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# Importance of time management skills during the COVID-19 pandemic: An exploratory learning analytics study in an introductory programming course

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Time management is an important self-regulation strategy that can improve student learning and lead to higher performance. Students who can manage their time effectively are more likely to exhibit consistent engagement in learning activities and to complete course assignments in a timely manner. Well planning of the study time is an essential part of online learning and has been particularly critical in remote education during the COVID-19 pandemic. During this period of crisis, programming courses have been exceptionally challenging since students needed to devote sufficient time in the practice of code-writing besides studying the theoretical foundations, while, at the same time, working on the learning tasks for other online courses. Therefore, students' time management skills have been a determining factor in how they engaged in programming courses during the emergency remote education. In this regard, this study explores the association between students' time management skills and their course engagement (extracted from the LMS log data) in an undergraduate-level programming course taught fully online during the pandemic. Results show varying levels of participation and different temporal patterns of engagement depending on the students' ability to manage their time. Additionally, students with strong time management skills performed slightly better than those with poor time management skills. Implications for future research and practice are shared.

## Introduction

Since the advent of the World Wide Web in 1991, followed by the increased access to the Internet, online education has been growing continuously in the whole world (Palvia et al., 2018). While many university courses are taught online, and the number of universities offering degree programs entirely online is increasing every day (Lederman, 2018). In the last two years, online education has expanded even more drastically thanks to the COVID-19 pandemic and has become the principal way of teaching and learning in most universities globally (Iglesias-Pradas et al., 2021).

Online education offers certain benefits favouring student learning such as the easy access to materials and more interaction opportunities with peers and teachers. However, some other factors, including the physical absence of teachers and the increased responsibility of students for their own learning, demands a systematic and continuous engagement from students to

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succeed in online education (Muilenburg & Berge, 2005). In this regard, self-regulated learning has been often considered a determining skill for students who study online (Chang, 2005). The literature provides rich evidence on the significant effects of self-regulation on online learners' engagement and success. While self-regulated learners show persistence in their engagement by regulating their online learning behaviours (Wong et al., 2019), those lacking such regulation skills exhibit behaviours detrimental to learning such as procrastination (Sheng & Xie, 2021).

One important characteristic of self-regulated learners is their ability to manage their time in a way that is both intentional and meaningful to their learning (Anthonysamy et al., 2020). For example, a student may plan to dedicate some time regularly a day before the online lecture to study the upcoming concepts beforehand or may create a regular study schedule to complete weekly lab assignments in time instead of leaving them until the last day of the submissions. Although some levels of time management skills are always necessary for academic success beyond the online space (Macan et al., 1990), they are particularly vital for students in online education, where there is a stronger need for an efficient organisation and productive use of the independent study time (Nawrot & Doucet, 2014). When lacking such self-regulatory skills, online learners are more likely to drop out than their peers in traditional face-to-face courses (Patterson & McFadden, 2009).

The transition to emergency remote education after the COVID-19 pandemic created extraordinary conditions where students' time management skills could make a huge difference in their learning gains and academic performance. During the pandemic, many university students, with minimal or no online education experience, had to switch to the online modality over a night (Bao, 2020). Afterwards, millions of learners were submerged in online education mostly without prior training or with minimal preparation. Likewise, many instructors had minimal online experience and were mostly unprepared for such a sudden shift. The courses, that were taught face-to-face for years, were abruptly adopted for online teaching, resulting in poor instructional designs that discard some fundamental principles of online learning (Güzel & Özeren, 2021). As a result, students had to study even harder and go beyond the minimum requirements to compensate for poor online pedagogies embraced in the pandemic. Thus, it would not be surprising that self-regulated students with sharp time management skills have managed to maintain their success under the extraordinary conditions of the pandemic.

Student learning in computer science-related courses has been quite difficult during the COVID-19 emergency remote education (Mbunge et al., 2021). In particular, programming courses usually demand considerable time for practising writing code besides studying hard to understand the fundamental concepts. Under the pandemic circumstances, developing a good understanding of the concepts and completing the programming tasks in time may require advanced time management skills. So far, only few studies have investigated the factors impacting computer science education in the COVID-19 pandemic (e.g., Crick et al., 2020; Mooney & Becker, 2021; Deus et al., 2020). However, to the best of our knowledge, the role of time management skills in students' online engagement in programming courses during the pandemic has not been studied.

Learning analytics is a field of research that focuses on harnessing big learning data (also called digital footprints) to understand and support student learning and the environments where the learning occurs (Siemens & Gašević, 2012; Gašević et al., 2015). Detailed digital footprints accumulate as learners interact with learning environments such as tutoring systems, educational games, or more commonly learning management systems. Recently, several learning analytics techniques have been used to process these digital footprints to automatically identify different time management strategies and tactics employed by students (Tabuenca et al., 2015; Uzir et al., 2020; Sher et al., 2022). However, in the learning analytics literature, the effects of how students' perceived time management skills on their engagement in online programming courses have been understudied. As a result, little is known about how students' engagement patterns have differed in programming courses according to their self-reported abilities to manage their time during the pandemic. In this period of crisis, such skills are expected to be play a critical role in student learning and success.

