universities'). The lack of motivation (amotiviation) for the study choice was measured using the amotivation items from the Situational Motivation Scale (SIMS) (Guay, Vallerand, & Blanchard, 2000). From this scale, three questions were adapted and translated into Dutch (e.g. 'There may be good reasons to do this program, but personally I don't see any'). External regulation occurs when a student choses a study program because of a felt obligation. This was measured using the external regulation items from the Situational Motivation Scale (SIMS) (Guay et al., 2000). This scale consists of four questions which were translated to Dutch (e.g. 'I choose this program because I'm supposed to do it'). All motivational factors were measured using a seven-point scale, ranging from 1 (completely disagree) to 7 (completely agree).

Overall, the ability/skills of the respondents were high: on average the students had a high GPA, high conscientiousness, high time management, high self-efficacy, and little lack of study strategy. These results are in line with a similar study previously conducted at the same university (Bipp et al., 2013). Moreover, the motivation factors were high as well. On average, the students had high connection with the study program, high confidence, and high motivation for the student choice. The external regulation for the study choice was low. Thus, even before the orientation activity took place, the students already had a high motivation for their study of their choice. An overview of the descriptive values of the skills/abilities and motivation factors can be found in Table 5.

Table 5: Descriptive values of learner data (unique students) used to predict student performance

Variable	N	Min	Max	*M*	*SD*
GPA prior education [b)]	394	5.49	8.70	6.87	0.52
Conscientiousness	426	2.33	5.00	3.77	0.50
Time management	426	1.50	5.00	3.75	0.65
Study strategy (lack of)	426	1.00	5.67	2.14	0.92
Self-efficacy	426	2.78	6.89	4.94	0.66
Connection with study program	426	3.00	7.00	5.55	0.64
Confidence study choice	426	2.75	7.00	5.57	0.89
Amotivation study choice	426	1.00	4.25	1.49	0.63
External regulation study choice	426	1.00	5.50	2.03	0.94

4.3 Performance data

The performance data collected for all 888 cases consisted of final exam grade and in-between assessment grade. All grades range from 0 to 10, where all grades ≥ 5.5 indicate that a student passed the specific assignment or course and all grades < 5.5 represent a fail. The final exam grades where quite low (M = 5.31, SD = 2.10): the average student failed the course. The in-between assessment grades were substantially higher (M = 6.93, SD = 1.33). In-between assessment grade consisted of the grades for the graded assessments during the course (e.g., entry test, assignments, online homework, offline homework, and midterm exam). These assessments could be completed either online in Moodle LMS or offline and handed-in on paper or via other systems. As the weights and types of in-between assessments differed across courses, the (unweighted) average of these grades were used to calculate the in-between assessment grade. We assumed these grades would be available at the end of week 5, as most in-between assessments took place in week 4 or 5. As in-between assessment grades are part of the final course grade in all five courses, we used final exam grade as outcome variable (as in study 1). A binary outcome variable is computed with grade ≥ 5.5 coded as pass (1), and grade < 5.5 as fail (0).

4.4 Data analyses

Like study 1, all analyses were conducted with Stata 14. As only students who filled in the questionnaire were used as sample for this study, this study uses a subsample of students in five courses. Therefore, *t*-tests and regression analyses were run to compare the subsample used in this study with the other students in the five courses. Subsequently, correlational analyses, multi-level analyses, and multiple linear regressions were run to compare the prediction models using learner data, LMS data, and learner data combined with LMS data. The prediction accuracy of these data sources was compared at the end of the course and during the course, to determine whether early prediction is possible. Lastly, correlational analyses were used to investigate the relation between LMS data and learner data.

For the multiple linear regressions stepwise backward regression was used, in which all predictors with a *p*-value > .2 were removed from the model. As the assumption of homoscedasticity was often not met, robust regressions were used. Robustness of all models was checked with 10-fold cross-validation, using the function 'crossfold', which runs ten regressions on subsamples and takes the average of these regressions (Daniels, 2012). Although most previous studies only report how well the regression or classification model performed in terms of (pseudo) R-squared values, this is not always a very useful metric. In most cases, it is more insightful to know how far away the predictions are from the true value, on average. This could for example give more insight into whether the model could be used for automated assessment. For this reason, we calculated such fit statistics as well.

4.5 Preliminary analysis: Differences between subsample and whole sample

As learner data were not available for all students, analyses in the second study were conducted on a subsample of students within five courses (888 cases instead of 3,371 cases). As subsample was not randomly chosen, the subsample might differ from the whole sample. In that case the results of the subsample cannot be generalized to the whole sample. To verify this, *t*-tests and multiple linear regressions were used to check whether the subsample significantly differed from the complete sample in these five courses.

The independent samples *t*-tests showed that there is a significant difference between students in the subsample and the other students in the five courses, for almost all predictor variables (all *p*'s < .05). Students in the subsample clicked more (M = 799, SD = 25.5) compared to the other students (M = 654, SD = 13.4), spent more time online ($M_{subsample}$ = 904 min, $SD_{subsample}$ = 15 min versus M = 979 min, SD = 22 min), and had smaller periods of inactivity ($M_{subsample}$ = 12.5 days, $SD_{subsample}$ = 0.24 days versus M = 13.4 days, SD = 0.18 days). They also had a higher number of sessions, number of views, and irregularity of study interval, while they had a lower irregularity of study time. Only the time until the first activity ($t(3369) = 1.22$, $p = .22$) and the average time per session ($t(3369) = -0.74$, $p = .46$) did not differ between the two samples. The outcome variable final exam grade did not differ between the two groups ($t(3369) = 0.59$, $p = .56$).

To investigate whether these differences affected the prediction of student performance, four regressions were run on final exam grade, comparing students within the subsample to students in the whole sample. The four multiple linear regressions shown in Table 6 indicate that being in the subsample had an effect on the prediction models of final exam grade.

