Dependencies between E-Learning Usage Patterns and Learning Results

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ABSTRACT
Recent studies come to the conclusion that Learning Management System (LMS) usage variables explain a higher variation in students' final grades than traditional student characteristics. Referring to such findings from literature our research aims at exploring dependencies between e-learning usage patterns and achieved learning results on the basis of LMS log-files from courses in different knowledge domains, and by analyzing courses not in isolation but by taking potential dependencies with students' activities in other courses into account. We examine correlations between usage variables and the students' performance in three blended learning courses with different topics based on large cohorts of students (n=883, n=389, n=578). In this context, an extended set of variables, including LMS usage beyond the three courses and usage patterns of students, are examined for interdependencies. Our results indicate that specific indicators, such as the number of active learning days and topic views, have a positive influence on learning results. In general, they show that at-risk students can be differentiated from well-performing students by their usage behavior. Moreover, we try to identify some significant patterns of LMS usage amongst the students. The paper shows how these patterns differ in our observations depending on the course domains.

Categories and Subject Descriptors
J.1 [**Computer Applications**]: Administrative Data Processing: *Education*, H.2.8 [**Information Systems**]: Database Applications: *Data mining*, I.5.1 [**Computing Methodologies**]: Pattern Recognition: *Models – Structural*, G.3 [**Mathematics of Computing**]: Probability and Statistics – *Correlation and regression analysis*.

General Terms
Measurement, Experimentation, Human Factors.

Keywords
Learning Analytics, Learning Management Systems, Educational Data Mining, Correlation Analysis, Variance Analysis.

1. INTRODUCTION
Currently, research in the field of Learning Analytics attempts to exploit user-generated data through Business Intelligence techniques in order to support different stakeholders (i.e., learners, teachers, service providers, researchers etc) and predict learning performance in educational activities [3]. Due to the wide-spread application of Learning Management System (LMS) technology and its importance for organizations, many analysis studies have been conducted in support of such platforms.

Amongst others, Whitmer [20] claims that LMS usage variables explain over four times the variation in final grades compared to traditional student characteristic variables, and that the combined consideration of both types of variables increases the quality of predicting learning results by more than 70%. Similarly other factors, such as the motivation, autonomy, effectiveness or efficiency of learners (and teachers) have been examined in an exploratory way and on the basis of data-sets from LMS technology usage (cf. [3]).

Against this background, this paper analyzes correlations between usage variables and learning results in blended learning courses within an intensely used, web-based LMS platform. Moreover, different learner groups are identified and characterized according to LMS usage variables.

The paper is structured as follows. Section 2 gives an overview of the field of Learning Analytics. In Section 3 we explain the background and the goal of our research. Thereafter, Section 4 describes an experimental study to examine correlations between LMS usage and learning results. Section 5 summarizes the findings of the study and discusses the results, before Section 6 draws conclusions and highlights future work.

2. LEARNING ANALYTICS IN LMS-BASED EDUCATIONAL SETTINGS
Learning Analytics covers a broad range of research, comprising different stakeholders and learner-generated data of different types and sources [14]. Thus, this section gives a brief and general overview of Learning Analytics and puts the focus of this discipline on LMS-based environments, without tackling issues concerning organizations, ethics or the society in full depth.

2.1 Learning Analytics
Learning Analytics (LA) comprises "*the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*" [14]. With respect to personalized user experiences in educational technologies, much attention is paid to "*the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues*" [10]. Stakeholders of LA include learners and teachers but also service providers (administrators, developers etc), researchers, or even educational institutions [12].

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2.2 Possibilities and Restrictions of LA in LMS Platforms

According to Chatti and his colleagues [5], the LA process includes (a) the collection and pre-processing of data, (b) the provision of indicators, visual feedback or other elements (e.g., recommendations) to learners and (c) the post-processing of data to improve Analytics. From the user perspective, LA approaches aim at supporting the following activities in the learning process [17]: (a) awareness, (b) (self-)reflection, (c) sensemaking, and (d) impact. Technical solutions range from awareness elements, such as indicators, diagrams, visualizations etc., to more sophisticated features, like context-aware recommendations or facilities to navigate Big Data according to relevant aspects; normally LA is brought to end-users by means of Dashboards [17].

LA approaches have been arisen in various areas, driven by different disciplines. Amongst others, educational institutions explore the possibilities of Analytics to fulfill their academic mission [12] but also to improve their LMS platforms [9]. However, institutions (e.g. universities or companies) restrict LA in two ways: (1) The gathering and exploitation of user-generated data might underlie e.g. policies for preserving nondisclosure of data or privacy of users [9]. This reflects an organizational perspective. (2) Data might be a problematic issue for different reasons. For instance, relevant data can be gathered and stored at different places. This reflects a rather technical perspective. It is obvious that LMS usage comprises course contents in the platform, the history of learner interactions captured in the log-files (or in the database), as well as the estimated success of learning, e.g. in the form of points and grades assigned by teachers or quizzes and possibly managed outside the LMS. The last aspect requires the integration of these distributed data-sets. Finally, also the availability, the access to, and the granularity of usage data play an important role. If the granularity of tracking is too detailed, processing of the data is very costly (cf. Section 4).

