Computers & Education 214 (2024) 105029

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Academic procrastination, incentivized and self-selected spaced practice, and quiz performance in an online programming problem system: An intensive longitudinal investigation

Yingbin Zhang[a,*], Luc Paquette[b], Xiaoyong Hu[a,c]

[a] Institute of Artificial Intelligence in Education, South China Normal University, No.55 West of Zhongshan Avenue, Guangzhou, Guangdong 510631, China
[b] Department of Curriculum & Instruction, University of Illinois at Urbana-Champaign, 1310 S Sixth Street, Champaign, IL 61820, United States
[c] School of Information Technology in Education, South China Normal University, No.55 West of Zhongshan Avenue, Guangzhou, Guangdong 510631, China

ARTICLE INFO

Keywords:
Learning strategy
Distance education and online learning
Post-secondary education

ABSTRACT

Time management is crucial for college students' academic success and learning of computer programming. Yet the changes of time management behaviors and their associations with learning outcomes are underexplored in online learning of programming. To address the gap, this study employed an intensive longitudinal approach to examine undergraduates' time management behaviors in an online programming problem system. Specifically, we analyzed weekly indicators of academic procrastination and spaced practice derived from programming traces. We applied dynamic structural equation modeling to examine the changes in these behaviors over time and their correlations with weekly quiz performance. Academic procrastination and self-selected spaced practice showed a significant upward trend over time, while incentivized spaced practice exhibited a significant downward trend. Moreover, students with prior programming experience showed a greater growth rate in spacing behaviors. At both within- and between-person levels, procrastination predicted quiz performance significantly and negatively, while self-selected spaced practice predicted quiz performance significantly and positively. In contrast, incentivized spaced practice predicted quiz performance positively at the within-person level but negatively at the between-person level. Additionally, quiz performance in the current week predicted subsequent time management behaviors significantly. These findings contribute to the understanding of procrastination and spaced practice in online programming learning and have implications for the design of scaffolding on time management. Furthermore, this study demonstrates the significance of combining intensive longitudinal approaches and action logs in examining the temporality of learning in online environments.

1. Introduction

Effective time management is a crucial factor for academic success, particularly for college students who must navigate the demands of academic, social, and extracurricular commitments (van der Meer et al., 2010). Novice programmers face an additional

* Corresponding author.
E-mail address: zyingbin@m.scnu.edu.cn (Y. Zhang).

https://doi.org/10.1016/j.compedu.2024.105029
Received 19 August 2023; Received in revised form 29 February 2024; Accepted 2 March 2024
Available online 5 March 2024
0360-1315/

challenge in time management because learning programming necessitates consistent practice and effective allocation of study time (Cheang et al., 2003). Online programming problem systems, which utilize automated assessment, bolster programming practice by providing immediate feedback (Wang et al., 2011). However, the responsibility of making, working on, and adjusting the practice schedule rests with the students themselves. Those who delay practice until right before a test are unlikely to perform as well as those who engage in practicing early and persistently. Therefore, effective self-regulated learning (SRL) skills, especially in time management, are essential for mastering programming, as emphasized in computing education research (Loksa et al., 2021; Lorås et al., 2021).

This study focused on undergraduates' time management and SRL in an online programming problem system, designed to facilitate persistent programming practice. We investigated two types of behaviors: academic procrastination and spaced practice. Spaced practice, sometimes named spacing of study, refers to distributing study time across spaced-out sessions (Son & Simon, 2012). This learning strategy is contrasted with massing, where study time is concentrated within a single session. While numerous laboratory studies have demonstrated the advantages of spaced practice, investigations in authentic educational settings remain scarce (Hartwig & Malain, 2022), especially in computing education. Without a thorough exploration of spaced practice based on naturally occurring data, we cannot depict its complete picture in learning (Carvalho et al., 2022).