Table 6: Effects of being in the subsample on final exam grade, compared to the whole sample

	Model 1	Model 2	Model 3	Model 4
in_subsample	-0.05	0.18	- 0.19*	- 0.17
Course 1		0.00		
Course 2		0.01		
Course 3		0.40*		
Course 4		- 0.71***		
Course 5		0.60**		
Course 1 * in_subsample		0.00		
Course 2 * in_subsample		- 0.27		
Course 3 * in_subsample		- 1.28**		
Course 4 * in_subsample		0.27		
Course 5 * in_subsample		0.40		
Total number of clicks			- 0.81***	- 0.98***
Number of online sessions			0.84***	0.80***
Total time online			- 0.40***	- 0.43***
Total number of views			0.75***	0.98***
Irregularity of study time			0.01	- 0.01
Irregularity of study interval			- 0.35***	- 0.35***
Largest period of inactivity			0.44***	0.45***
Time until first activity			- 0.11*	- 0.07
Average time per session			0.22*	0.28*
in_subsample * Total number of clicks				0.39**
in_subsample * Number of online sessions				- 0.17
in_subsample * Total time online				0.58*
in_subsample * Total number of views				- 0.81***
in_subsample * Irregularity of study time				0.07
in_subsample * Irregularity of study interval				- 0.40
in_subsample * Largest period of inactivity				0.15
in_subsample * Time until first activity				- 0.19
in_subsample * Average time per session				- 0.43*
R^2	.00	.03	.14	.15
N	3371	3371	3371	3371

[a] Standardized values for all predictors
[b] * p < .05, ** p < .01, *** p < .001
[c] Constants omitted from table

The first model, with the dummy in_subsample as only predictor, shows that being in the subsample dis not have a significant effect on final exam grade. However, when we look at the separate courses (model 2) we do see a significant effect of being in the sample for one of the courses. For Applied Physical Sciences formal, being in the subsample led to a 1.3 lower grade, compared to the other students of course 3. Moreover, when the basic and study pattern predictors were added to the model, being in the subsample did have a significant (negative) effect on final grade (model 3). Thus, students in the subsample who showed the same online behaviour as students in the whole sample had a significant lower grade than students who were not in the subsample. Lastly, the interaction effects of the predictors with being in the subsample were included (model 4). This model shows that some of the predictors had a different effect inside and outside the subsample. The total number of clicks and the total time online had a significantly less negative effect on final exam grade in the subsample, compared to the whole sample. In contrast, the total amount of views and the average time online had a significantly less positive effect on final exam grade in the subsample. Interestingly, the sign of one of the predictors even differed between the two groups: average time per session was found a negative predictor in the subsample, while it was a positive predictor in the whole sample.

Thus, the models show that there indeed is a difference between the effects of some of the predictors on final exam grade between students within the subsample and students outside the subsample. These differences might be explained by the study program, as only students from the departments of Industrial Engineering & Innovation Sciences and Built Environment completed the questionnaire and were thus included in the subsample. The whole sample also consisted of students from more traditional engineering programs, such as Physics and Mathematics. These students may perform better on the basic Calculus and Applied Physics courses, with similar amounts of learning in the LMS. The difference between the whole sample and the subsample points out that we cannot use the results from the subsample to draw conclusions about the whole sample (i.e., generalize), especially not about the predictors which show different effects. Moreover, the findings corroborate the results of study 1, showing that the effects of predictors are different per sample (model 4) and that we cannot generalize the effects of a single predictor. Additionally, this points to a potential explanation that the different study programs or backgrounds of the students across courses might result in different effects of LMS behaviour on final exam grade across the courses.

Although we cannot generalize the effects of the subsample to the whole sample, we can still compare the prediction models within the subsample. Thus, the comparisons among the effects of using learner data, performance data, and LMS data for predicting student performance within the subsample remain valid.

5 Study 2 – LMS data and learner data: Results

5.1 Predicting student performance

First, a multi-variate analysis on final exam grade with crossed-random effects for course and student was run to determine to what extent the variance in final exam grade could be explained by student variables (i.e. LMS data and learner data). The analysis showed that 9% of the variance could be explained at course level and 37% at student level (54% of the variance is unexplained). This means that we cannot simply ignore the clustering at course and student level. Moreover, it showed that a lot of variance can be explained using student variables. Accordingly, in the following we examine the prediction of student performance using student variables from LMS data, learner data, and LMS data and learner data combined.

5.1.1 Correlational analyses

To identify which variables from LMS data, learner data, and performance data are related to final exam grade Pearson correlational analyses were run for all five courses separately. The results (Table 7) show that almost all LMS variables were significantly correlated with final exam grade within at least one course, except from the average time per session. The number of online sessions and the total number of views had significant correlations in the most courses (4 out of 5). Most correlations had a small to moderate effect size. Contrary to study 1, using a larger sample size of 17 courses, no differences were found in the direction of coefficients. This indicates that the relation between the LMS variables and final exam grade are more similar in this sample compared to the previous used larger sample. This may be due to the fact that the current sample is smaller, with more homogenous courses, and a more homogenous sample of students (as only students from the departments of Industrial Engineering & Innovation Sciences and Built Environment were included).

The learner data variables, except for prior GPA, showed less robust correlations with final exam grade: they correlated significantly in none, only one, or two of the courses. The results further showed that the predictors that correlated significantly with final grade differ per course. Only prior GPA correlated significantly in every course, with a moderate effect size (r = .38 - .54). Interestingly, the significant correlations of the motivational variables (in at most one course) were in the opposite direction of what was expected: a higher connecting with and certainty about the study program, and lower amotivation are correlated with a lower grade. This may be due to the fact that these courses were basic courses that every student had to take and which are often not directly related to the students' major (and thus, to their core interest).

The correlations between performance data (in-between assessment grades) and final exam grade were robust. Significantly positive correlations were obtained for every course, with a moderate to high effect size (r = .50 - .70).

Table 7: Bi-variate correlations of LMS data, learner data, and performance data with final exam grade per course (Pearson's r)

	Calculus A	Calculus B	Applied Physical Sciences formal	Applied Physical Sciences conceptual	Introduction to Psychology & Technology
Total number of clicks	.005	- .077	.398**	.213***	.370**
Number of online sessions	.175	.365***	.504***	.213***	.375**
Total time online	.074	.272***	.453**	.196***	.168
Total number of views	.158	.222***	.369*	.207***	.353*
Irregularity of study time	- .096	- .002	.202	.133*	- .107
Irregularity of study interval	- .135	- .329***	- .063	- .020	- .264*
Largest period of inactivity	- .131	- .175**	.136	.102	- .088
Time until first activity	- .278**	- .150**	.002	- .131*	- .176
Average time per session	- .119	- .038	- .043	.056	- .128
Male	.084	.220***	.022	- .044	.274*
Major IE		- .139*	- .001	- .009	
Major P&T	- .260**	.146*	- .005	.014	
Major SI	- .192*	.018	.010	- .065	
Major BE	.324***			.025	
Science-oriented profile	- .021	- .023	- .068	.093	.183
Prior GPA	.406***	.427***	.535***	.377***	.394**
Conscientiousness	.174	.166**	.173	.070	.294*
Time management	.232*	.217***	.180	.047	.226
Lack of study strategy	- .225*	- .126*	- .015	- .017	- .161
Self-efficacy	.089	- .040	.040	.059	- .172
Connection with study program	.049	- .025	.114	- .112*	- .005
Confidence study choice	- .007	- .026	- .296*	- .001	.079
Amotivation for study choice	- .006	.073	- .044	.159**	- .196
External regulation study choice	.015	.004	.237	.079	- .063
In-between assessment grade	.574***	.503***	.699***	.434***	.564***
N	122	297	45	350	74