2.3 Analysis Techniques for LMS Usage

Depending on the scope and goal of a LA approach, a wide range of techniques is applicable for LMS usage data. Although content-based methods, like Sentiment Analysis, Natural Language Processing etc., can be useful for specific application areas, LMS usage implies that data is available in a quantitative and structured way, i.e. in the log-files. Thus, we consider the following two approaches as highly relevant for analyzing LMS usage data.

Data Mining (DM) and Knowledge Discovery from Databases (KDD) aims at providing methods and a process to extract semantics (knowledge) from low-level and large data-sets. In this context, semantics refers to "*compact (for example, a short report), more abstract (for example, a descriptive approximation or model of the process that generated the data), or more useful (for example, a predictive model for estimating the value of future cases)*" data [8]. For LMS platforms Web Usage Mining [15] seems to be a useful instrument for retrieving (i.e., reconstructing) the browsing sessions from the log-files and generating further statistics on the users' browsing sessions.

Furthermore, the implementation of LA in LMS platforms requires the application of methods of ***Educational Data Mining (EDM)*** and of ***statistics***, such as correlation analysis (i.e., for exploring and evidencing correlations between LMS usage variables and learning results) or regression analysis (e.g., for predicting future performance of students). Moreover, this set of LMS usage analysis techniques can also include pattern mining (e.g., for identifying patterns of LMS usage), clustering (e.g., for grouping different kinds of learners), network analysis and visualization (e.g., for providing visual feedback to the LA stakeholders) or Collaborative Filtering (e.g., for generating personalized recommendations) [2, 13].

With respect to the phase of implementing LA in practice, research is designed in different ways, reaching from exploratory methods in the early phase of such a development to experimental research to evaluate and improve the solution. Due to the cyclic nature of the LA process [17] analysis techniques are applied for exploring data-sets as well as for experimental studies iteratively.

2.4 Related Work and Experiences

Correlations between learning performance and LMS usage have been examined ever since this kind of technology has been applied in practice. Many results and findings are considered to be sensitive data and thus are not published. However, early measurements addressed the usage of LMS and analyzed dropouts in online learning courses (cf. [5]). Driven by the field of LA, current research also focuses on more sophisticated analysis methods, such as the dynamics of LMS usage over time, effects of learning and forgetting [16], the impact and quality of didactical strategies and models [7] or interactions between different entities and networked structures in learning ecologies [11].

In the last decade many institutions have started to investigate in analyzing the usage behavior of their LMS users. Amongst others, Whitmer [20] outlines that the LMS is a potentially valuable source to improve online courses and to support at-risk students. The dissertation study shows that LMS usage variables explain four times the variation in final grades (25%) compared to traditional student characteristics, i.e. demographic data of the highly diverse student population, and even 35% if usage variables and student characteristics are combined. These findings are based on a data-set of LMS interactions within one course with n=377 students. Yet, the usage behavior in the platform beyond this course has not been considered at all. Moreover, only few demographic variables (e.g., being from a racial/ethical under-represented minority and being qualified for federal Pell grant which indicates a low income), 5 LMS usage categories (i.e., administration, assessment, content activity, engagement activity, overall course activity) and only one usage indicator (i.e., the number of hits) have been examined.

With respect to this study we see a lot of potential to examine LMS usage behavior on the basis of data-sets that include data on the courses and the user interactions within the platform. Therefore, the following section gives an overview of the situation at our university and outlines the overall goal of our research.

3. BACKGROUND AND AIM OF OUR RESEARCH ON LEARNING ANALYTICS

Motivated by the number of students that have increased dramatically in recent years, we have started to investigate in LA to develop new ideas and functionality for the LMS platform at our university. The goal is to enhance teaching and learning in this 'mass education situation' through useful LA elements.

3.1 University Facts

Currently, the Vienna University of Economics and Business (WU) offers Bachelor, Master and PhD study programs for about 26,000 students (winter semester 2011/12)[1]. The Bachelor

[1] http://www.wu.ac.at/academicstaff/info/facts/study/anzahl_insgesamt_zugelassene_studierende_ws11.pdf

program in "Business, Economics and Social Sciences" of the WU is divided into 3 phases: the Introductory and Orientation Phase, the Common Body of Knowledge, and the Major. In this mass education situation the WU is supported by an institution-wide LMS, the Learn@WU platform [1] which is used according to a blended learning strategy. All 5,000 courses offered by the university per year are supported in this LMS. Learn@WU offers a broad range of applications, including lecturecasts, forums, wikis, multiple-choice sample exams, homework exercises, etc.

