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UTILIZING LEARNING ANALYTICS IN LARGE ONLINE COURSES

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Abstract

In courses with hundreds of students, online or hybrid implementation may become more practical than standard classroom teaching. However, it can be difficult for teachers to track student progress in all areas reliably in large courses. In this paper, we present a study where two large online computer science courses were analyzed. Detailed data about student performance in different types of exercises and assignments were collected. In addition, students' perceptions about their learning performance, and the quality and difficulty level of learning materials were collected during all seven weeks of the course. The performance data was analyzed to try to recognize the effectiveness and quality of different course areas. Moreover, we found out if the time usage or perceived difficulty level affected students' performance. The strong correlations between different types of exercises and exam scores indicate that the material is effective and the exam measures the learning properly. However, time usage and perceived difficulty level seem to have little effect on the result.

Keywords: *Learning analytics, programming, online learning, feedback*.

1. Introduction

Keeping up student motivation is important. However, it can be difficult as well. In smaller courses or classes an experienced teacher can easily collect informal feedback and adjust the teaching accordingly when needed. In larger courses, this can be difficult, especially when the number of students reaches several hundreds. Online learning makes this even more difficult. Although it has its benefits in making education more reachable and independent of time and location, the lack of contact can make it difficult for teachers to track the learning experience as a whole.

Learning analytics is usually defined as collecting and analyzing data collected on learning and teaching (for a more precise definition see e.g., Elias 2011). Utilizing learning analytics can potentially enable us to track students' progress and their perceptions on a detailed level and use the results of analysis in course design and to improve teaching processes (Leitner et al. 2017). The problem, however, is often the data: collecting enough up-to-date data on learning during the courses can be difficult.

In this paper, we present a study where two large online courses were researched. We used an educational platform that automatically collected data on students' solutions to exercises. The scores of the assignments done outside the platform were also manually inputted there, providing teachers and students with a real-time and holistic view of the progress. Additionally, weekly surveys were used to collect students' perceptions about their time usage and difficulty level of the tasks.

2. Related work

There are many different frameworks and approaches for learning analytics (LA). The term ‘learning analytics’ covers a significant area of different fields and techniques, often utilizing vast amounts of data. According to Clow (2013), some of the possible application areas for learning analytics are predictive modeling, social network analysis, recommendation engines, content and semantic analysis, and usage tracking e.g. of an LMS. A quite common way to define LA into different categories is to separate learning analytics into three categories, as defined by Daniel (2015). These three different categories are descriptive, predictive, and prescriptive analytics. Descriptive analytics aims to describe what has happened. Descriptive analytics is based on the data gathered from students, teaching, research, policies, and other administrative processes. Predictive analytics aims, as the name suggests, to predict future events and performance based on the collected data. As a more concrete example, predictive analytics could be used to identify students who are at risk of failing the course. Prescriptive analytics combines the previously mentioned analytics to explain what should be done next and why. It is important to note that no LA framework is perfect in predicting students holistically. Hence, it is important to consider the ethical aspects of analytics as well. As a more concrete example, Susnjak, Ramaswami, and Mathrani (2022) note that misclassification of a student to "at-risk" student might lead to actions that discourage the student and thus cause a potential negative impact on the student performance in the course.

Additionally, some LA frameworks are only conceptual, while some have concrete implementations. Quite often, the designed frameworks are designed to work across disciplines. In a systematic review, Khalil, Prinsloo, and Slade (2022) compared different LA frameworks. They noted that 40 of the 46 analyzed frameworks, presented in papers published between 2011 and 2021, were designed to be used across disciplines. Furthermore, according to the review, "12 papers mentioned a prototype or case study application". On a graver note, out of 46 LA frameworks that they analyzed, only about 1 in 3 mentioned privacy and ethics. They also pointed out that although interest in these themes has increased over time, not even all relatively new frameworks have considered ethics or privacy. Additionally, there is still room for improvement in LAs. According to Susnjak, Ramaswami, and Mathrani (2022), most LA dashboards presented in studies published between 2018 and 2021 utilize only shallow, surface-level descriptive analytics. Learning analytics have had a concrete impact as well. For example, Lim et al. (2021) utilized a learning analytics-based feedback system for students on a large course and found that students given personalized feedback via email had significantly higher marks on the final exam compared to a control group that did not receive feedback. Furthermore, another study conducted by Kew and Tasir (2022) noted, that utilizing LA for intervention seemed to improve the student's motivation in e-learning. These findings emphasize the potential impact LA can have on students.

Combining data from different sources might work as well. For example, López-Pernas, Saqr, and Viberg (2021) combined data related to study material viewing from LMS and submission data from an automated assessment tool to understand the learning process of students learning basics of web development. They were able to cluster students into three distinct groups based on their learning behavior and noted how in different scenarios, students seemed to prefer their study materials in different formats.