Attending the mentioned gaps, the goal of this study is to identify the possible effects of time management skills on students' engagement and performance in an introductory level programming course taught during the pandemic. In particular, students were divided into two groups based on their (self-reported) time management skills (high-skilled vs low-skilled) measured through a questionnaire. Then, using the course activity logs, (1) the participation levels in different components of the course were calculated per group separately, and (2) temporal analysis was performed to reveal students' daily participation patterns across groups. In addition, students' weekly quiz scores were also compared to identify any effects on student performance. This research attempts to answer the following research questions:

- RQ1: How do the participation levels in various course components differ based on the level of time management skills?
- RQ2: How do the daily engagement patterns in various course components differ based on the level of time management skills?
- RQ3: How do the quiz performances differ based on the level of time management skills?

## Method

This is a quantitative study focusing on the relationship between students' time management skills and their engagement and performance in a programming course taught during the COVID-19 pandemic. This research was approved by the METU Human Research Ethics Committee on February 15, 2022, with the document number 28620816.

### *Context and Participants*

The context of this study is an introductory programming course taught in the fall semester of the 2021/2022 academic year in a Turkish university. This course was a mandatory course for the second-year students in the department of Computer Education and Instructional Technology. The course was delivered completely online because of the pandemic and was taught for the first time by the course instructor. The descriptions of the course components are provided in Table 1. Among the students enrolled in the programming course, 30 of them gave consent to participate in this research study. The female participants were the majority among the participants (n=16).

### *Data Collection and Analysis*

To measure students' perceived time management skills, an online questionnaire was administered at the end of the semester. This questionnaire was adopted from the Time and Study Environment subscale of the Motivated Strategies for Learning Questionnaire (Pintrich & Groot, 1990), and contained the following items:

- I usually study in a place where I can concentrate on my coursework.
- I make good use of my study time for this course.
- I find it hard to stick to a study schedule [Reversed].
- I have a regular place set aside for studying.
- I make sure that I keep up with the weekly assignments for this course.
- I watch the lecture videos regularly (especially for the classes that I miss).

**Table 1.** Principle components in the course

| Component | Description | Quantity |
|---|---|---|
| Chapter slides | The slides for each week were uploaded as a PDF file to the learning management system. | 11 |
| Video recordings | The Zoom lectures were video recorded and uploaded to the learning management system after each lecture. | 13 |
| In-class exercises | These were the programming exercises performed during the class. Students were expected to write the necessary code as guided by the instructor. | 11 |
| Quizzes | In some weeks on the lecture day, a short quiz was administered to measure students' conceptual understanding of the topics covered. The quizzes contained five true/false or multiple-choice questions. | 6 |
| Lab assignments | In most weeks, there was a lab assignment to help students go beyond the in-class exercises and develop some programs individually. | 10 |

Previous research noted high reliability and validity for this questionnaire (Bembenutty, 2009; Jo et al., 2019). The participants were asked to indicate their agreement to the questionnaire items using a four-point scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). The average score was computed for each participant as the measure of their time management skills. Based on their average scores, participants in the 50 percentile (that is the median value) were considered as the low-skilled group and the rest were marked as the high-skilled group in terms of time management.

Students' course engagement was identified from the log activity data. Log data was filtered to contain the activities from starting from the first week until the end of the last week in the course. The log data was further pre-processed to remove all identifying columns as well as the rows pertaining to the students who did not give consent for the research. The pre-processing of the data was performed in Python using the Pandas library (McKinney, 2010).

Since the data was not normally distributed and the sample size was small, a nonparametric test called Mann-Whitney U test (Ruxton, 2006) was applied to make comparisons between the high- and low-skilled groups. The statistical analyses were performed using the Python library called SciPy (Virtanen et al., 2020).

## Results

The results of the analysis are presented in three sections, each of which is linked to one of the research questions, respectively.

### *RQ1: Engagement Levels in Different Course Components*

This section presents the results regarding the engagement levels of two student groups in different course components. First, average visits to chapter slides were examined. There were chapter slides for 11 weeks in total. The comparison of the high- with the low-skilled group in terms of the frequency of visiting the chapter slides is provided in Table 2. According to the table, although in both groups there was a tendency of decline in the number visits to the chapter slides throughout the semester, the high-skilled group consistently visited the chapter slides more frequently than the other group, with statistically significant differences noted in week six (U=59.5, p=0.01), week nine (U=58.5, p=0.003), and week ten (U=71.6, p=0.026).