The lecturers choose the applications they need in their courses from this pool. Furthermore, the system currently contains about 160,000 learning resources developed over the last 10 years primarily for the first study year. Particularly the courses of the Bachelor programs, which are faced with large cohorts of students, make intense use of the LMS platform. Indeed, Learn@WU is one of the most intensely used e-learning platforms world-wide; students solve up to 600,000 exercises per day online, the system serves up to 3.8 million page views per day.

3.2 Vision and Objectives

Against this background, we have started first activities addressing LA with the aim to increase the quality of learning (and teaching). Early work is manifested e.g. in [2]. The overall vision of our research on LA focuses on the development of new features for Learn@WU, so that at-risk learners are supported in a (semi-)automated way and that all learners (and teachers) are made aware of course-relevant factors and events.

By investigating the possibilities of analyzing large LMS log-files (up to 1 GB and several million entries per day), we calculated Web Analytics indicators, mined browsing sessions and clustered them according to similar usage behavior, and identified seasonal effects in LMS usage data (cf. [2]). The next step to specifically address learners is to identify potential correlations between LMS usage variables and the students' overall course performance.

4. CASE STUDY

In order to examine correlations between LMS usage and learning results we analyzed log-file and course-related data (final points and grades) collected during the exam preparation of the students. The study is restricted to analyzing online activities of students only – for examining offline activities other methods, like qualitative interviews, are required.

4.1 Context and Setup of Case Study

The data for the empirical study were collected in the winter semester 2012/13. We chose a sample of three courses of different knowledge domains (law, business, IT) within the Common Body of Knowledge. The online activities in these three courses were then related to the overall LMS usage of these users. With this approach, we aimed at (a) minimizing domain-specific particularities in the analysis results, (b) detecting dependencies between LMS usage and final grades which can be generalized to a broader set of courses and (c) gaining an understanding of LMS usage beyond the scope of one course only, for instance displacement effects. In this paper the three courses are referred to as C1, C2 and C3. All three courses are offered as half-semester courses with durations of two months and end with a final test, which is a multiple-choice test in all cases. Students are supposed to be at the beginning of a Bachelor study. If they study according to the recommended study plan, they usually attend all three courses in parallel.

Table 1 gives an overview of the numbers of participants in the 3 exams and their final grades. Only those students who attended the exam are listed, because only these students were considered in the data analysis.

Table 1: Participants and final grades of students in the 3 courses in November 2012

	C1	C2	C3
Participants	n=883	n=389	n=578
Grade=1	n=34 (3.9%) >=90%	n=13 (3.3%) >=80%	n=6 (1%) >=87%
Grade=2	n=104 (11.8%) >=80%	n=21 (5.4%) >=70%	n=22 (3.8%) >=80%
Grade=3	n=169 19.1% >=70%	n=59 15.1% >=60%	n=129 22.3% >=70%
Grade=4	n=225 25.5% >=60%	n=118 30.3% >=50%	n=155 26.8% >=60%
Grade=5	n=351 39.7% <60%	n=178 45.8% <50%	n=266 46% <60%
No. exam questions	n=45	n=26	n=40
No. exam points	120	60	40

It can be seen that in general, only small percentages of students pass the exam with the highest grade (grade=1). Almost 50% of the students in C2 and C3, and more than 66% of the students in C1, failed in the exam in the investigated course period. These are, however, typical numbers for these courses.

Finally, as pointed out by cf. [9], learning analytics is both a moral and educational practice, serving better and more successful learning. We have tried within this research to protect the privacy of the participants as far as possible while trying to obtain insights to increase the quality and effectiveness of teaching and learning for future versions of our LMS.

4.2 Characterization of Data-sets, LMS Usage Variables and Learner Groups

The web server usage-data of the students attending the exam was collected for the exam preparation period of 14 days before the actual exams. This led to log-file extracts with the following characteristics: C1: 2.3 Mio. user activities, C2: 1.2 Mio. user activities, C3: 1.6 Mio. user activities. The log-files are available in a slightly extended Combined Log format. In addition to the standard fields (IP address of client, remote user, HTTP user, timestamp, HTTP request, HTTP response, HTTP response size, HTTP referrer, user agent), we added LMS-specific data to the log-file entries, such as additional information for certain activities (e.g., exercises or exams) and the identifier of the user.