3. Research setup

The research was conducted during the academic year of 2023 to 2024 at the Department of Computing at the University of Turku. Two large programming courses were selected for the study (see next subsection for details). The courses are typically the first two programming courses taken by students at our university. In addition to computer science majors, students from many other subjects participate in the courses. The students can take the courses fully online, but live workshops are organized additionally for students who prefer contact learning.

Both courses lasted for seven weeks. The exams were organized after seven weeks. Each week, a 2-hour online lecture was given via Zoom. There was a Discord server with an online discussion forum, which the students could use to ask for help with any exercises. Course instructors were present in Discord and at live workshops at given times, but naturally, the students could ask questions at any time online. To enable this, peer support was encouraged. AI tools (such as ChatGPT, Copilot, or similar) were allowed, but there was a strict set of rules for using them.

3.1. Course instances and data collection

The details of the course instances are displayed in Table 1.

Table 1. The details of the course instances studied.

Course abbreviation	Course 1	Course 2
Name	Fundamentals of Programming	Introduction to Object-Oriented Programming
Students (N)	602	381
Programming Language	Python	Java
Time	Fall 2023	Spring 2024

Each week the topics were covered in a tutorial, a combination of course materials (such as text, images, and example code) and automatically assessed exercises. An educational platform called ViLLE (Kaila, 2018) was used for tutorials. The exercises were mainly coding tasks, where the students needed to write a program (or a part of it) according to the instructions. The code could be executed in the platform without additional programs or plugins. The students received immediate feedback after execution and could modify their code immediately and execute it again, if necessary. Other exercises types included code sorting exercises and quizzes. The students needed to collect at least half of the available tutorial points to pass the course. In total, there were 171 tutorial exercises in Course 1 and 139 in Course 2.

Another form of learning was demonstration assignments. In these assignments, the students practiced topics that are more advanced. The demonstrations were completed with an external coding editor. The same editor is widely used in the industry to write program code. The course staff manually assessed all the assignment answers. Again, the students needed to complete at least half of the assignment points to pass the course. At the end of the course, the students completed an exam. The exam consisted of 5 to 7 programming tasks and was completed in ViLLE. All the tasks were automatically assessed and scored. Students' final grade was based on tutorial, assignment, and exam points.

There was a short feedback survey at the end of each week on both courses. In this survey, the students were asked to list what they had learned, what remained unclear, and how they would improve the session. Additionally, they were asked to estimate the time they had used to complete the exercises and the perceived difficulty level of the tasks. In addition to research purposes, this data was evaluated each week and changes to lectures, materials, and exercises were made based on the student feedback. A more detailed analysis of the feedback on earlier courses can be found for example in Kaila & Lokkila (2022).

3.2. Research methodology

ViLLE automatically collects all the points for all the students in the course. In addition, the instructors inputted the manually assessed assignment points in ViLLE. For analysis, all the scores were exported from ViLLE as Excel spreadsheet. After this, the data was fully anonymized by replacing all the student identifiers with randomly generated codes. Common statistical descriptors (such as averages) were calculated using Microsoft Excel. The advanced analysis and some data cleanup was done by using the Python programming language.

4. Results

The course results after the first exam are displayed in Table 2. It should be noted, that both courses provide three exams for students to try, but we focus on the first exam, as that was the only exam we had comprehensive data at the time of the writing. The grade level used is 0 to 5, where one is the first accepted grade and five is the best possible grade.

Table 2. Results after the first exam.

Grade	Course 1	Course 2
5	334 (55%)	171 (45%)
4	56 (9%)	45 (12%)
3	35 (6%)	34 (9%)
2	11 (2%)	29 (8%)
1	11 (2%)	8 (2%)
Total passed	447 (74%)	287 (75%)
Fail	155 (26%)	94 (25%)

As seen in the table, the results are quite similar at both courses: majority of students has passed the course with the highest grade or failed it. The mean points collected from different parts of both courses are displayed in Table 3. The points are calculated distinctively for student who passed the course and for all students.

Table 3. Points collected from different sections of the course. Points are displayed separately for students who passed the course and for all students.