**Table 2.** Comparison of the visits to chapter slides between the high- and low-skilled groups

| Weeks | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 1 | 2.47 | 1.80 | 93.5 | 0.214 |
| 2 | 2.20 | 1.73 | 97.5 | 0.270 |
| 3 | 2.53 | 1.67 | 89.0 | 0.164 |
| 4 | 1.80 | 1.00 | 82.0 | 0.096 |
| 5 | 0.67 | 1.07 | 101.5 | 0.311 |
| 6 | 1.80 | 0.67 | 59.5 | 0.010* |
| 7 | 1.07 | 0.53 | 94.5 | 0.193 |
| 8 | 1.20 | 0.60 | 85.5 | 0.101 |
| 9 | 0.73 | 0.07 | 58.5 | 0.003* |
| 10 | 1.40 | 0.40 | 71.5 | 0.026* |
| 11 | 0.27 | 0.20 | 105.5 | 0.339 |

** Significant differences at 0.01 or 0.05 levels.*

The statistical analysis about the visits to the video recordings is provided in Table 3. Overall, the video recordings were seldom visited in both groups. The lecture video in the first week where the instructor provided an overview of the course was visited the most. Nevertheless, the high-skilled group's total visits were higher in most weeks. Significant differences were noted in week one (U=69.5, p=0.037), week 6 (U=59.0, p=0.007), and week 9 (U=72.0, p=0.039).

The analysis results regarding the visits to the in-class exercises are provided in Table 4. According to the results, both student groups were engaged in the in-class exercises somehow similarly until the end of week seven. With the start of week eight, while the high-skilled group maintained their active engagement, the low-skilled group demonstrated a decreasing interest until the end of the semester. Statistically significant differences were noted between the groups from week eight to twelve. This finding indicates that the students with better time management skills could dedicate specific time regularly throughout the semester for reviewing the codes and, possibly for writing some code.

Moreover, students' visits to the lab-assignment pages were analysed (see Table 5). There was no lab assignment in week three, and the lab assignments in week two and week four were submitted using a different system. For the rest of the lab assignments, a decrease in the number of visits were observed for both groups after week five, where the highest number of visits was noted. In all lab assignments, the high-skilled group demonstrated a higher engagement, with statistically significant differences between week five to eleven. These results corroborate the student engagement in in-class exercises, signalling the persistence of the high-skilled group in spending time writing code on a regular basis throughout the semester.

**Table 3.** Comparison of the visits to video recordings between the high- and low-skilled groups

| Week | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 1 | 8.20 | 5.20 | 69.5 | 0.037* |
| 2 | 1.80 | 0.67 | 102.5 | 0.328 |
| 3 | 0.67 | 0.80 | 86.0 | 0.099 |
| 4 | 0.60 | 0.27 | 90.5 | 0.114 |
| 5 | 0.73 | 0.67 | 112.0 | 0.500 |
| 6 | 0.93 | 0.27 | 59.0 | 0.007* |
| 7 | 0.6 | 0.33 | 97.5 | 0.240 |
| 8 | 0.20 | 0.27 | 111.0 | 0.476 |
| 9 | 1.47 | 0.80 | 72.0 | 0.039* |
| 10 | 0.53 | 0.93 | 107.5 | 0.416 |
| 11 | 0.27 | 0.07 | 90.0 | 0.079 |
| 12 | 0.13 | 0.20 | 111.5 | 0.486 |

* Significant differences at 0.01 or 0.05 levels.

**Table 4.** Comparison of the visits to in-class exercises between the high- and low-skilled groups

| Week | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 2 | 19.27 | 13.67 | 75.0 | 0.061 |
| 3 | 12.93 | 10.73 | 96.5 | 0.255 |
| 4 | 12.53 | 11.33 | 100.5 | 0.314 |
| 5 | 13.13 | 11.73 | 108.5 | 0.441 |
| 6 | 12.73 | 10.67 | 101.0 | 0.321 |
| 7 | 13.27 | 12.60 | 101.5 | 0.329 |
| 8 | 18.80 | 13.60 | 72.0 | 0.048* |
| 9 | 17.53 | 15.40 | 59.5 | 0.014* |
| 10 | 16.87 | 10.53 | 69.5 | 0.038* |
| 11 | 13.80 | 7.27 | 56.5 | 0.010* |
| 12 | 10.73 | 6.27 | 63.5 | 0.018* |

** Significant differences at 0.01 or 0.05 levels.*

Last in this section, students' visits to the quiz pages were analysed. There were in total six quizzes, distributed between week two to week seven. According to the results (see Table 6), both student groups were highly engaged in the quizzes throughout the semester. The high-skilled group's visits were relatively more frequent. The only significant difference was noted in week six (U=46.5, p=0.003). Nevertheless, the overall effect of students' time management skills were minor on their quiz engagement. This result might be due to the fact that taking quizzes were not very time consuming as they contained only five true-false and/or multiple-choice questions and did not require advanced time management skills.

