The Impact of Learning Analytics on Student Performance and Satisfaction in a Higher Education Course

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ABSTRACT

Learning analytics (LA) is collecting, processing, and visualization of big data to optimize learning. This article aims to interpret the impact of analyzing learning data for tertiary education. The article describes a semester-long mixed methods study for 63 students enrolled in a Greek technical university laboratory, retrieving data from the learning management system (LMS). We applied minimal LA guidance in the experimental group and no LA guidance in the control group. The research questions are as follows: Can a student-facing learning analytics approach at minimal level guidance improve students' LMS access and learning performance levels? Are the students' LMS access, discussion forums, and submitted assignments, critical predictors for students' course grades? What are students' opinions about learning analytics as a tool for data-driven decision-making strategy? The study followed the do-analyze-change-reflect LA model. The data collected included students' time spent on LMS, exercises, and discussion posts, while the dependent variable was the course grade. Results indicate that it increased the students' LMS access and satisfaction when we applied LA but not their final grade. Future research could apply higher effort interventions and stronger teacher guidance to provide insights into student performance, engagement, and satisfaction.

Keywords

Student-facing learning analytics, Performance, Satisfaction, Teacher guidance, Post-secondary education.

1. INTRODUCTION

Learning analytics is a multidisciplinary field between computer science and education that fosters the learning process based on big data monitoring [10]. In [29], the authors defined LA as the measurement, analysis and reporting of data about learners and their contexts, for purposes of optimizing learning and the environments in which it occurs. Furthermore, the LA tasks are a set of handy tools to collect and analyze the data accumulated in a smart classroom for data-based decision-making [1]. Consequently, without analytics, instructors cannot provide guidance at appropriate times when students encounter difficulties [11]. In parallel, institutions have embedded LA techniques to enhance retention rates, use resources effectively, and increase students' engagement, satisfaction, and motivation [26].

The authors conducted this mixed-methods study with the research objective of mapping student-facing learning analytics (LA) in real tertiary educational settings. The article is organized as follows: (1) we conduct a short literature review, (2) we explain how the research questions were formulated, (3) we illustrate the design and results of the experiment, and (4) we present the discussion and conclusions reached.

2. RELATED WORK

Student-facing LA is a subfield of LA and focuses on the reporting phase, such as LA dashboards, educational recommender and feedback systems [5, 6]. It is challenging to show students a dashboard or automated emailing systems and conduct surveys to extract usage insights [20]. According to [20], a well-established student-facing LA system consists of four learning design phases (do-analyze-change-reflect). To provide a theoretical framework and extract the research questions, we conducted a short literature review about student-facing LA. The studies can be classified in terms of (1) improvement of performance, (2) prediction of student course grade, (3) improvement of LMS access, and (4) student opinions and satisfaction of LA.

A series of studies [23, 30] have explored the idea of student-facing LA improving levels of performance. Students' final marks could determine the assessment of their academic achievement [19, 33]. In contrast, academic performance and attainment are not related to student access behavior perforce [17]. Nevertheless, we argue that only a few studies examine under LA interventions the correlations between LMS use, the number of submitted assignments, and forum posts as metrics for performance. Furthermore, we need more research to examine if the low effort LA interventions could positively affect students' performance. After all, explaining the students' learning performance is a continual research question.

LA predictive modeling is a core practice of scholars focusing on student success [22]. In [18], a data mining process constructs variables that reflect the theoretical evidence and measure a prediction model's accuracy. In addition, [31] presented a prediction model for failure-prone students using neural networks techniques. These studies emphasize that student-performance prediction is a dominant research domain. Despite the above studies, we argue that building a predictive model for students' performance based on critical predictors such as LMS participation and submitted assignments is an interesting research question.

Engagement can substantially impact students' performance [4, 14]. In [6], the authors have explored the idea of student-facing LA, improving levels of engagement. They have indicated that academic engagement is a multi-dimensional construct and refers to students' level of involvement [8, 15]. However, we argue that not many studies examine the effect of student-facing LA interventions on students' level of engagement.