From the log-files, a set of LMS usage variables was calculated for each student. Thereby we differentiated between usage within the course ("topic") and outside the course ("other"). For each aspect we considered the following variables:

- **Sessions:** number of sessions of the course participant, (sessions topic, sessions other)
- **Views:** number of page views of a course participant (views topic, views other)

- **Duration:** amount of time in seconds spent in a course (topic duration) and in other courses (other duration)
- **Days:** number of days being active in the LMS platform (topic days, other days)
- **Excs:** number of different exercises (provided for self-evaluation of the students to monitor the learning progress) solved by this student (excs topic, excs other)
- **Exam:** number of different exam examples (provided to the students for the preparation for the final exam) solved by this student (exam topic, exam other)
- **Lecturecast duration:** amount of time a participant has spent on lecturecasts (lecturecast topic duration, lecture-cast other duration)

All together we analyzed 14 variables in order to find correlations between LMS usage and points/grades. Moreover, we assumed that learners who got different grades evidence a different LMS usage behavior. Thus we have defined the following groups of students for the courses (grades range from 1/best to 5/negative):

- **Best learners:** All students with the best grade (1)
- **Good learners:** Students with grade better than 3 (1,2)
- **Positive learners:** Students with a positive grade (1-4)
- **Bad learners:** Students with a negative grade (5)

Based on these data-sets, LMS usage variables and assumptions, we conducted the analysis study in the following way.

4.3 Methodology of this Study

We implemented a Web Usage Mining process that includes the typical phases according to, e.g., [15]: (1) usage preprocessing, (2) pattern discovery, and (3) pattern analysis (see also [2]).

The ***usage pre-processing*** phase comprises the cleaning and filtering of the log-files, e.g. through removing invalid HTTP requests or requests by anonymous users. Filtering deals with collecting the request of the participants to be examined. Hereby, the focus is not only set to interactions in the course but also to the usage within the platform. Preprocessing also includes that sensitive user data, like user-id or student number, is substituted or removed from the data-set. Substitution of user-ids includes the information on grades so that LMS usage data can be linked to the final grade. Finally, this phase also groups the click-streams for each user and divides them into sessions (including the consideration of a session timeout of 20 minutes).

From the raw log data, we produced a concise data structure containing all information on the sessions. A session consists of:

- a unique session identifier (user and counter);
- the chronological sequence of interactions with the duration, course, and a classified activity (exercise, exam, lecturecast) derived from the HTTP method and the URL path of the request;
- statistical data summarizing a session, including the session's total duration and the number of interactions.

The users' Web sessions were then split into course-specific sessions, i.e. if students worked on more than one course in one browsing session, the session was split up into individual sessions relating to each course.

Then, ***pattern discovery*** deals with calculating the statistics on the LMS usage, i.e. on the browsing sessions and the specific usage variables used for further analysis. In this phase the participants' usage variables are set in relation to their final points.

Finally, ***pattern analysis*** describes the phase in which the analysis takes place. In particular we conducted Pearson correlation tests and ANOVA variance analysis. Furthermore, we generated scatter plots and box plots to visualize potential interdependencies between our variables and the exam final points, and potential differences between the various user groups. This analysis was conducted with R, an open-source software for statistical computing and graphics (cf. http://cran.r-project.org).

5. FINDINGS AND DISCUSSION

The findings of your study are discussed along three aspects: the influence of student online-activities on the final results; the influence of time factors on the final results; and the differences of LMS usage of various student groups.

5.1 Influence of Student Activities on Results

A first issue to be addressed deals with student online-activities and their influence on the final exam points. Table 2 lists the Pearson coefficients of the correlations between the number of sessions spent in the LMS on the specific course (sessions topic) and on other courses (sessions other), the number of page views in this course (views topic) and in other courses (views other), the number of different online exercises solved in this course (excs topic) or other courses (excs other), and the number of different exercises within sample exams solved in this course (exam topic) and in other courses (exam other).

Table 2: Pearson correlations between final points and sessions, views, exercises and exams within each course (topic) and outside them (other); grey: lower significance (P > 5%)

	C1		C2		C3	
	Topic	*Other*	*Topic*	*Other*	*Topic*	*Other*
Sessions	0.19	0.14	**0.34**	0.09	0.19	0.16
Views	0.27	0.09	0.27	0.01	0.25	0.11
Excs	0.27	0.09	0.24	0.02	**0.34**	0.10
Exam	**0.33**	0.12	0.23	0.04	0.26	0.10

Table 2 indicates that all of the topic specific variables show a small correlation (from 0.1 to 0.3) with the achieved final points in the exam. The variables with the highest correlations differ between every course. The highest correlations are observable for the topic sessions (C2) and topic exercises (C3). Interestingly, the activities from other courses do not negatively influence the learning results. Rather, we see the weak tendency that students with more activities in other courses achieve quite good results on the topic course as well.

The scatter plots of Figure 1, Figure 2 and Figure 3 refer to the three highest Pearson coefficients of the correlations identified in Table 2. In Figure 1, the linear approximation (green line) visualizes the increase of the final points depending on the number of solved exam items in the topic course. The median of the points is around 70. The interquartile range shows that 50% of the students solve between 5 and 95 exam items. Figure 2 displays the relationship between the points and the number of topic sessions. One can see that the behavior of the students differs much stronger than in Figure 1. One student performed more than 150 topic sessions during exam preparation, while 50% of the students performed between 5 and 25 sessions (median 10). The median of the session duration was 18 minutes.