### *RQ2: Daily Engagement Patterns in Different Course Components*

Students' engagement patterns on different days were analysed to identify how their time management skills were associated with their daily course participation. In this regard, daily engagement patterns in different course components were identified and visualised using heat maps. In the heat maps depicted in this paper, the cells with lighter colours represent the higher frequencies whereas the darker cells correspond to the lower frequencies of visits. The top grey row in all heat maps represents the sum of the visits per each day, thus showing the daily total engagement during the semester.

**Table 5.** Comparison of the visits to lab-assignment between the high- and low-skilled groups

| Week | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 2 | 6.60 | 5.20 | 80.5 | 0.094 |
| 4 | 2.73 | 2.27 | 105.0 | 0.348 |
| 5 | 40.33 | 20.07 | 62.0 | 0.019* |
| 6 | 33.93 | 20.93 | 51.0 | 0.006* |
| 7 | 16.27 | 8.80 | 55.0 | 0.009* |
| 8 | 19.73 | 7.20 | 33.0 | 0.001* |
| 9 | 17.20 | 6.40 | 43.5 | 0.002* |
| 10 | 14.67 | 8.27 | 52.0 | 0.006* |
| 11 | 6.80 | 2.00 | 38.0 | 0.001* |

** Significant differences at 0.01 or 0.05 levels.*

**Table 6.** Comparison of the visits to quiz pages between the high- and low-skilled groups

| Week | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 2 | 26.20 | 26.27 | 110.5 | 0.475 |
| 3 | 20.60 | 17.53 | 98.5 | 0.287 |
| 4 | 23.53 | 20.27 | 74.0 | 0.057 |
| 5 | 17.27 | 14.73 | 83.0 | 0.114 |
| 6 | 20.67 | 12.80 | 46.5 | 0.003* |
| 7 | 18.00 | 14.40 | 80.5 | 0.094 |

** Significant differences at 0.01 or 0.05 levels.*

First, students' daily visits to chapter slides (see Figure 1) were examined. According to Figure 1, students in both groups visited the chapter slides mostly on the lecture day, which was every Friday. One main difference between the groups is that the high-skilled groups viewed the chapter slides on other weekdays as well even though this behaviour was not very frequent. In particular, on Wednesdays, students with better time management skills revisited some chapter slides before the lecture on Fridays. That is, although few, some high-skilled students intended to review some content to prepare themselves for the lectures. Moreover, in both groups the engagement decreased in the later weeks, but this decrease was sharper in the low skilled group.

Regarding the engagement in lecture videos (see Figure 2), both groups' engagement was low on most days when compared with the other course components. In general, students visited the videos usually on Thursdays and Fridays. Most days the students in the high-skilled group visited the videos more often. While visits on many days indicate these students' scheduling skills, the higher visits on Thursdays and Fridays indicate their efforts in staying on the weekly track even if the lecture was missed. Nonetheless, considering the importance of lecture videos in online education, the observed engagement in videos were low in both groups.

According to students' daily engagement in the in-class exercises (see Figure 3), the high-skilled group was fairly active on Fridays, suggesting that these students intended to regularly participate in the lectures and worked on the exercises under the guidance of the instructor. On the other hand, on Fridays the low-skilled group was relatively less active. These students worked on the in-class exercises heavily on Saturdays as well, suggesting the possible late submissions of the in-class exercises by the students with lower time management skills.