[a] * p < .05, ** p < .01, *** p < .001

5.1.2 Multi-level analyses

The correlations suggest that the LMS data, learner data, and performance data can be used to predict student performance. To verify this, eight multi-level analyses on final exam grade were run with all combinations of the data sources (LMS data, learner data, and performance data) and crossed-random effects for course and student on the five courses. The findings (Table 8) show that the variance residing at student level dropped when LMS data, learner data, or performance data (in-between assessment grade) were added. Thus, LMS data, learner data, and in-between assessment data can explain a part of the variance in final exam grade. Moreover, the variance residing at student level when in-between assessment grades or learner data were added, were substantially lower than when LMS data were added. This indicates that performance data or learner data may be even more useful than LMS data for predicting student performance.

When LMS data were added to learner data, the variance residing at student level dropped even further, indicating that LMS data can still explain some of the variance in final exam grade next to learner data. When in-between assessment grade were added, the variance residing at student level dropped even further. Interestingly, when LMS data were added to learner data and in-between assessment grade, the variance did not drop any further, indicating that LMS data has little to no added value in predicting student performance next to learner data and performance data. When all data sources were added there was still some variance residing at student level and course level, thus not all variance can be explained using these sources.

Table 8: Multi-level analyses on final exam grade with LMS data and learner data and crossed-random effects for course and student

	Variance residing at Student level	Variance residing at Course level
Empty model	37%	9%
LMS data	31%	9%
Learner data	21%	15%
In-between assessment grade	20%	12%
LMS data and learner data	17%	15%
LMS data and in-between assessment grade	19%	12%
Learner data and in-between assessment grade	13%	15%
LMS data, learner data, and in-between assessment grade	13%	15%

5.1.3 Multiple linear regressions

To determine which learner variables play a role in predicting student performance, multiple linear regressions were run. As the correlations between variables and final exam grade differed per course and students could take multiple courses, separate multiple regressions were run per course. Models were created using LMS data, LMS data and performance data, learner data, and LMS data combined with performance data and learner data. The models were created using stepwise backward regression, where all predictors with a p-value > .2 were removed from the model. To facilitate the comparison, all final models are shown in Table 9.

The regressions showed that LMS data (model 1) could explain some of the variance in final exam grade for each course. However, the predictor variables included in the final models differed to a great extent. None of the predictors was present in all of the final models. The total number of clicks, irregularity of study interval, and largest period of inactivity were present in most models (4 out of 5), whereas the irregularity of study time per session was present in none of the five models.

Compared to the models using LMS data, the models using LMS data and performance data (model 2) explained substantially more of the variance in final exam grade. In-between assessment grade was present in the prediction models of all courses, while the LMS variables again differed per course. Total time online and the total amount of views were present in the most models (3 out of 5), next to in-between assessment grade. The number of online sessions and the time until the first activity were present in none of the five models. Interestingly, with the inclusion of in-between assessment data, other LMS variables were found significant predictors compared to the model using LMS data only.

The model with learner data (model 3) had a higher predictive value compared to the model with LMS data only (model 1), with R^2 values between .02 and .19 higher. However, it performed less well compared to the model with LMS data and performance data combined (model 2), with R^2 values between .03 and .11 lower. Prior GPA was found a significant predictor for student performance in all courses. The effects of the other learner data predictors again differed per course, and were present in at most two of the models. Lack of study strategy was even not present in any of the models.

The models using both learner data and LMS data (model 4) –with higher R^2 values than those for the other three models for all five courses– again showed that especially the measurements of performance, such as past GPA and in-between assessment grade, have a high and robust predictive power. Next to these performance measures, some learner and LMS data had some additional predictive value, but these predictors differed across the courses. Thus, a lot of the predictive power comes from performance measures. This indicates that time-consuming questionnaires about capacities and motivation, and analyses of LMS data might not be necessary when some measures of performance are available.

As the sample sizes per course are quite small, the models may explain too much of the error in the data. Therefore, 10-fold cross-validation was conducted on all models (see Table 9) to determine whether the models overfit the data. The cross-validation indeed resulted in a substantial lower pseudo R^2 on average. Hence the models presumably perform less on new data. As expected, the difference between the original R^2 and the cross-validated R^2 was highest in the courses with the smallest sample sizes. Interestingly, for the Introduction to Psychology & Technology course, the cross-validated pseudo R^2 for all sources combined was even lower than the cross-validated R^2 for the model with learner data. This indicates that adding LMS data and performance data to learner data does not have much added value in this course for the prediction of final exam grade and even results in overfitting.

The pseudo R^2 values and mean residuals of all models show that the accuracy of the prediction models, even with all sources combined, was rather low. The mean residuals ranging from 1.40 to 2.24, with an extreme value of 8.36 in Introduction to Psychology and Technology indicate that the predictions deviate on average 1.40 to 8.36 points from the final exam grade (on a scale from 0-10). Thus, the way LMS data are currently used appears to be less useful for predicting student performance than the literature suggested. However, LMS data might still be useful for early prediction when in-between assessment data are not available. Accordingly, in the next section we determine the predictive value of learner data, LMS data and performance data for early prediction.

Table 9: Multiple linear regressions on final exam grade using learner data and LMS data, separated per course