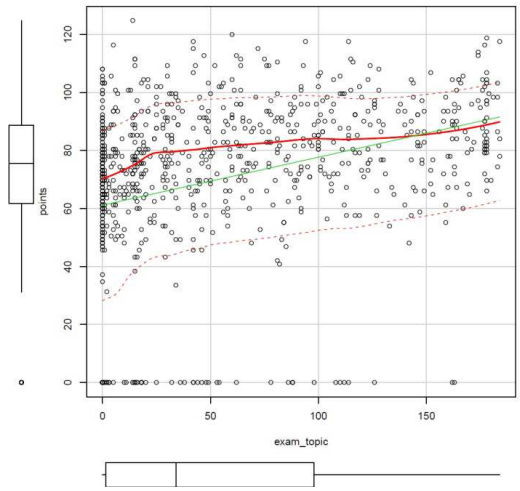

Figure 1: Scatter plot of final points and topic exam items(C1)

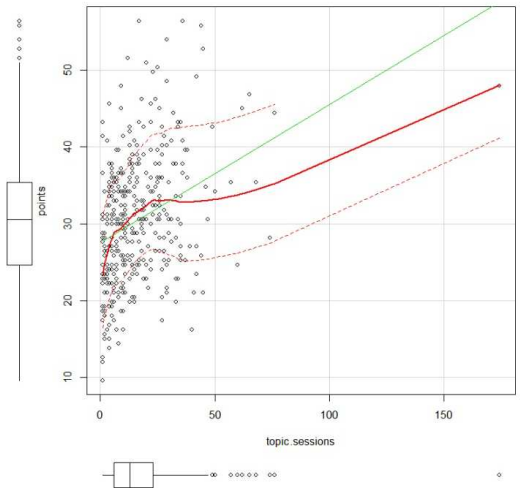

Figure 2: Scatter plot of final points and topic sessions (C2)

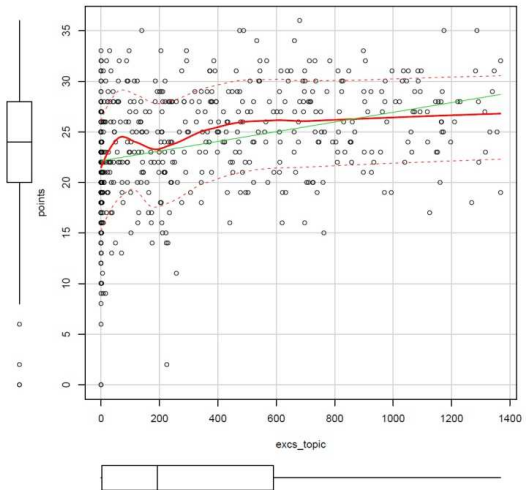

Figure 3: Scatter plot of final points and excs topics (C3)

Figure 3 provides a picture similar to Figure 1, showing the relation between solved exercises and results. On the left there are some students with no such activities, some of them perform quite well, but the tendency is that more examples lead to better results.

5.2 Influence of Time Factors on Results

Next to student activities, time-dependent LMS usage variables are relevant for our analysis study, as there exists a rich amount of literature on strategies for efficient learning (cf. [7]) and thus the influence of time-dependent factors on learning is widely accepted. Our analysis exhibits that there are (small and medium) positive correlations between time-dependent usage variables and the final grades in all three courses.

Table 3: Pearson correlation between final points and days, duration and lecturecast duration within each course (topic) and outside them (other); grey: lower significance (P > 5%)

	C1		C2		C3	
	Topic	Other	Topic	Other	Topic	Other
Days	0.30	0.21	**0.41**	0.15	**0.24**	0.24
Duration	**0.34**	0.07	0.27	0.03	**0.24**	0.08
Lecture-cast dur.	-0.02	0.01	0.10	-0.03	0.05	-0.05

Table 3 gives an overview of the Pearson coefficients of the correlations between the final points and the number of days spent in the LMS (topic or other), the time spent in this course or other courses and the time spent on lecturecasts. Since the lecturecasts (the recording of the lectures) are rather time-consuming, it was interesting to look at the influence on the final points when using this learning material. The highest correlations are observable for the topic days (C2) and topic duration (C1). The correlation of 0.41 is a medium correlation, which is the highest measured in our study and hints to the 'spacing effect' ([4], cf. Section 5.5) for C2. In the other courses, the effect seems to be weaker. For a better understanding, one should extend the observation interval to a longer time period (e.g. the full semester). Interestingly, the lecturecast duration is not significant for the final points.