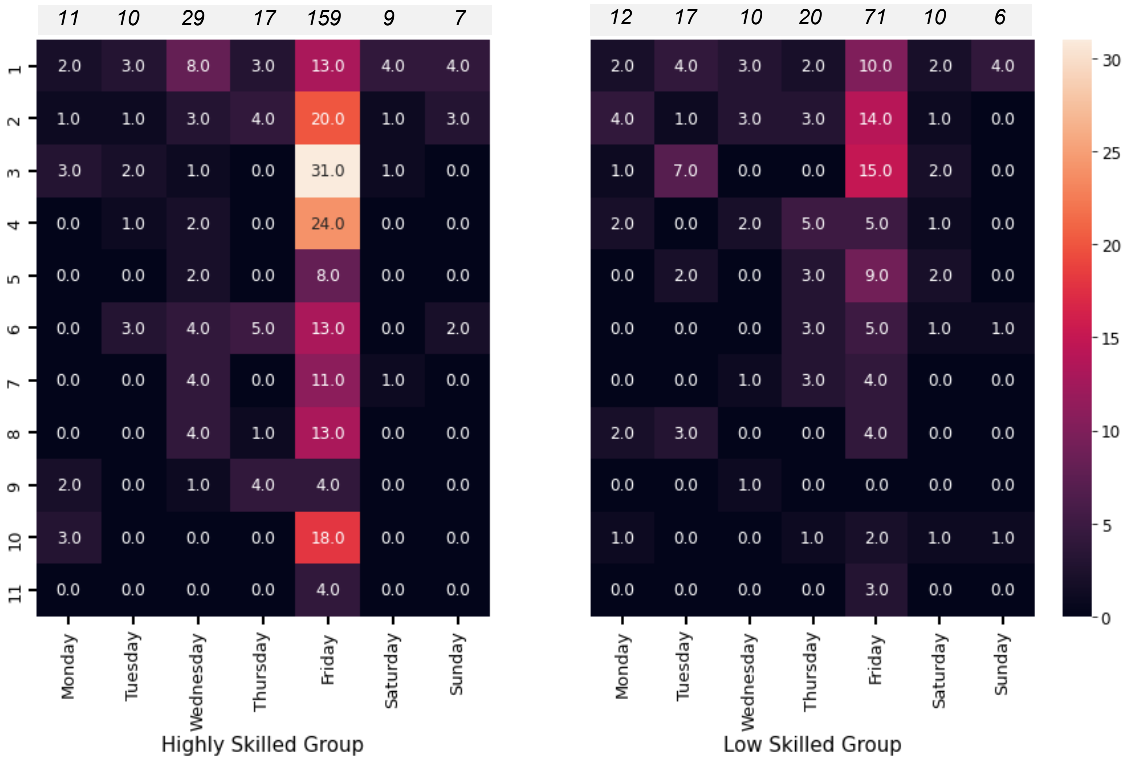


**Figure 1.** Daily engagement in chapter slides

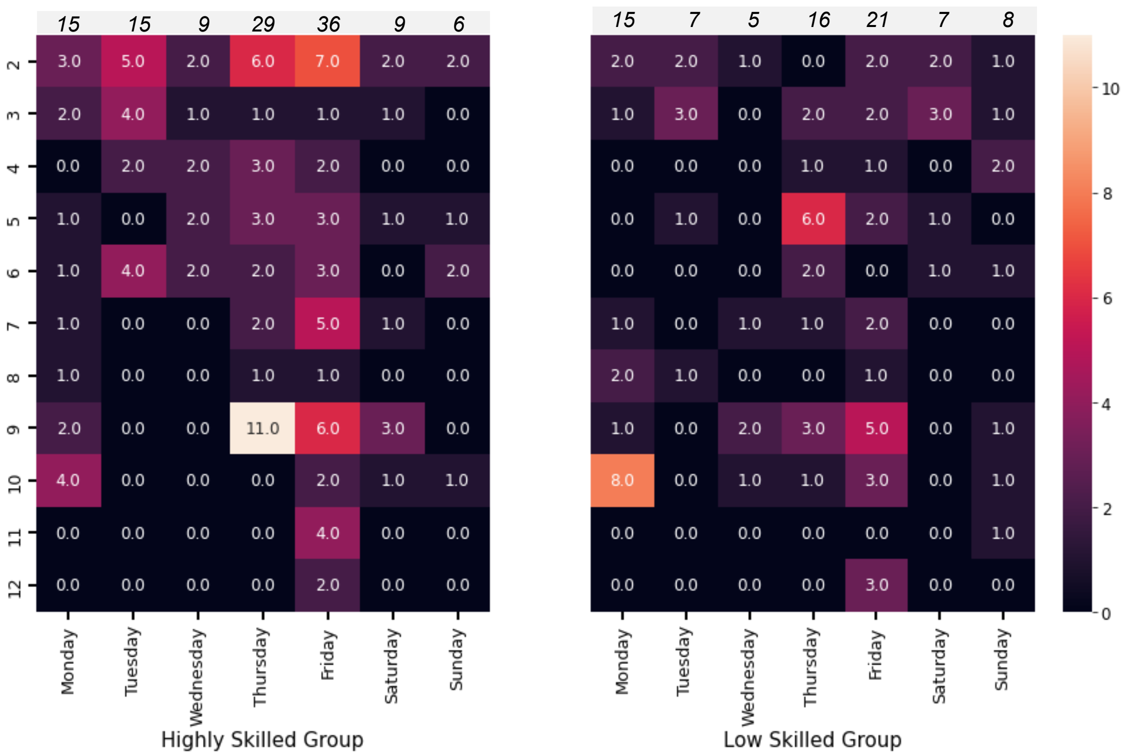


**Figure 2.** Daily engagement in lecture videos

Additionally, although the low-skilled group focused on the in-class exercises particularly on Fridays and Saturdays, the high-skilled group were better able to distribute their engagement over several days, mostly Monday, Tuesday, Saturday, and Sunday. However, this behaviour faded away with the start of week nine. Moreover, both groups' engagement on Fridays were substantially higher after week nine compared to previous weeks, which may indicate that the exercises on that week and afterwards were more engaging and demanding.