	Calculus A				Calculus B				Applied Physical Sciences formal				Applied Physical Sciences conceptual				Introduction to Psychology & Technology			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Total number of clicks	-0.20	-0.16		-0.37**	-0.36***	-0.32***		-0.22***	-0.49				0.15*	0.11*						0.34**
Number of online sessions								0.20**									0.24**			
Total time online					0.16*	0.22**			0.99**	0.54*		0.59*				0.15*		0.30*		
Total number of views	0.26*	0.23**		0.39**	0.21*	0.22*		0.13		-0.56**		-0.62**								
Irregularity of study time						-0.12*										0.10		-0.24		-0.50*
Irregularity of study interval		-0.14		-0.23**	-0.37***				-0.40	-0.60*		-0.47*	-0.28	0.14*		0.15*	-0.47**			-0.13
Largest period of inactivity					0.17				0.47	0.58*		0.43	0.36**				0.35			
Time until first activity	-0.24**				-0.08															
Average time per session		-0.11							-0.43**	-0.26		-0.29				-0.16*				0.51**
Male							0.11*	0.10*				-0.24**			-0.10	-0.10				
Major IE																				
Major P&T											0.28									
Major SI			-0.10	-0.09							-0.02									
Major BE			0.24**	0.12																
Science-oriented profile				0.08*															0.17	
GPA prior education			0.32***	0.20*			0.42***	0.26***			0.53***	0.18			0.38***	0.31***			0.33**	0.29*
Conscientiousness															0.08				0.20	0.22
Time management			0.26**	0.23**			0.11													-0.30*
Study strategy (lack of)																				
Self-efficacy							-0.18**	-0.11*			-0.21					0.09			-0.31**	-0.11
Connection with study program											0.35*				-0.10	-0.15**				
Confidence study choice							-0.08				-0.38**	-0.13								
Amotivation study choice															0.10				-0.16	-0.14
External regulation			0.11								0.38*									0.20
In-between assessment grade		0.60***		0.43***		0.43***		0.31***		0.66***		0.70***		0.43***		0.33***		0.50***		0.29*
R^2	0.11	0.42	0.30	0.53	0.22	0.35	0.24	0.41	0.36	0.63	0.57	0.75	0.07	0.21	0.18	0.31	0.18	0.36	0.28	0.51
Pseudo R^2 cross-validated	0.08	0.21	0.11	0.19	0.08	0.25	0.15	0.29	0.04	0.14	0.10	0.13	0.01	0.09	0.15	0.24	0.07	0.12	0.08	0.02
M residual	1.61	1.79	1.73	2.16	1.78	1.45	1.57	1.40	3.81	2.09	2.81	2.24	2.06	1.77	1.56	1.46	1.92	3.32	1.81	8.36
N	122	122	116	116	297	297	273	273	45	45	38	38	350	350	328	328	74	74	64	64

[a)] Standardized betas reported

[b)] (1) LMS data, (2) LMS data and performance data, (3) Learner data, (4) LMS data, learner data, and performance data

[c)] * p < .05, ** p < .01, *** p < .001

[d)] Constants omitted from table

5.2 *Predicting student performance over time*

To analyse whether early intervention is possible using LMS data and learner data, and how the prediction evolves over time, predictions were compared over the weeks. Learner data were available before the course started, LMS data were available and aggregated per week, and in-between assessment grades were available after week 5. For the LMS data, only the basic predictors (the total amount of clicks, the number of online sessions, the total time online, and the total amount of views) were used, as study patterns (e.g. the regularity of study time) were often not available (for example *SD* of study interval for two sessions and hence one interval) or not yet meaningful (for example *SD* of study time for two sessions). Multiple linear regressions were run on the eleven weeks of the courses, with interactions for the courses and student clustered standard errors. Six different combinations of the data sources were used: (1) learner data, LMS data, and in-between assessments; (2) learner data and in-between assessments; (3) learner data and LMS data; (4) LMS data and in-between assessments; (5) learner data; (6) LMS data. The R^2 and the mean residual of these six models over time are shown in Figure 1.

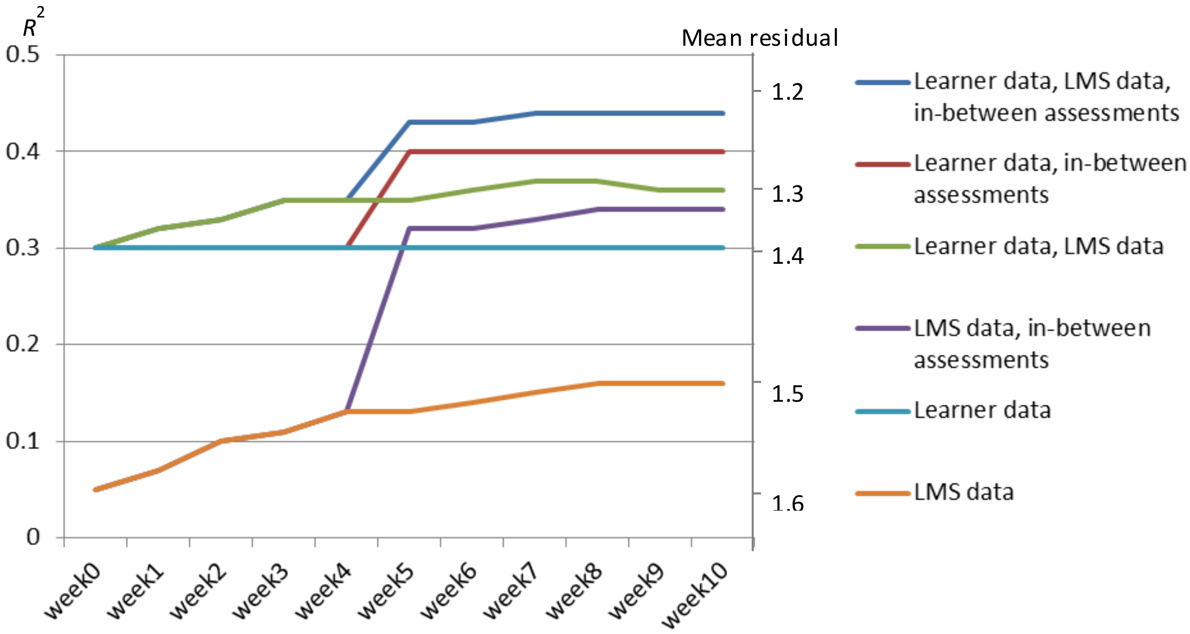

Figure 1: R^2 and mean residual (approximated) for predicting final exam grade over time for six combinations of the different data sources

As expected, it was found that the predictions using LMS data improved slightly over time. Also, when in-between assessment data were added at the end of week 5, a high increase in explained variance was found. The combination of learner data, LMS data, and in-between assessment data resulted in the highest predictive power during the whole course. When there is no access to the raw LMS log data, using learner data with in-between assessment data is a good second best for predicting final exam grade. For early prediction, before in-between assessment data are available, learner data was the most useful source. Because these data are already available before the course starts, these data are valuable for early intervention. The addition of LMS data in the first weeks led to a slight increase in the prediction. The best compromise between early feedback and accuracy seems to be after week 3, as the prediction did not improve much after that. However, at that point in time, the mean residual is 1.35, hence the prediction is on average 1.35 off away from an accurate prediction of final exam grade (on a scale from 0 to 10). This may however not be a major issue as there is no need to predict the exact final exam grade. It would be enough for intervention to be able to predict whether a student will pass or fail a course.