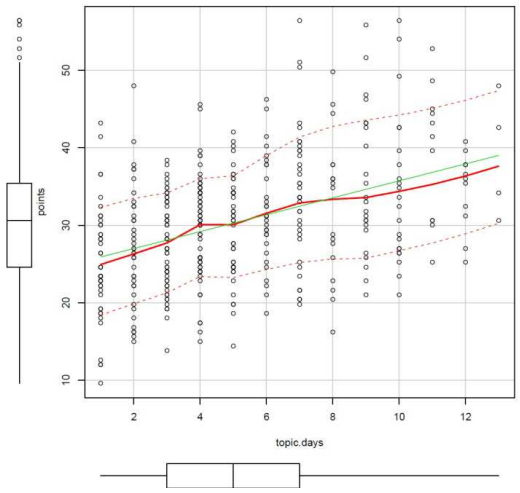

Figure 4: Scatter plot of final points and topic days (C2)

The highest Pearson correlation coefficients of Table 3 are once again further explored through scatter plots. Figure 4 depicts the scatter plot for the correlations between the final points and the number of days spent in the topic course (C2), Figure 5 and Figure 6 depict the scatter plots for the correlations between the final points and the total time duration spent in the topic course (C1; C3). Again, the linear approximation (green line) shows an

increase of final points with a higher number of days (Figure 4) and duration (Figures 5 and 6). As median, the students prepared 5 days on the LMS platform. Students preparing between 7 and 11 days (of the 12 potential days for this exam) achieved the best results. The dependency of points and learning days is quite linear. For the exams C1 and C3 the median days were much higher, which explains a worse correlation.

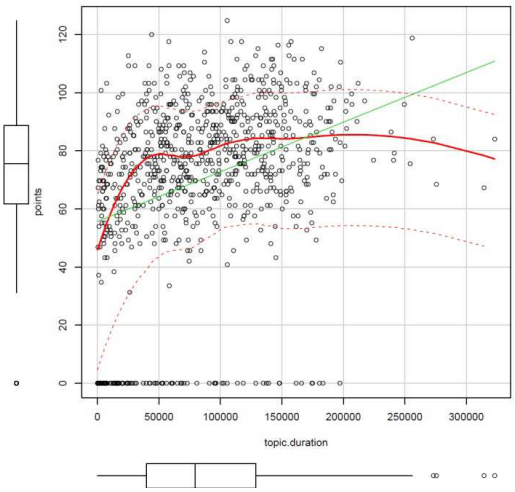

Figure 5: Scatter plot of final points and topic duration (C1)

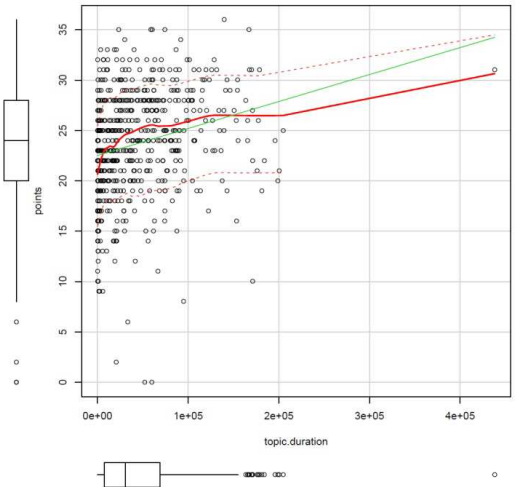

Figure 6: Scatter plot of final points and topic duration (C3)

A more differentiated picture emerges for the correlations between the final points and the topic duration (Figure 5, Figure 6). While in the course C3 the red curve shows a slight raise or horizontal progression throughout the plot (Figure 6), the curve of C1 has a different characteristic (Figure 5). For C1, after an online learning time of about 33 hours (120,000 sec), a peak is reached with no improvement up to about 61 hours (220,000 sec). A decline in final exam performance is observable beyond that time. Although this concerns only a few students (with positive results in the exam), it can be concluded that spending more than 61 hours for the exam preparation does not improve the results.

The peak in the average points over the topic duration and the decline to a range around the minimum points for a positive grade could be an indicator that some students only spend a minimum amount of time for learning and speculate with passing the exam, although with a low grade. A similar learning behavior is observable in the course C3 (but not in C1). Therefore we have examined different groups of learners in the upcoming subsection.

5.3 LMS Usage of Different Student Groups

To obtain a deeper understanding of the interdependency of variables and of the factors explaining the variance, we performed an ANOVA variance analysis of the usage data of the three courses. The results confirm our findings so far regarding the most significant influencing variables on the final points in the students' exams. Thereby the influence of each LMS usage variable was examined separately (one-way ANOVA; Degree of Freedom (Df) is 1 and the sum of squares (Sum Sq) equals the mean square (Mean Sq)). As highlighted in Table 4, the topic duration has the highest statistical significance of all variables in C1, which is manifested by a good F-value (i.e., the ratio between between-group and in-group variability) and a small Pr(>F) value (i.e., the null hypothesis is rejected even for the significance level of 0.1%). In C2 the topic days and topic sessions show the highest significance. In C3, the variable excs topic is statistically significant, too, although in this course, total views have the highest significance. Combinations of variables (n-way ANOVA) did not improve the explanation.