Part	Course 1	Course 2
Tutorial points (passed)	87%	88%
Demo assignment points (passed)	79%	69%
Exam points (passed)	94%	87%
Tutorial points (all)	72%	74%
Demo assignment points (all)	63%	56%
Exam points (all)	70%	67%

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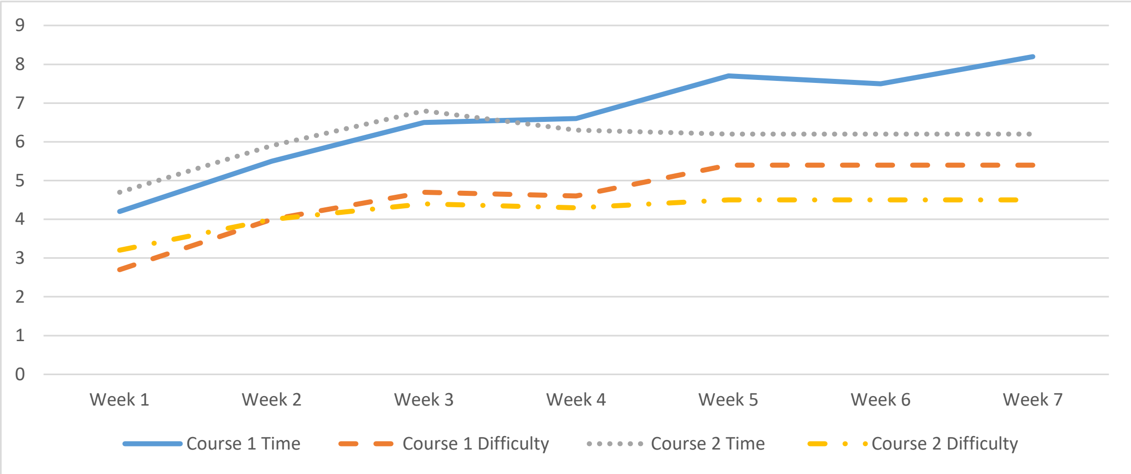
While the trends between the two observed courses seem to be somewhat similar, the students who passed the course seemed to do remarkably well in the Course 1 exam. Students' perceived difficulty levels for all weeks as well as their estimate of the time usage is displayed in Figure 1.

Figure 1. Students' perceived time usage (in hours) and difficulty level (1…7, 7 most difficult) at each week.



In both courses, the time usage and the perceived difficulty level increased until the end of the first two or three weeks, but seem to remain quite steady after that. However, the time usage in Course 1 seems to keep increasing until the end of the course. The correlations between different course sections are displayed in Tables 4 and 5.

Table 4 and Table 5. Correlations between different sections of the courses (calculated using the Pearson correlation). A correlation is a decimal value between –1 and 1, with values over 0.7 (or under –0.7) typically indicating strong correlation between two variables.

Course 1				
	Tutorial	Demo	Exam	Time
Demos	0.87			
Exam	0.83	0.78		
Time usage	0.13	0.12	0.08	
Difficulty	0.09	0.10	0.05	0.55

Course 2				
	Tutorial	Demo	Exam	Time
Demos	0.80			
Exam	0.76	0.76		
Time usage	-0.08	-0.11	-0.07	
Difficulty	-0.18	-0.17	-0.08	0.58

The correlations between different sections seem to be quite similar in both courses. Notably, there is a strong correlation between tutorial, demonstration assignments and course final exam. The perceived time usage and difficulty level have a correlation with each other, but do not seem to correlate with any other parts of the course.

5. Discussion

Mostly, the two courses' statistics are quite similar. There is a statistical difference between the grade distribution (Table 2) between courses (Mann-Whitney U-test gives a p-value <0.01), but the majority of grades in both courses still seem to be either the highest possible or a failure. This indicates, that the students who are determined to complete the course, do so as well as possible. The high amount of points collected from different parts of the course (Table 3) also indicates that the students who passed the course have worked much more than the required minimum (which was 50% in all parts). The workload of the courses, based on students' perceived time usage and difficulty level, seems to increase steadily during the first three weeks (Figure 1). After that, it seems to stay at the level except for the time usage in Course 1, which kept increasing until the last week.

There is a strong correlation (Table 4) between all three major sections in both courses: tutorials, demonstration assignments, and the final exam. The fact that the performance in tutorials and demonstration assignments correlates strongly with the final exam indicates that the students, who work hard during the course also succeed in the final exam. Time usage had a moderate correlation with difficulty level, which seems logical: if the tasks feel more difficult, you need to spend more time doing them. However, neither the time-usage nor the difficulty level had any correlation between performance in tutorials, demonstrations, or exams. This is likely due to high variance in both of these variables: some students spend less or more time on some exercises or find them easier or more difficult, but this does not seem to correlate with learning outcomes.

6. Conclusion and future work

Overall, it seems that analyzing the learning data can provide useful information and insights for teachers, students, and researchers. The strong correlation between coursework and the final exam indicates the importance of working hard during the course. The difficulty level and time usage can provide teachers with important information in keeping the workload at an acceptable level. Moreover, by comparing the performance of two separate but similar courses, it is possible to recognize anomalies in different areas of materials and teaching. In the future, we are going to observe the feedback provided by the students even closer and try to isolate factors that affect student performance and motivation by combining the feedback data with the performance data.

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