5.2.1 Predicting pass/fail probabilities

To predict whether a student would pass or fail the course, binary logistic regressions were run on learner data, in-between assessment data, and LMS data grouped per week, with interactions for the courses. As we are particularly interested in whether a student would fail (e.g. to provide feedback or help), students with a final exam grade < 5.5 were coded as at risk (1), while student with a final exam grade ≥ 5.5 were coded not at risk (0). In total 450 of the 888 students were coded as at risk (51%). The same six combinations of the data sources were considered as in the multiple linear regressions. The pseudo R^2 for these six models over time are shown in Figure 2.

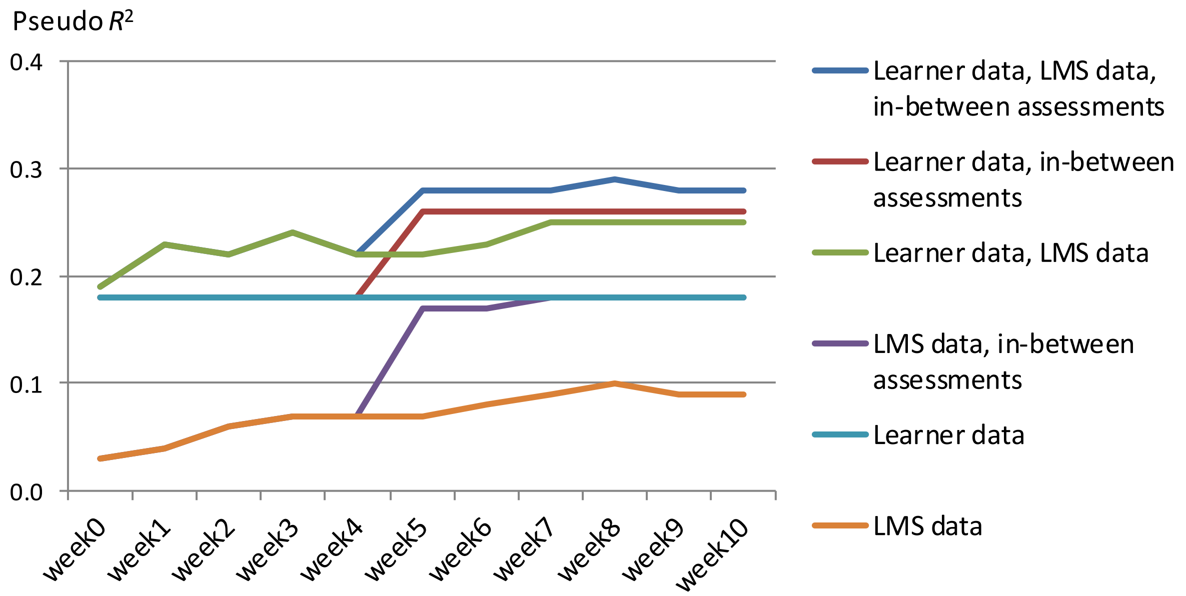

Figure 2: Pseudo R^2 for predicting pass/fail probabilities over time for six combinations of the different data sources

Similarly as for the prediction of the final exam grade, it was found that the prediction using LMS data improves slightly over time and that learner data are better in predicting final exam grade compared to LMS data. Additionally, a high increase in the prediction can be found after the in-between assessments are added. Contrary to predicting final exam grade, after in-between assessment data have become available learner data are still equal or even somewhat better in predicting pass/fail probabilities than LMS data. Using only LMS data, the total classification accuracy was rather low and ranged from 54% after week 0 to 62% after week 10. Interestingly, when we divided the total prediction accuracy into the accurate predictions of students who passed and failed, LMS data was shown to be especially bad in predicting whether a student will pass (specificity). In week 0 LMS data could only accurately predict 24% of the passing students as not at risk, increasing to 57% in week 5, while learner data could predict 69% of the passing students as not at risk. Thus, when the exact grade is not needed, but just an estimate of pass versus fail, learner data are of more value than LMS data.

Unfortunately, the prediction whether a student would pass or fail is also far away from accurate prediction. The binary logistic regression showed that after week 10, when all data sources are combined, the total classification accuracy equals 74%. Week 1 was the best compromise between early feedback and accuracy, with a total classification accuracy of 72%, a false positive rate of 29%, and a false negative rate of 26%. Thus, one should proceed with caution when intervening with students based on these statistics. With all data included still 26% of the students would not get an intervention, while they actually needed the help. Moreover, 29% of the students would get an intervention while they did not need it, which might influence a students' self-efficacy and motivation.

Thus even when all data sources were combined, predicting final exam grade or pass/fail probabilities was not accurate. Additionally, LMS data had low additional value next to learner data. Hence, LMS data, at least in the way we currently use it, may not be really useful for predicting student performance. However, LMS data may still be useful to predict other variables such as student characteristic. In this way, LMS data can be seen as a 'live' way of measuring student characteristics. Therefore, in the next section we determine whether LMS data can be used for the prediction of student characteristics.

5.3 Predicting student characteristics

To determine whether LMS data can be used for predicting student characteristics, we first conducted correlational analyses between LMS data and learner data and performance data. For brevity, the correlations are reported on the full dataset (not per course), with the LMS variables normalized per course. The results (Table 10) show that the relationship between LMS data and learner data was rather weak. The lack of study strategy, self-efficacy, connection with study program, confidence study choice, and external regulation study choice showed no significant correlations with any of the LMS variables. Conscientiousness and time management had significant correlations with most LMS variables, and prior GPA and amotivation study choice had significant correlations with some of the LMS variables, but all these effect sizes were small (r = .07 - .15).

The relationship between LMS data and performance data was somewhat more robust. In-between assessment grade showed significant correlations with all of the LMS variables, with a small to moderate effect size (r = .07 - .32). Interestingly, final exam grade had weaker correlations with the LMS data compared to in-between assessment grade. Irregularity of study time, largest period of inactivity, and average time per session were not significantly correlated with final exam grade. This indicates that LMS data might be better for predicting in-between assessment grade than final exam grade.