Targeted studies exist on students' opinions of LA [20, 28]. The [32] study empirically explored the effects of a mobile LA tool in student satisfaction. Nevertheless, we consider that students' opinions before and after LA interventions need further research and could extract valuable insights concerning students' satisfaction and expectations. The surveys' results will confirm or not the existing ones.

Drawing upon the findings of the above studies, our purpose is to investigate the open issues. It would be meaningful to know whether subjects in the feedback conditions gain learning benefits such as performance and satisfaction. In parallel, integrating the LA concepts into tertiary classroom practice has been slow [12]. This article replicates similar research and aims to interpret analyzing learning data for higher education institutions (HEI).

2.1 Research Questions

Within this context, the current experimentation study poses the following research questions:

1. Can a student-facing learning analytics approach at minimal level guidance improve students' LMS access and learning performance levels?

2. Are the students' LMS access, discussion forums, and submitted assignments, critical predictors for students' course grades?

3. What are students' opinions about learning analytics as a tool for data-driven decision-making strategy?

3. METHOD

3.1 Participants and Context

This study took place in the authentic context of a sixth-semester 13-week undergraduate department laboratory course, "digital signal processing" (DSP), at a Greek HEI computer science department between February 2018 and June 2018. The reason for selecting this particular blended course was the high dropout and failure rate in the past exams. This study focused on 31 students as an experimental group receiving the LA intervention ("treatment") with minimal teacher guidance tested for comparison purposes. Participants were 26% female. The control group had 32 students who received no particular LA intervention. The instructor had two-hour lectures and face-to-face meetings/office hours on Mondays every week with the students.

An overview of the LA tool that students used follows: The Open eClass platform is an open-source LMS and is developed by the non-profit civil company called "Greek Universities Network" (GUNET) (https://www.gunet.gr/en/). The platform's main features follow: Management of electronic courses and educational content; Student management; Information, communication, collaboration, evaluation and feedback tools. The structure of the course was as follows:

Week 1. Module 1: The nature of DSP was explored. To ensure transparency and institution-wide adoption [34], we informed the department principal in detail about the experiment, after which she enthusiastically gave her consent. It was then defined what types of data should be tracked and that the feedback (dashboard and messages) would be intended for students.

Week 2. Module 2: Fundamental signals. The first coding exercise was performed in addition to weekly discussion threads and office hours. We gave a detailed description of which student-facing LA will be used and how students will utilize them.

Week 3. Module 3: Digital signal sampling. For usability testing, the students described their initial experience of using LA. The students were surprised, as many claimed that it was impossible to support concepts such as monitoring, analyzing, and feedback.

Week 4. The first quiz assignment and second coding exercise took place. The instructor contributed to the discussion forum to give a sense of learning community. We provided verbal encouragement for students to access their statistics and figures via the LA tool to reflect and meditate.

Week 5. The second quiz assignment and third coding exercise took place—module 4: Fourier transformation principles. We discussed the self-reflection and meditation process.

Week 6. Active intervention and feedback with personalized messages containing the grades of the students' assignments, recommendations, and comparisons of their performance with aggregated data (e.g., participation in discussions and submission of assignments). The encouraging wording of the messages was designed to benefit pedagogically and not harm the student. For instance, "do you need some support?" or "you could participate more in the discussion forum." We provided personalized feedback with visualizations for tracking students' learning progress.

Week 8 and 9. Module 5: Digital filters. Provide in-class feedback (figure 1), recommendations, and scheduling for personalized scaffolding. Verbal suggestions informed students about what to do based on analytics.

Week 10 and 11. The third quiz and an exercise took place. We provided in-class information about absences, participation, and homework. Students received personalized messages with visualizations of their learning progress for mirroring, self-reflection, and motivation.

Week 12 and 13. A revision session and a collaborative quiz were conducted in addition to weekly monitoring and analysis. We used a think-aloud protocol to understand how students reclaimed feedback. A final questionnaire took place—Week 14. The final examination was conducted.