Table 4: ANOVA of the three courses showing some significant variables

C1	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Topic Duration	1	33945	33945	49.33	4.4e-12
C2	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Topic Sessions	1	2980	2980	54.87	8.9e-13
Topic Days	1	1552	1552	28.58	1.6e-7
C3	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Total Views	1	1214	1214	52.52	1.4e-12
Excs Topic	1	155	155	6.71	0.0099

Based on the finding that both the Pearson and ANOVA tests yielded to similar variables influencing the final exam points, we compared different student groups along these variables in the three courses. As shown in Table 1, almost half of the students (45.8%) failed in the exam of C2. Only 3.3% were able to get the best grade. Thus, we examined LMS usage variables of different groups of learners to get insights into the learning behavior, namely of the groups of best, good, positive, and bad learners. The box plots of Figure 7 and Figure 8 show a comparison of the best, good, positive and bad learners along the variables which had the highest Pearson coefficient in the previous section. Figure 7 (left side) shows that in C1, the best learners and thus those with the highest grade, on average have spent almost the double amount of time on the LMS, in the course of the topic, than those students who failed in the exam. There is, however, not much difference between best and good students. Figure 7 (right side) shows the amount of days spent in the course C2 of the four student groups. It evidences that bad learners (those with a negative grade) can be clearly distinguished from best and good learners, e.g. through a threshold of 7 days being active in the course C2. Yet there are overlaps between positive learners (grades 1 to 4) and the other three groups of students.

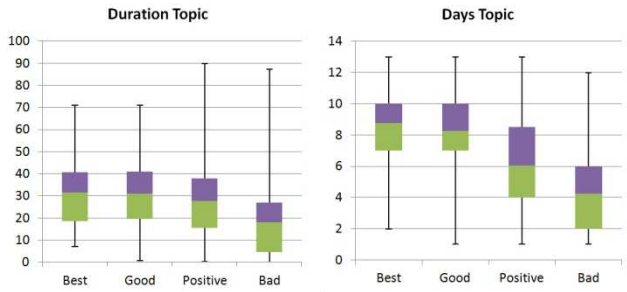

Figure 7: Box plot comparing topic duration (h) between best, good, positive and bad learners in course C1 (left side) and topic days in course C2 (right side)

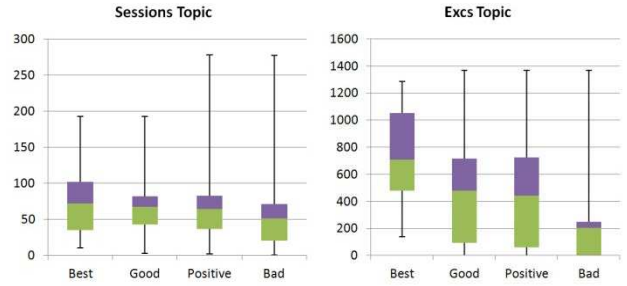

Figure 8: Box plot comparing sessions topic between best, good, positive and bad learners in course C2 (left side) and excs topic in course C3 (right side)

Figure 8 (left side) shows the amount of sessions gone through by the students in course C2. In this case, although topic sessions showed a relatively high Pearson coefficient and significance in the ANOVA, only slight differences appear between best and bad students in the box plots. Finally, Figure 8 (right side) shows the amount of different exercises solved in the course C3 by the learner groups. A comparison between best and bad learners shows a big gap regarding the exercises, where the best learners have solved a much broader variety of exercises (about 700) than the bad learners (about 200) on average.

5.4 Discussion of Results

Our findings on the correlation between ***student activity*** and learning results is in line with experiences and results from the literature. On the one hand, Whitmer [20] measured the 5 LMS usage categories (i.e., administration, assessment, content, engagement and total) according to students' activities (hits) in the course. Correlation with course grades ranges from 0.35 (administrative activities) to 0.48 (total hits). Assessment activities which are similar to our usage variable 'exercises' (C1: 0.27, C2: 0.24, C3: 0.34) showed a correlation of 0.47. The total hits are similar to our variable 'topic views' (0.48 vs. C1: 0.27, C2: 0.27, C3: 0.25). Differences can be explained by the types of the courses (online vs. blended learning).

Next to the pure number of page views, practicing is considered an important factor in learning (cf. effective learning strategies [7]), which is also indicated by the correlation between 'solved examples' and final grades (C1: 0.33, C2: 0.23, C3: 0.26). Yet, the study by Whitmer [20] does not differentiate between successful and unsuccessful assessment activities.