Table 10: Bi-variate correlations of LMS data with learner data (Pearson's *r*)

	GPA prior education	Conscientiousness	Time management	Study strategy (lack of)	Self-efficacy	Connection with study program	Confidence study choice	Amotivation study choice	External regulation study choice	In-between assessment grade	Final exam grade
Total number of clicks	-.02	.15***	.12***	-.00	-.01	.06	.05	.04	-.01	.23***	.11**
Number of online sessions	.09**	.13***	.12***	-.01	-.05	.02	-.02	.03	-.02	.32***	.28***
Total time online	.08*	.13***	.06	-.02	-.03	.03	.00	.09**	.01	.27***	.21***
Total number of views	.07*	.14***	.14***	.00	-.03	.05	.02	.04	.00	.28***	.22***
Irregularity of study time	.03	.06	-.00	-.01	.02	.04	.05	.06	.02	.16***	.05
Irregularity of study interval	-.07	-.15***	-.13***	.02	.05	.00	-.04	.00	.06	-.24***	-.15***
Largest period of inactivity	-.04	-.10**	-.11***	-.00	.02	.02	-.02	.01	.06	-.07*	-.03
Time until first activity	-.01	-.11**	-.05	.02	.03	-.03	-.02	-.00	.02	-.19***	-.15***
Average time per session	.02	.03	-.04	-.01	-.00	.02	.04	.09**	.05	.07*	-.01
N	888	888	888	888	888	888	888	888	888	888	888

a) * p < .05, ** p < .01, *** p < .001

To conclude, the LMS variables we currently have, were not shown to be very useful for the accurate prediction of final exam grade. Moreover, the LMS data show weak correlations with the learner data, indicating that LMS data might not be well suited as a 'live' way of measuring learner data either. However, the in-between assessment grades show stronger correlations, indicating that LMS data might be useful to predict in-between assessment grades. As in-between grades are quite good and very robust predictors of the final course grade, this may be useful as well to indicate which students are at risk of failing a course. In turn, this could be used for intervention purposes.

6 Discussion and Conclusion

In this study we investigated how LMS data can be used for learning analytics and the value of using LMS data for learning analytics. For this, data was collected from seventeen blended courses with 4,989 students at Eindhoven University of Technology. Data included online behaviour data from the learning management system Moodle, learner data (including capacities and motivation), and performance data. First, we determined the differences between the seventeen courses and analysed the portability of the prediction models using LMS data across courses. Moreover, we compared the value is of using LMS data for the (early) prediction of student performance with using learner data and performance data. Lastly, we investigated the relationship between LMS data, learner data and performance data.

6.1 Course characteristics

The first aim of study 1 was to determine the characteristics of blended courses taught at Eindhoven University of Technology which used the learning management system Moodle. It was found that courses somewhat in the level, type, assessments, and course design, but the courses also showed similarities. Most courses were first-year courses, which were taught in the fields of Mathematics and Physics. Sixteen out of the seventeen courses used multiple assessments to calculate the final course grade. All of the courses used a final exam, which had the highest weight in the final course grade.

The LMS was designed similarly in most courses. All courses implemented a discussion forum, however this was rarely used by the students. Most courses also provided content online, but the most activity of the students could be found in the assignments and quizzes, which were available in all courses in Moodle. Only a few courses implemented peer-reviewed assignments or a wiki. Hence, the LMS design in most courses is not focussed on collaboration and communication, but rather on sharing content and submitting assignments (Park et al., 2016). Thus, the full potential of learning management systems, using more interactive features is not yet utilized in the courses using Moodle at Eindhoven University of Technology.

6.2 Portability of models predicting student performance

The second aim of the first study was to determine the portability of models predicting student performance using LMS data across courses. Gašević et al. (2016) already found substantive differences in the prediction models of nine blended courses using LMS data. However, these differences could be explained by the fact that their predictor variables were based on the different features within the LMS. Due to the different course designs this resulted in different predictors across courses. Moreover, the topic of the courses varied to a great extent, resulting in a more heterogeneous group of students.

Therefore, in the current study, we used predictor variables which were available in all courses and used in previous research as well (e.g. Tempelaar et al., 2015; Zacharis, 2015). Basic predictors were used, including the total number of clicks, the number of sessions, the total time online, and the number of views. Additionally, more complex variables based on the study patterns and (ir)regularities were included: the irregularity of study time, the irregularity of study interval, the largest period of inactivity, the time until the first activity, and the average time per session.

Moreover, our previous research question showed that the courses in the current study were more similar in LMS design and type. Additionally, a more homogeneous group of students was used: all students are from a technical university and mostly first-year courses are included thus most students are first-year students. However, using a more generic set of variables, more similar courses, and a more homogeneous student sample compared to Gašević et al. (2016), still substantial differences were found between the prediction models. Correlational analyses, ordinary least squares regressions, multi-variate analyses, and multiple linear regressions all showed that the effects of the predictors on final exam grade differ across courses.

These results corroborates with previous findings on predicting student success, which showed different results in correlations and prediction models. We tried to explain these differences between previous studies with the different analytical techniques, different sets of predictor variables, and different LMSs used. However, while keeping the contextual effects more constant, we still found substantial differences in the sign and size of the predictors. Only two variables were found more robust: the number of sessions always showed a positive coefficient and the time until the first activity which always shows a negative coefficient. This shows that even within one institution, using one LMS, and one set of predictor variables, the portability of the prediction models across courses is low. The data of several courses can thus neither be simply combined for analysis nor to construct general models. However, the data can still be used to predict student performance within a specific course.

The low portability of the models across courses might be explained by the differences in course characteristics and student characteristics. Theory on self-regulated learning states that learning is not only affected by task conditions (such as course characteristics), but also by internal factors, such as student dispositions and motivational factors (Winne & Hadwin, 1998). However, as the current sample of courses is too small (17 courses), we cannot determine if and which course characteristics have an effect on the prediction models. Therefore, in our second study we only included student characteristics.

The learner data used in the second study consisted of the demographical variables gender, science-oriented profile, and current major; the capacities prior GPA, conscientiousness, time management, lack of study strategy, and self-efficacy; and the motivational factors connection with study program, confidence study choice, amotivation study choice, and external regulation. When learner data were added to the LMS data, the prediction models still differed. Adding these student characteristics therefore seems to be not sufficient for increasing the portability of the prediction models; course characteristics or other student characteristics still need to be considered. However, the second study used only a small sample of five courses, which makes it hard to draw strong conclusions about the differences between the prediction models. Future work should use a larger sample of courses to determine whether these student characteristics could improve the portability of the prediction models across courses.

To conclude, the prediction models for student performance are useful for specific courses. The portability of the prediction models across courses is however low, even when controlling for student characteristics. Only the total number of sessions, and the time until the first activity showed robust (although not always significant) results across the courses. This indicates that more general conclusions should be restricted to these variables. To improve the portability across courses, future work should consider course characteristics as well, using a larger sample for courses. For example, courses could be analysed over multiple years, where course characteristics are kept relatively similar over years. In this way, it could be determined which characteristics need to be similar to be able to use a prediction model in multiple courses.