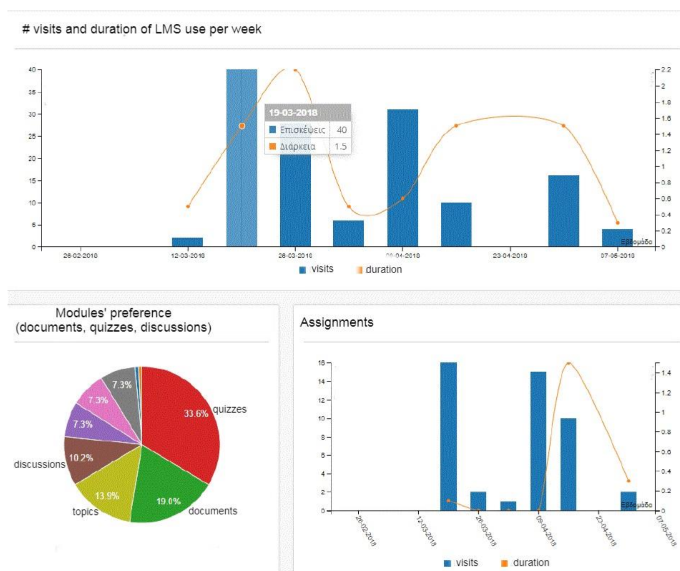

Figure 1. Personalized feedback with visualizations for mirroring.

3.2 Research Design

A mixed quantitative and qualitative method case study was utilized to provide an instantiation of the LA framework with a description of the methodology for others to use a similar process. To answer the first and second research questions, we conducted a causal research design.

3.3 Measures and Instruments

The target of our intervention is students' LMS access, performance, and learning satisfaction. The analysis object is discussion forum use, the number of exercises submissions, and LMS access, while all variables are numeric.

Performance: The performance is measured by a simple dependent variable, the final course grade, that has convenient properties for causal and statistical analysis. The grading system of the final exam is as follows: Scale: 0.00 – 10.00 / Pass: 5:00 (excellent: 8.50 – 10.00 / very good: 6.5 – 8.49 / good: 5.00 – 6.49). The independent scale variables and their definitions that we have considered were: "discussions" that counts the number of posts per student, thus the LMS discussion forum's involvement; "exercises" that counts the submitted assignments accumulated. Each weekly assignment asked true/false, multiple-choice, open-ended questions, and coding exercises; "hoursonlms" that counts, in hours, students' LMS access.

LMS access: Student engagement is a complicated measured construct but vital for students' success that encloses more than participation, motivation, and self-regulation [21]. Therefore, student LMS access in time is an indicator of student engagement.

Satisfaction: The instruments that we used to collect student opinion data are two student opinion questionnaires. An individual questionnaire was administered at the beginning of the course and another at the end. The questionnaire data incorporated participants' reflections on the activity and helped us to collect qualitative data about their opinions as an evaluation.

3.4 Data Collection and Analysis

The level of significance was set at p = 0.05. Graphically, we examined the same assumptions and checked for no outliers. Some visualizations (i.e., dot plot, histogram, a boxplot for density, skewness, and variability) were produced. Finally, for data processing and analysis, the SPSS 25.0 statistical application processed the data.

4. RESULTS

We first applied normality (Shapiro-Wilks) and variance (Levene) controls on available data. The results (p > 0.05) indicated statistical non-significance suggesting that sample data come from normal distributions and populations with the same variance, therefore appropriate for parametric test analysis.

4.1 Research Question 1

Hypothesis 1: The performance, as measured by the course grade of the experimental group, is not statistically significantly different from that of the control group.

The mean score of the experimental group (M = 6.08, SD = 2.62) was slightly higher than that of the control group (M = 5.49, SD = 1.60). However, the independent samples t-test comparing course grades between the groups revealed no statistically significant differences (t = 1.077, p = 0.287) (Table 2). Overall, the null hypothesis failed to be rejected.

Table 2. The t-test results of the experimental and control groups for performance

Group	N	Mean	SD	t	p
Experimental	31	6.08	2.62	1.077	0.287
Control	32	5.49	1.60		

Hypothesis 2: The experimental group's LMS access (in hours) is not statistically significantly different from that of the control group.