In contrast, academic procrastination, typically referring to the behavior of delaying the initiation of academic tasks (Steel, 2007; Suárez-Perdomo et al., 2022), has received greater attention (Pereira et al., 2020; Zhang, Cunningham, et al., 2022). The reason may be that programming courses typically contain many assignments, but procrastination on programming assignments have been found common and related to poorer learning outcomes (Aggarwal & Ashok, 2022; Leinonen et al., 2021). Academic procrastination is seen as the opposite of spaced practice because the later a student starts an assignment, the less time they have to space out practices (Yeckehzaare et al., 2022). Nevertheless, the simultaneous investigation of these behaviors and their associations with learning outcomes in a single study has rarely been conducted (Riel et al., 2018; Yeckehzaare et al., 2022). Moreover, in terms of self-regulated learning (SRL), students may adapt time management behaviors throughout the learning process (Wolters & Brady, 2021), but the adaptation of spaced practice and procrastination within online programming learning remains understudied.

To bridge these gaps, measurements of spaced practice and procrastination were derived from programming traces. We used dynamic structural equation modeling to analyze the changes in these behaviors over time as well as the within- and between-person correlations among the behaviors and learning outcomes. The findings contribute to the conceptual understanding of time management and SRL within the domain of computing education and guide the development of online programming problem environments that promote effective time management.

2. Literature review

2.1. Online programming problem systems

In online programming problem systems, as in other online learning environments, instructors can employ interventions to motivate students to manage their study time, such as awarding extra credits to students who meet a specified daily practice target (YeckehZaare et al., 2019) or complete assignments in advance (Allevato & Edwards, 2013). Nevertheless, the central component of an online programming problem system is typically automated assessment (Paiva et al., 2022). The reason is that practice plays a vital role in learning programming (Cheang et al., 2003), but practice without feedback is limited in its efficiency and effectiveness. Manual grading of programming assignments demands significant time investment from instructors and is impractical for classes with hundreds of students, which is common in introductory computer science (CS1) courses (Garcia et al., 2016). Automated assessment for programming assignments alleviates instructors' grading workload and provides learners with immediate feedback on their practice (Cheang et al., 2003; Wang et al., 2011). Specifically, it evaluates various features of a submitted program, such as its compilability, execution, and output conformity (Paiva et al., 2022). Based on the evaluation, it can offer feedback that encompasses mistakes, conceptual understanding, task constraints, recommended approaches, and metacognitive guidance (Keuning et al., 2018).

The feedback assists students in evaluating and adapting their solutions, which are basic SRL activities. Tools for supporting the other SRL activities have been developed in the context of online programming learning (Garcia et al., 2018). For example, INCOM promotes students to conduct task analysis before coding (Le & Pinkwart, 2011). The most of the tools target on the cognition and metacognition dimensions of SRL. However, time is also a critical SRL dimension.

2.2. Time management as a SRL process

The relationship between time management and self-regulated learning (SRL) is widely acknowledged. For instance, time is a component of the Motivated Strategies for Learning Questionnaire (MSLQ ; Pintrich et al., 1993), one of the most used instruments for assessing SRL (Roth et al., 2016). In Zimmerman's (2000) social cognitive theory of SRL, self-regulatory efficacy beliefs impact the use of time management strategies. Recently, Wolters and Brady (2021) argued that time is a dimension of the learning process that learners can self-regulate and elaborated on how the regulation of time is linked to the regulation of other dimensions, such as cognition and motivation.

According to Wolters and Brady's (2021) model, time management activities occur throughout the various phases and processes of SRL. For instance, in the forethought phase, learners set time-related goals, such as determining when and for how long they will study, and select time management strategies. In the performance phase, learners begin working on the task according to the planned schedule. They monitor their use of time and evaluate it by comparing the amount of time used and its chronology with the initial plan. This evaluation, along with the evaluation of learning progress, may prompt learners to adjust their time usage plan. In the post-performance phase, Wolters and Brady suggest that learners reflect on two types of time-related outcomes, including the amount of time for completing the task and the time usage chronology. Learners consider these outcomes based on task performance as well as initial expectations and plans, such as the estimate of time cost and personal schedule. The reflection result, along with learners' belief about the stability and controllability of the time-related outcomes, influence their attribution for success or failure on the task and emotional reactions. The learner may also use the reflection on time-related outcomes to update their knowledge, belief, and attitudes, which influence time management activities in future tasks.