6.3 (Early) prediction of student performance

The second aim of our study was to determine the value of using LMS data, learner data, and performance data for the (early) prediction student performance. Study 1 showed that LMS data could account on average for 20% of the variance in final grade within the seventeen blended courses. This is somewhat low compared to other studies who predicted student success (Macfadyen & Dawson, 2010; Morris, Finnegan, & Wu, 2005; Rafaeli & Ravid, 1997; Yu & Jo, 2014; Zacharis, 2015). This could be due to the differences in types of LMSs used, the sets of predictor variables examined, and the course characteristics. Moreover, the limited predictive value of the LMS variables in the current study may be due to the (lack of) relation between the final exam and the activities in the LMS. Most courses used final exams written on paper, while the activities in the course made use of different online tools typically not available at the exam.

Although the prediction accuracy might seem low for precise prediction, these numbers are not uncommon in social sciences. Additionally, the prediction analyses still provide insight in which LMS variables influence student performance.

Contrary to LMS data, learner data do provide more concrete and robust measurements, and might thus be more useful in predicting student performance. Therefore, in our second study we combined LMS data with learner data, to determine which source is most useful in predicting student performance, and whether learner data and LMS data explain a unique part of the variance in final exam grade. Unfortunately, as learner data was not available for all courses, the analyses of study 2 were restricted to five courses. As the subsample in study 2 was significantly different from the whole sample in study 1, no general conclusions could be draw about the whole sample. Therefore, all conclusions are restricted to these five courses.

First, it was examined whether learner data could explain part of the variance at the student level. It was found that learner data could account on average for 29% of the variance in final exam grade in the five courses. This amount is within the range of what other studies found when analysing the effects of trait and state variables on student performance (Britton & Tesser, 1991; Dollinger et al., 2008; Kaufman, Agars, & Lopez-Wagner, 2008). The amount of variance explained was mostly due to prior GPA, which corroborates previous findings that past performance is an important and robust predictor for student performance. All other predictors showed no effect, or only a small effect in one or two of the courses. This is in contrast with previous literature in social sciences which reported robust effects of these predictors on student performance. For example, conscientiousness was found a stable predictor in a meta-analysis on personality traits (O'Connor & Paunonen, 2007), and time management and motivation have been pointed out as significant predictors as well (Britton & Tesser, 1991; Kaufman et al., 2008). Moreover, a previous longitudinal study on the same university, with similar measures for the capacities, external regulation, and amotivation, did find a significant result for all these measures on study progress and study drop-out (Bipp et al., 2013).

These differences in results can be (partly) explained by the fact that in the questionnaire the current study was completed two to seven months before the students started their study program at the university. Thus, some of the state variables (all motivational variables, time management, (lack of) learning strategy, and self-efficacy), might have been changed in the meanwhile. Moreover, the motivational variables measured motivation for the study program as a whole, not for a specific course.

Future work should include motivations for courses itself, measured right before the start of the course, as these might have more influence on the final exam grade of the specific course. Future work should also reassess the motivation when the course has started for a few weeks, when the students know somewhat better what to expect of the course. This might have an even better predictive power.

Furthermore, in study 2 the predictive value of LMS data was compared to learner data and performance data. It was found that learner data could explain less variance in final exam grade compared to LMS data. However, when performance data was added to the learner data, learner data could explain substantially more variance than LMS data. When LMS data was added to learner data and performance data, multi-level and regression analyses showed that the amount did increase a bit, but not much. Hence, LMS data has limited predictive value next to learner and performance data.

Regressions over time showed that learner data are especially useful for early prediction of final exam grade and pass/fail probabilities, when in-between assessment grades are not available yet. These findings are in line with Tempelaar et al. (2015), who also found that up to in-between performance measures were available, learner dispositions were highly useful predictors. However, with all sources combined, the predictions are still not accurate. Early prediction of final exam grade is on average 1.35 away from accurate prediction (on a scale from 0 to 10). Additionally, binary logistic regressions showed that predicting pass or fail probabilities is also less accurate than would be desirable for intervention purposes. When these predictions would be used for intervention, 26% of the students will not get feedback, while they needed it, and therefore still might fail the course. Moreover, 29% of the students who did not need the intervention do get feedback. This might even influence their self-efficacy and motivation. For example, Jayaprakash et al. (2014) found that students who did get an intervention showed higher withdrawal rates than students who did not get an intervention. Hence, the prediction must be as accurate as possible, to avoid the chance of an unnecessary withdrawal.

Thus, even when all data sources are used, the predictability is still low. The low predictability, and also the low portability of the LMS variables, might be improved by adding more variables, such as more course characteristics and student characteristics (as stated above). Moreover, more complex LMS variables could be added, such as the order of events or types of interaction. For example, Agudo-Peregrina and colleagues (2014) generated LMS predictors from the raw data based on the types of interaction. Also quantitative LMS data could be added. Especially data from the discussion forum or wikis might give more information on the type of participation of the student in the LMS (Davies & Graff, 2005; Nandi, Hamilton, Harland, & Warburton, 2011) and could thereby improve the prediction models. Lastly, as not all learning behaviour occurs within the LMS, behaviour outside the LMS should be considered too. For example, lecture attendance (Agudo-Peregrina et al., 2014), behaviour in informal networks, and behaviour in other (informal) learning tools (Tempelaar et al., 2015), could be included as well to improve the prediction models.

6.4 Relationship between LMS data and learner data

The last aim of the second study was to investigate the relationship between data from learning management systems and learner data, to determine whether LMS data could be used as a 'live' way of measuring student characteristics. It was found that the correlations between LMS data and learner data was limited. Most student characteristics did not correlate with any of the LMS variables. Time management, conscientiousness, and in-between assessment grade did significantly correlate with the LMS variables, but these effect sizes were low. These results are in line with Iglesias-Pradas et al. (2015) who also found no relationship between commitment and teamwork and LMS behaviour. The correlations between LMS data and in-between assessment data were more robust. All LMS variables were significantly correlated with in-between assessment grade, with a low to moderate effect size.

Thus, the LMS data used are of limited use for measuring student characteristics as motivation and capacities. The significant relationship between conscientiousness and time management and LMS data indicate that there might be some way to measure these characteristics using LMS data. To improve the accuracy, future work could consider some more complex LMS variables, such as the order of events or time until the deadline. Moreover, the significant relationship between in-between assessment grade and LMS data indicate that LMS data may be used for the prediction of in-between assessment grades as well. As in-between assessment grades are a part of the final exam grade, this can also give an indication of whether a student is at risk of failing the course.