Table 3 shows that the mean of the overall LMS access for the experimental group was higher than that of the control group. The independent samples t-test comparing LMS use between the control and experimental groups revealed statistically significant differences (t = 4.610, p = 0.000). Overall, the null hypothesis is rejected.

Table 3: The t-test results for LMS access

Group	N	Mean	SD	t	p
Experimental	31	10.03	7.79	4.610	0.000
Control	32	3.41	1.84		

4.2 Research Question 2

Focusing on the experimental group, we examined the Pearson correlations (Table 4), extracting that the submitted exercises ("exercises") are highly positively correlated with the final course grade ("finalgrade"). Also, time spent on LMS ("hoursonlms") is weakly positively correlated with the final course grade. However, there is a tendency but no statistically significant correlation between forum posts ("discussions") and the final course grade.

Afterward, a simple regression analysis was conducted for "exercises" to estimate the final grade. The check (ANOVA) of the hypothesis that no regression showed that this hypothesis is rejected (F = 18.156, p = 0.000). To evaluate this regression model, the Pearson correlation coefficient (Table 4) (R = 0.620, p = 0.000) reflects the predictor importance; thus, we extracted a good predictor. Then, the model accuracy (quality) is 61.1% and the determination factor (R-squared = 0.385 < 0.5) is considered a low effect size. Finally, the model's equation is y=1.002*x+3.954 (y: final grade, x: exercises).

Then, a simple regression analysis was conducted for "hoursonlms" to estimate the final grade. The Pearson correlation coefficient (Table 4) (R = 0.392, p = 0.015) reflects the predictor importance. Thus, we extracted a weak predictor with a determination factor (R-squared = 0.154 < 0.3) to be considered a weak effect size. Furthermore, we observe a high correlation (R = 0.749, p = 0.000) between the above two predictors. As a result, we decided that there is no need to conduct a multiple regression analysis.

Table 4. Pearson correlations, in parentheses Sig. (two-tailed)*

	finalgrade	hoursonlms	exercises	discussions
finalgrade	1.000	0.392 (0.015)	0.620 (0.000)	0.284 (0.061)
hoursonlms		1.000	0.749 (0.000)	0.525 (0.001)
exercises			1.000	0.314 (0.043)

*Significant difference at the 0.05 level

4.3 Research Question 3

We applied two questionnaires to address the third research question (What are students' opinions about learning analytics as a tool for data-driven decision-making strategy?). Twenty-three students submitted the first questionnaire (appendix), and the purpose was to determine as a baseline their prior knowledge of the LA field. Fifteen students submitted the final questionnaire. The purpose was to determine their thoughts about the LA experience and their overall satisfaction and acceptance. Students gave responses in the free comments field. Based on the mining of students' opinions and perceptions, the LA experience increased students' learning satisfaction. To summarize, students argue that: LA feedback is helpful for their learning progress; they expect that LA is applied in most courses; student-facing LA tools via smartphone would have an added-value impact; peer-comparison progress dashboards increase their engagement.

5. DISCUSSION AND CONCLUSIONS

5.1 Research Question 1

Table 3 shows that LMS access was significantly higher for the treatment group who used LA. This result is consistent with that mentioned by [3] and [25]. Students were triggered using LA to submit more quizzes and exercises (cognitive activities). In addition, students increased their sense of belonging to an online community. However, the findings suggest that high LMS access does not necessarily affect performance [36].

The experimental group had slightly higher scores than the control group (Table 2). This result is consistent with the one mentioned by [27], who stated that "students valued the information, but, despite high engagement with the information, students' study behavior and learning outcome remained rather unaffected." In contrast, many studies [3, 13, 16, 24, 25] have stated that students tend to perform better when the students accept LA interventions. An explanation is that our LA approach resulted in delayed and low effort interventions, which affected the students' overall performance. The standard deviation (SD) values in Table 2 show high diaspora, especially in the experimental group, so we argue that the LA impact affected the students in an outspread way. We conclude that there is no performance improvement without the instructor's strong guidance and targeted interventions.