Academic procrastination concerns when to start an academic task, while spaced practice concerns how to distribute study time. Both are important time management behaviors that have received an increasing attention in the field of programming education. The next two sections discuss how these behaviors are related to SRL and their associations with learning outcome in online programming problem systems.

2.3. Self-selected and incentivized spaced practice

Spaced practice refers to distributing study time or practices across spaced-out sessions, given the amount of study time (Son & Simon, 2012). Self-selected spaced practice means that learners have the autonomy to distribute study time (Hartwig & Malain, 2022; Son & Simon, 2012). This type of spaced practice is distinct from the one imposed by instructors and experimenters. Imagine an experiment where participants are given 10 min to study ten complex words. There are two strategies of using the study time: massing the study time into a single session versus distributing the study time into two short sessions of 5 min with a 2-min pause between sessions. If the experimenter decides which strategy a participant should use, the spaced practice is considered imposed. In contrast, if the participants choose the strategy, the spaced practice is self-selected. YeckehZaare et al. (2021) further distinguished self-selected spaced practice from incentivized spaced practice. They defined spacing behavior primarily driven by intrinsic motivation (e.g., the desire to master a skill) as self-selected spaced practice and that primarily driven by external motivation (e.g., course grades) as incentivized spaced practice.

2.3.1. Self-selected spaced practice and SRL

Self-selected spaced practice is a SRL behavior (Son & Simon, 2012), in contrast to spaced practice imposed by others, which is external regulation (Tekin, 2022). Laboratory studies have found a strong association between self-selected spaced practice and the metacognition dimension of self-regulated learning, and thus, it has been regarded as the product of metacognitive knowledge and control (Benjamin & Bird, 2006; Son, 2010). Specifically, learners use their knowledge about the spacing effect (metacognitive knowledge) to develop and implement a plan for distributing study time (metacognitive control). Research in real-world settings has supported this association. For instance, de Barba et al. (2020) found that MOOC learners who distributed practices more often self-reported better regulation of time and effort. Nevertheless, learners may be unaware of the spacing effect and not use this strategy (Bjork et al., 2013). For instance, in Hartwig and Malain's (2022) study, undergraduates in a social psychology course had more than ten days to study for a chapter using an e-book and a quiz tool. However, among the students that used these resources, 82.8% read the e-book only in three days, and 94.7% used the quiz tool only in two days.

2.3.2. Spaced practice in online programming problem systems

Several studies have examined self-selected and incentivized spaced practice in online programming problem systems. In a series of studies, YeckehZaare et al. (2019, 2021, 2022) have discovered a positive correlation between incentivized spaced practice and final exam scores. In contrast, the findings on the benefit of self-selected spaced practice are mixed. Two studies have reported a positive correlation between self-selected spaced practice and final exam scores (Li et al., 2021; Zhang et al., 2020), while two other studies have found a weak and negative correlation (Leinonen et al., 2021; Leppänen et al., 2016). For example, in Zhang et al.'s (2020) study, undergraduates who spread practices over time received higher exam scores than the group massing practices, given the same quantities of practices. By contrast, Leppänen et al. (2016) found that those spreading practices obtained lower exam scores. One potential explanation for the inconsistent findings is that Li's and Zhang's studies controlled confounding variables, such as students' time investment and the number of practices, but Leinonen's and Leppänen's studies did not.

Additionally, a limitation of the above studies is their emphasis on between-person comparisons. For the same student, it is unclear whether distributed programming practices over time lead to better learning outcomes compared to concentrating practices within a shorter period. Furthermore, the temporal changes in incentivized and self-selected spaced practice in the context of programming learning are underexplored.