Another important issue to discuss is the dependency between learning and ***time-dependent factors*** in learning. Next to well-established techniques for effective learning [7], such as distributed practicing, time-on-task limitations etc, comparison of time-dependent factors with earlier, pre e-learning studies shows some correlation. Cotton [6] conducted a meta-study including 57 research studies about the difference between (teacher-)allocated time for learning and the real time of students' engagement, i.e. the time-on-task which includes dead times and times of learning above or below the appropriate experience level of students. Hereby, the allocated time showed a small positive, the time-on-task a positive and the times of learning a strong influence on learning results (grades). Although we cannot distinguish between these different kinds of learning times, we also have found a positive correlation between grades and e.g. the active days and the duration in the course (or even in the LMS platform).

More conclusions can be drawn from a comparison of time factors and repetition reported in [19]. This literature survey examined training procedures for enhancing learning, retention, and transfer of verbal and perceptual-motor skills. Findings include that "*once training begins, repetition is necessary to achieve proficiency on all but the simplest of verbal and perceptual-motor tasks*" and "*retention of verbal tasks is better when repetitions are spaced (e.g., separated in time) than when they are massed (e.g., performed in succession without an intervening time interval)*". Benefits from spacing increase as the interval between repetitions increases, provided this interval is not excessive. Also Vlach and Sandhofer [18] highlight findings about spaced scheduling of lessons having positive effects on learning. In their study with elementary school children they investigate which of the three schedules (massed, clumped or spaced lessons) does result in the best performance regarding simple and complex generalization. Results show that spaced lessons (i.e., lessons that are "*spaced apart in time, rather than massed in immediate succession*" [18]) provide the best foundation for generalization performance.

Our findings point to a similar direction. We identified better points and grades for those students who were active on more days before the exam, and had more and longer sessions. In particular, different groups of learners (in particular, the best and the bad learners) can be characterized along time-dependent variables. Cepeda et al [4] start from insights in the literature about spaced learning having positive effects on learning. In their large-scale study with more than 1,300 participants they raise the question which is the optimal spacing of learning for best results. They found that "*if you want to know the optimal distribution of your study time, you need to decide how long you wish to remember something*". Thus, for a long-time retention of knowledge, spacing learning over at least several months is favorable for best results. These findings are backed up by our analysis of the correlation between time factors and learning results. However, the question should be posed whether a half-semester is a good time frame for supporting spaced learning.

Finally, Thalheimer [16] reviews research on the spacing effect and related factors and finds that: (a) repetitions are very effective in supporting learning, (b) "*spaced repetitions are generally more effective than non-spaced repetitions*", (c) "*spacing is particularly beneficial if long-term retention is the goal*". The study in this paper gives evidence for the validity of spacing and repeating learning in order to improve the learning results.

6. CONCLUSIONS AND FUTURE WORK

In this paper we reported about an analysis study in order to approach a strategy towards the realization of LA functionality in the Learn@WU platform. In order to learn about the dependencies between LMS usage patterns and learning results, we examined the influence of 14 usage variables and the final grades of the participants of three large blended learning courses. Good

correlations were found for students' online activities within the platform, such assolved examples in the selected courses. Moreover, spaced learning seems to be a better strategy than investing a lot of efforts for one or a few times before the exam.

A particular focus has been set to examine LMS usage of different student groups (i.e., the best, good, positive and bad learners) due to significant dependencies of usage variables and grades. Hereby, the variance analysis validated the findings of the formerly conducted correlation analysis of student activities and time factors. Outliers concerning usage behavior normally indicate that something might be wrong with the didactical model of the course or the achieved learning result. Here, we see the potential to open the possibility to analyze such cases. Moreover, future work should address a characterization of learners along the time-on-task, thus differentiating between serious learners and 'gamblers'.

It should be noted, however, that the analysis of usage data only covers time and activities spent online in the LMS over the time span of exam preparation. Offline activities, such as reading course-related books or discussions with peers, are not tracked in the LMS. Therefore, next steps include qualitative interviews with students: What is the amount of time they learn over the LMS platform? What is their perception of learning time? Is it similar to the learning time calculated from the log files? Moreover, we examined only one lecture period with three courses. Further research could expand either on the amount of courses included in the data, or do a longitudinal comparison over a full or even several semesters with selected courses. Another limitation of the study is the focus on those students who attended the final exam. Next steps will include comparisons between non-attenders and attenders to detect potential differences in the LMS usage.

Furthermore, with regard to the spaced learning effects and the literature review discussed in the previous section, it was discussed that repetition in spaced learning is a very important factor for retention (cf. [16]). Thus, next steps in our research include a more fine-granular investigation of the nature of spaced learning of the students over longer time periods. Does spaced learning usually include repetition sessions, or do the students only split up the learning materials over several days? How do good and bad performers differ with regard to repetition activities? Also, we will aim at getting deeper insights about whether spaced learning depends on the learning design/subject or on the learner.

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