5.2 Research Question 2

Some of our findings are consistent with the results of other related studies. Based on Table 4, we observe moderate statistical correlations between time spent on LMS and the final grade and between the number of assignments' submissions and the final course grade. This result is aligned with that mentioned by [2] and [15]. Our prediction model for academic performance confirms the results of related studies; thus, we need models with higher accuracy and effect size [7, 9].

5.3 Research Question 3

We conclude that the students' satisfaction was high, in agreement with findings in [25]. Students' positive response to the usefulness of student-facing LA is in agreement with the literature [6, 30]. In addition, the students' responses in the reflection phase confirm the discussion of [20] that students should analyze their behavior using their self-regulated methods. In accordance with [35], the above findings strengthen understanding students' opinions of LA qualitatively rather than as technical methods. Furthermore, interpreting students' comments, we argue that students liked this new learning approach following personalized reports. Students would like LA personalized interventions with a smartphone application and comparisons of their learning progress with their classmates. In conclusion, students' sample quotes extract emerging themes: awareness of others in the class, motivation, increased satisfaction and self-regulation, and technical proposals.

5.4 Limitations

We acknowledge that there are certain limitations to this small-scale study that prevent its findings from being generalized. First, the small sample size and the context of the dataset limit the findings. The data covers one semester on a very domain-specific course at one Greek university, and institutional factors influence the results. Furthermore, the LMS captures a subset of all the events in a learning experience, while other student characteristics may influence student outcomes. It would be useful to search for other factors or latent variables that might differ between the two groups in order to improve the results. Second, engagement was measured in terms of quantity rather than quality. More factors that influence student engagement quality should be studied, such as teacher participation and student effort. Third, the questionnaire's answers indicate that students in the experimental group are satisfied with the LA tool; however, we do not know how LA impacts students' decision-making strategy.

5.5 Future work

It is our intention to replicate the study with another treatment group applying a strong (high effort) teacher guidance to see the impact in relation to the minimal (low effort) group. We will evaluate the impact of three levels of LA interventions: mirroring, metacognitive activities, and explicit guidance. Furthermore, we intend to focus on replicating the experiment in other course settings with larger populations, different profiles, and the use of a mobile-based user-centered LA application. It would be constructive to build and test a predictive model with higher accuracy and stronger effect size applying sophisticated machine learning or deep learning algorithms.

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Appendix

First questionnaire

Question	Answer		
	Yes	**No**	**No answer**
Do you know what analytics is?	10	13	-
Do you know what learning analytics is?	6	17	-
Do you believe that the collection and processing of your learning data and behavior will be helpful to your learning experience?	22	1	-
Would you be interested in being informed about your learning progress concerning your classmates?	13	6	4
Would it be helpful to have feedback (e.g., personalized monitoring and individualized learning material) on your learning progress?	22	1	-

Final questionnaire

Question	Answer		
	Yes	**No**	**No answer**
Were the personalized notifications about your engagement, absences, and performance useful for the course?	14	1	-
Would you prefer more detailed information?	4	8	3
Would you prefer to receive notifications and messages through a smartphone?	10	2	3
Is the comparison of your learning progress with that of your classmates useful?	11	2	2
Please provide free comments: "It is the first time for me that a teacher has sent personalized messages to all students about their learning progress. I have nothing more to suggest. It would be great to convince the other teachers to do the same". "The whole procedure with the exercises, the open discussions, and generally the lecturers' teaching methods helped me very much to self-regulate. I enjoyed both class time and homework". "It was the first time that we had received such refined, analytical, and informed monitoring about our progress and performance on a course." "I would like access to an LA android-based application." "I liked the quizzes the most, and I would prefer to be informed via a smartphone app." "There was sufficient and motivational guidance from the instructor about online exercises." "Instructor's comments about the exercises on LMS were constructive, analytical, and motivational." "I would like more teacher guidance about the exercises, the learning material, and the overall learning procedure."			