6.5 The need for theory

Thus LMS data are of limited value for predicting student performance, next to learner data, especially when in-between assessment grades are available. Moreover, the last part of study 2 also showed that the correlations between LMS data and learner data are low. LMS data is still useful for analysing a single course, for example to evaluate a course design or to determine which factors influence student performance (Lockyer, Heathcote, & Dawson, 2013). However, for more generalizable results we first need to consider whether we are actually using LMS data in the right way. What *does* a click mean and how can we use that information to improve learning and teaching? Adding more and more variables might improve the prediction slightly, but our study showed that adding more variables only has limited value for increasing the portability and predictability. Therefore, we argue that inclusion of theory is necessary in future studies on learning analytics.

Learning management systems provide us with raw log data, but these are not concrete measurements of any previously defined theoretical concept. To improve the usefulness of LMS data, more insight needs to be gained in what the LMS data represent and how they relate to theoretical concepts. These theoretical arguments can guide the inclusion of additional predictors and the interpretation of results. Likewise, Shaffer et al. (2009) argued that theoretical reasoning is needed to generate more generalizable results. Some researchers addressed this issue by creating general theoretical frameworks for dealing with LMS data (Petropoulou, Retalis, Siassiakos, Karamouzis, & Kargidis, 2008; Rankine, Stevenson, Malfroy, & Ashford-Rowe, 2009). However, these frameworks do not yet show how LMS data can be used to measure theoretical concepts.

Therefore, future work should investigate how educational theories can be utilized to make better sense out of LMS data. For example, LMS data might only be used to predict student performance for specific types of students or theory may be used to distinguish between groups of students for whom the same LMS data may mean different things. We argue that the adequate inclusion of educational theory will provide more insight in the meaning and the usefulness of LMS data. Moreover, LMS data can be used for the prediction of student performance. Although the prediction models of final exam grade vary across the courses, and hence the portability is low, we showed that in-between assessment grades, the number of sessions, and the time until the first activity were quite robust predictors across courses. Additionally, LMS data are still useful for the prediction of student performance in a single course. When learner data or in-between assessment data are added to LMS data, the accuracy of the prediction and especially the early prediction improves. Lastly, LMS data showed to have some relation with in-between assessment grades, conscientiousness, and time management as well.

To conclude, this study provided insight in how LMS data, produced as a by-product of online learning, can be used to predict student performance to improve learning and teaching. These findings, combined with the inclusion of theoretical concepts, create many opportunities for future research to explore the full potential of LMS data and to improve learning and teaching.

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Appendix A: Questionnaire learner data (Dutch)

Abilities and skills 1: – Gemiddeld VWO cijfer [1-10]:

Gemiddelde van alle eindcijfers op het VWO, met extra gewicht voor Wiskunde B bij Technische Bedrijfskunde, Psychology & Technology en Sustainable Innovation en extra gewicht voor Wiskunde B en Natuurkunde bij Bouwkunde.

Abilities and skills 2 – Consciëntieusheid [1 - 5]:

1. Ik ben een persoon die grondig te werk gaat
2. Ik ben een persoon die volhoudt tot de taak af is
3. Ik ben een persoon die doorgaans geneigd is tot slordigheid (1↔5)
4. Ik ben een persoon die geneigd is lui te zijn (1↔5)
5. Ik ben een persoon die een werker waar men van op aan kan
6. Ik ben een persoon die dingen efficiënt doet
7. Ik ben een persoon die plannen maakt en deze doorzet
8. Ik ben een persoon die gemakkelijk afgeleid is (1↔5)
9. Ik ben een persoon die een beetje nonchalant kan zijn (1↔5)

Abilities and skills 3 – Timemanagement [1 - 5]:

1. Ik heb grote moeite om studie en vrije tijd te combineren (1↔5)
2. Ik kan studie en vrije tijd goed indelen
3. Ik heb grote moeite om geregeld te studeren (1↔5)
4. Ik begin op tijd een proefwerk/tentamen voor te bereiden

Abilities and skills 4 – Leerstrategie [1 - 7]:

1. Ik weet niet zeker hoe ik moet studeren voor de vakken in de opleiding die ik op dit moment volg
2. Ik merk vaak dat ik niet weet wat ik moet bestuderen of waar ik moet beginnen
3. Het ontbreekt me aan een studiestrategie voor de opleiding die ik op dit moment volg

Abilities and skills 5 – Academisch zelfvertrouwen [1 - 7]:

1. Ik verwacht goed te presteren vergeleken met andere studenten die deze opleiding gaan volgen
2. Ik denk dat ik in deze opleiding goede cijfers zal halen
3. Ik denk dat ik vergeleken met anderen een goede student ben
4. Ik weet dat ik in staat ben de lesstof van deze opleiding te leren
5. Mijn studievaardigheden zijn uitmuntend vergeleken met andere studenten die deze opleiding gaan volgen
6. Ik denk dat ik vergeleken met andere studenten in deze opleiding veel weet van het vakgebied
7. Ik verwacht het heel goed te doen op deze opleiding
8. Ik weet zeker dat ik uitstekend kan presteren bij de cases en taken die ik in deze opleiding moet doen
9. Ik ben er zeker van dat ik de stof kan begrijpen die in deze opleiding onderwezen wordt

Motivation 1 – Binding met opleiding [1 - 7]:

1. Deze opleiding past heel goed bij mijn interesses
2. De beroepen die ik na deze opleiding kan uitoefenen passen heel goed bij mijn interesses
3. Ik heb een goed beeld van wat deze opleiding inhoudt
4. Als ik deze opleiding zou kiezen, dan zou ik mijn toekomst met vertrouwen en optimisme tegemoet kunnen zien
5. Het is mij duidelijk wat de opleiding van mij verwacht
6. Ik heb een goed beeld van wat voor werk en carrière ik na mijn opleiding wil

Motivation 2 – Zekerheid studiekeuze [1 - 7]:

1. Ik weet zeker dat het een goede keuze is om deze opleiding te gaan volgen
2. Een HBO-opleiding is een reëel alternatief voor mij (1↔7)
3. Ik twijfel tussen meerdere TU/e opleidingen (1↔7)
4. Ik twijfel tussen TU/e en andere universiteiten (1↔7)

Motivation 3 – Motivatie studiekeuze [1 - 7]:

1. Er zijn wellicht goede redenen om deze opleiding te doen, maar persoonlijk zie ik er geen
2. Als ik deze opleiding zou volgen, zou ik er bij de eerste de beste tegenslag zomaar mee op kunnen houden
3. Ik zie niet in wat deze opleiding me oplevert

Motivation 4 – Zelfregulatie [1 - 7]:

Stel dat je deze opleiding kiest. In welke mate zijn onderstaande redenen dan van toepassing.

1. Omdat ik geen enkele keus heb
2. Omdat het iets is dat ik moet doen
3. Omdat ik verondersteld word om dit te doen
4. Omdat ik het gevoel heb dat ik het moet doen