There is a noticeable difference in how students engaged in lab activities depending on their time management skills. According to the heat map depicted in Figure 4, the engagement of the students in the high-skilled group was higher and relatively more distributed. That is, the students with better time management skills spent some time on the assignments a few days before the deadlines, whereas those with poor time management skills worked on the assignments mostly on the last days. Moreover, both groups were mostly engaged on Thursdays until Week 8, which was the deadline for the submissions. Afterwards, the deadlines were changed to Fridays, which explains the reason for the shift in student engagement to Fridays from Thursdays. This finding highlights the importance of recognizing the context when interpreting the learning analytics results (Er et al., 2019).

Regarding students' daily quiz activities (see Figure 5), all students were engaged almost only on Fridays, which is an expected result since the quizzes were always released on Fridays. The principal difference between the groups is that the high-skilled group was more actively engaged except week ten. This engagement may include taking the quiz, navigating through the questions, and reviewing the results after the quiz.

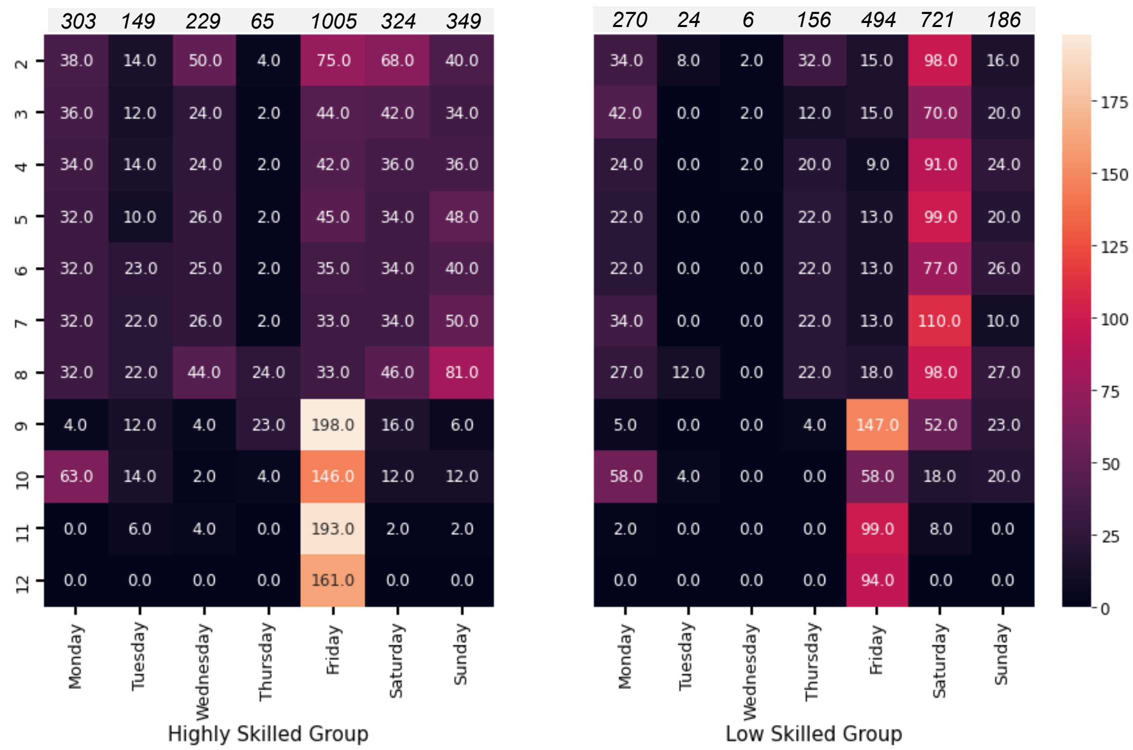


**Figure 3.** Daily engagement in in-class exercises

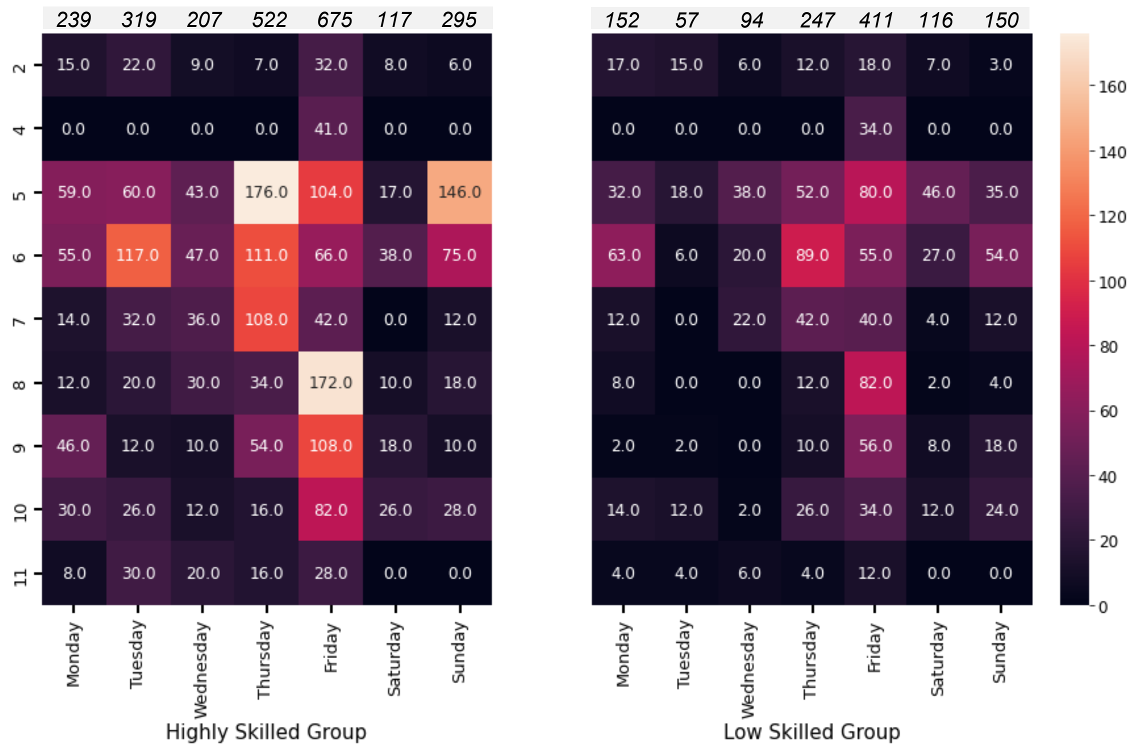


**Figure 4**. Daily engagement in lab assignments

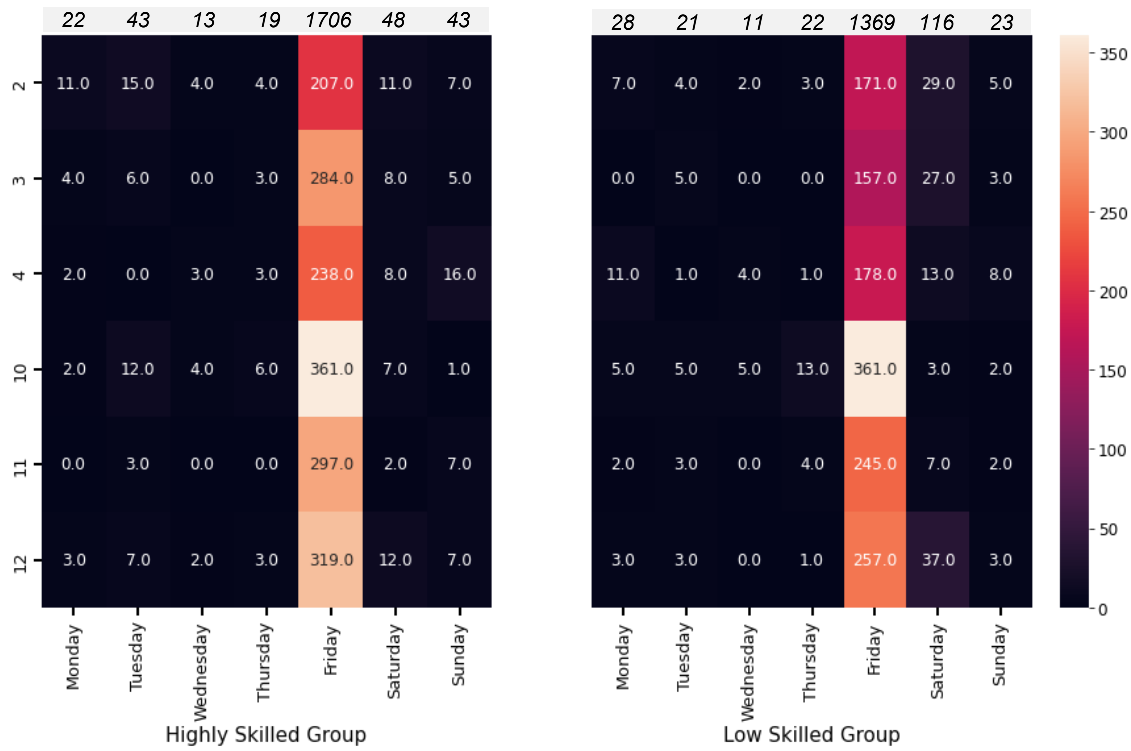


**Figure 5.** Daily engagement in quizzes

***RQ3: Quiz Performances***

The student groups were compared in terms of their quiz scores to detect if the time management skills had some possible effects on student performances. Almost in all quizzes the high-skilled group performed better, with an increasing performance gap between the groups. The significant difference was found in Quiz 7 (U=69.7, p=0.037). The better quiz performances by the high-skilled group might be associated with their active and distributed engagement in different course activities. The performance difference was the most significant in the last quiz in week seven, suggesting that the students with better time management could sustain their success late in the semester. If there were more quizzes in the rest of the semester, it is possible that the performance margin between the groups could grow further.