2.4. Academic procrastination

Academic procrastination refers to delaying working on academic tasks irrationally (Steel, 2007). Its correlates range from task characteristics, personality differences, demographics, to the consequences of procrastinating. The next subsection discusses its relation with SRL and its distinction from strategic delay.

2.4.1. Academic procrastination and SRL

Procrastination is commonly characterized as the opposite of self-regulated behavior, such as maladaptive behavior (Wolters, 2003) and "quintessential self-regulatory failure" (Steel, 2007). Research on college students has consistently shown negative associations between academic procrastination and various components of SRL, such as motivational beliefs (Cheng & Xie, 2021; Li et al.,

2020) and time management strategies (Hong et al., 2021; Wolters et al., 2017). Beyond the dysfunctional form of procrastination, researchers have investigated purposeful and strategic postponement and delay on tasks (e.g., due to low priority), which are named active procrastination in early studies (Chu & Choi, 2005; Schraw et al., 2007). Active procrastination is viewed as adaptive behavior and manifestation of self-regulated learning (Corkin et al., 2011). However, more recent studies have criticized the construct of active procrastination (Chowdhury & Pychyl, 2018; Hensley, 2014). For instance, Hensley (2014) found that behavioral procrastination was related to self-reported (passive) procrastination more than self-reported active procrastination. Chowdhury and Pychyl (2018) argued that active procrastination did not include the behavioral feature of procrastination. It may be better to conceptualize active procrastination as strategic delay rather than a type of procrastination (Klingsieck, 2013). Therefore, the current study adopts the notion that procrastination is a form of self-regulatory failure.

2.4.2. Academic procrastination in online programming problem systems

Similar to other contexts, academic procrastination in online programming problem systems has been found common (Fouh et al., 2014; Leinonen et al., 2021) and related to poorer learning outcomes (Aggarwal & Ashok, 2022; Pereira et al., 2020). Not only did students starting assignments earlier obtain better course grades than those starting later (Aggarwal & Ashok, 2022; Zhang, Cunningham, et al., 2022), but also individual students received higher scores in assignments started earlier than in those started later (Edwards et al., 2009; Martin et al., 2015). The harmful effects of procrastination were particularly acute for low-performing students, as documented by Liao et al. (2019), primarily because they had greater challenges in completing assignments, while procrastination resulted in limited time to seek help.

Two studies have found that students procrastinated more as the course progressed (Allevato & Edwards, 2013; Leinonen et al., 2021). In Allevato and Edwards's (2013) research, students needed to complete four programming projects sequentially. They started the first two projects earlier than the last two, even though completing the last two three days before the deadline could earn extra points. Leinonen et al. (2021) found that some students starting assignments early in the first week of a CS1 course delayed their start time in the subsequent weeks. Nevertheless, the factors contributing to the change in procrastination are unclear.

3. Research questions

The current study explores the temporal changes in undergraduates' time management behaviors, including academic procrastination, self-selected spaced practice, and incentivized spaced practice, in an online programming problem system. Additionally, it examines the relationships between these behaviors and learning outcomes. The following research questions (RQs) were investigated.

RQ1. : Do time management behaviors change over weeks?

Studies have found an increasing trend in academic procrastination within a semester in online programming problem systems (Allevato & Edwards, 2013; Leinonen et al., 2021). In other online environments, variation in self-selected spaced practice over time has been revealed (de Barba et al., 2020). Given that temporal change is a prominent characteristic of learning behaviors (Molenaar & Järvelä, 2014), we expect to find the change in time management behaviors in the current study. For academic procrastination, we anticipate an increase over time; for incentivized and self-selected spaced practice, we have no hypothesis as no theory or empirical evidence exists yet.

RQ2. : Does previous programming experience predict the temporal change of time management behaviors?