**Table 7.** Comparison of the quiz performances between the high- and low-skilled groups

| Quiz | High | Low | Mann-Whitney U | p value |
|---|---|---|---|---|
| 2 | 0.81 | 0.83 | 99.5 | 0.295 |
| 3 | 0.65 | 0.57 | 80.5 | 0.085 |
| 4 | 0.91 | 0.80 | 84.5 | 0.092 |
| 5 | 0.65 | 0.59 | 110.5 | 0.474 |
| 6 | 0.86 | 0.78 | 82.5 | 0.083 |
| 7 | 0.84 | 0.52 | 69.5 | 0.037* |

** Significant differences at 0.01 or 0.05 levels.*

**Discussion**

Time management is a key component of self-regulated learning (Thibodeaux et al., 2017). Students with strong time management skills show higher capacity in using their time in a planned manner, persisting in their learning, and performing better (Adams & Blair, 2019). In the learning analytics literature, there has been an increasing interest in using trace data to investigate students' time management behaviour (Tabuenca et al., 2015; Uzir et al., 2020; Sher et al., 2022). However, there has been a dearth of research on how students' self-reported time management skills are associated with their online engagement in programming courses, particularly during the emergency remote education due to COVID-19.

The findings of this study provide new insights into the role of time management skills in online learning in the context of a programming course. First, students' engagement levels in various course components differed considerably depending on their (self-reported) abilities of time management. Although all students' engagement decreased throughout the semester, the decline in the low-skilled group was stronger, thus leading to a bigger difference in engagement levels across the low- and high-skilled student groups towards the end of the semester. The high-skilled group showed higher engagement in all course components in most of the weeks.

The differences between the groups were more noticeable in their visits to the in-class exercises and lab-assignments, two components that involved active code writing, therefore requiring dedication of significant time. Regarding these two components, engagement levels differed statistically significantly between the high- and low-skilled groups in most of the weeks. Thus, the students confident with their time management skills were better able to plan their study time and distribute their efforts more equally among different activities, including those that take up a great deal of time (such as coding). Considering that this course was taught during the pandemic where all courses were delivered online, this study provides some evidence that the students with strong time management skills were better able to balance their efforts between multiple online courses taken during the pandemic.

Moreover, students' daily engagement patterns diverged depending on their (reported) skills to manage their times. According to the findings, the students in the high-skilled group were better at distributing their engagement over multiple days of the week. Among all, this behaviour was more noticeable in lab assignments. Students with strong time management skills worked on the lab assignments actively almost all days except on Saturdays, one day after the lab submissions, whereas other students demonstrated quite low engagement on most days other than Fridays. Moreover, the finding regarding the higher quiz engagement of the high-skilled group on Fridays suggests that these students were less like to miss the quizzes compared to the students in the low-skilled group. Another example of timely participation was the high-skilled group's regular engagement in in-class exercises on Fridays, indicating their timely engagement in code-writing under the lead of the instructor during the lecture, as opposed to the low-skilled students who caught up with the in-class exercises on Saturdays.

The main commonality between the student groups was the higher overall engagement on Fridays, which was the lecture day. Additionally, the engagement in the lecture-related components, namely chapter slides and lecture videos, was the lowest regardless students' time management skills. However, these components are critical to students' conceptual understanding of the programming concepts especially in online education. Techniques such as gamification could be employed to promote student engagement in such important components of online education (Ding et al., 2018), which may help promote students' understanding of programming.

Last, this study provides some evidence that students' performances in quizzes were affected by their time management skills. As the semester progressed, the performance gap between the groups increased. This finding is in alignment with previous research indicating the role of time management in student performance (Uzir et al., 2020).

## Conclusion

This study explored how students' time management skills are associated with their course engagement in a context of a programming course taught online in the COVID-19 pandemic. Participation levels, temporal patterns of engagement, and performances in quizzes differed depending on the students' time management skills.

This study shows that students' self-reported time management skills can be used as an early indicator of their ability to manage their times in a semester. Through a questionnaire, students with poorer time management skills can be identified early in the semester, and these students can be provided with adaptive support to help them regulate their engagement in a timely manner. Such support can be particularly important for programming courses to assist learners in planning their study time properly and dedicate a considerable amount of time in practising code writing.

The main limitation of this study is the small sample size, which implicates low statistical power in the analysis. Future research is needed to replicate this study in a larger sample of students in computing education. Moreover, the daily engagement analysis could be enhanced using some advanced learning analytics techniques. For example, clustering and sequence pattern analysis (Boroujeni & Dillenbourg, 2018) can be performed to identify distinct groups of students based on their temporal engagement in a course. Similarly, predictive models (Er, et al., 2019) can be applied to identify the predictive power of temporal engagement indicators in estimating students' final course performance.

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