The temporal change in SRL behaviors may indicate students' ability to adapt learning strategies (Greene et al., 2021). Past research has found that prior domain knowledge was related to adaptation in offline environments (Taub & Azevedo, 2019; Zhang, Paquette, et al., 2022). We expect to replicate this association in an online programming problem system. Specifically, we anticipate that students with programming experience exhibited better adaptation over time, e.g., more spaced practice and less procrastination.

RQ3. : Do time management behaviors predict weekly learning outcomes at the student (RQ3.1) and week levels (RQ3.2)?

RQ3.1 examines the between-person relationship, e.g., whether students with less procrastination achieve better overall learning outcomes. RQ3.2 explores the within-person relationship, e.g., whether a student obtains better learning outcomes in a week with more spacing behaviors than in a week with fewer spacing behaviors. Based on previous findings (Aggarwal & Ashok, 2022; Martin et al., 2015), we expect a negative association between academic procrastination and learning outcomes at both the student and week levels. For spaced practice, although prior computing research has yielded inconsistent findings (e.g., Leppänen et al., 2016; Li et al., 2021), possibly due to uncontrolled effort investment, we anticipate a positive association in both incentivized and self-selected spaced practice at both levels when effort investment is controlled.

RQ4. : Do learning outcomes in the current week predict time management behaviors in the next week?

In terms of SRL, the current learning outcomes serve as feedback informing learners about their progress and its deviation from the goal, based on which learners may adapt their time management behaviors (Wolters & Brady, 2021). However, the associations have not been empirically validated in an online environment. We expect to uncover such associations.

4. Methods

4.1. Participants

Participants in this study were 951 undergraduates from a large university in the Midwestern region of the United States. They enrolled in and completed an introductory computer science (CS1) course during either Fall 2019 (617 students) or Spring 2020(334 students). No student repeated the course. Of the participants, 27.44% were female, and 78.49% were freshmen. The proportion of students majoring in a CS program, a program of CS plus another discipline, and a program unrelated to CS were 11.24%, 18.49%, and 70.27%, respectively.

4.2. Course structure and the problem system

The CS1 course taught Java programming in a blended form, combining in-person lectures and lab sections as well as online programming exercises. A single teacher instructed all classes in both semesters. The exercises were identical across classes. There were minor differences in some lectures and lab sections between classes, but the material in the lectures and lab sections was comparable across classes.

Programming problems were hosted on PrairieLearn, a web-based and problem-driven learning system (West et al., 2015). The instructor uploaded and released problems and set correct solutions and test cases for the problems. When students entered a programming problem, the top left of the interface described the task requirement (see Fig. 1a), under which was a coding area where students typed the solution. PrairieLearn automatically graded the solution after students clicked the *Save & Grade* button and immediately presented feedback below the coding area. For multiple-choice and fill-in-the-blank problems, the feedback primarily indicated correctness. For coding problems, the feedback additionally delineated errors in the submission, including checkstyle errors (whether the submitted code adhered to the required format), syntactic errors, and semantic errors (see Fig. 1b; in the system, the semantic errors were named test errors). Students could save their code without grading using the *Save only* button. This button was mainly used when students were finishing quizzes because multiple-choice and fill-in-blank problems in quizzes allowed limited attempts. The right area of the interface mainly contained two panels. The *Question* panel summarized students' submission histories on the current problem. The *Assessment overview* panel was for quizzes and showed students' progress in a quiz, including the scores that they earned, the remaining time, and the number of attempts left (only for multiple-choice and fill-in-blank problems).

The problems included 69 daily assignments and 14 weekly quizzes. Each assignment was a small coding task. A new assignment was released on almost every weekday at 00:00, and students could submit solutions an unlimited number of times but needed to solve it within a 24-h window to earn credits. The instructor explained the reason for such an assignment schedule to students in the course syllabus: programming takes regular consistent practice. The instructor encouraged students to practice programming in smaller, consistent sessions rather than in extensive, single sittings.

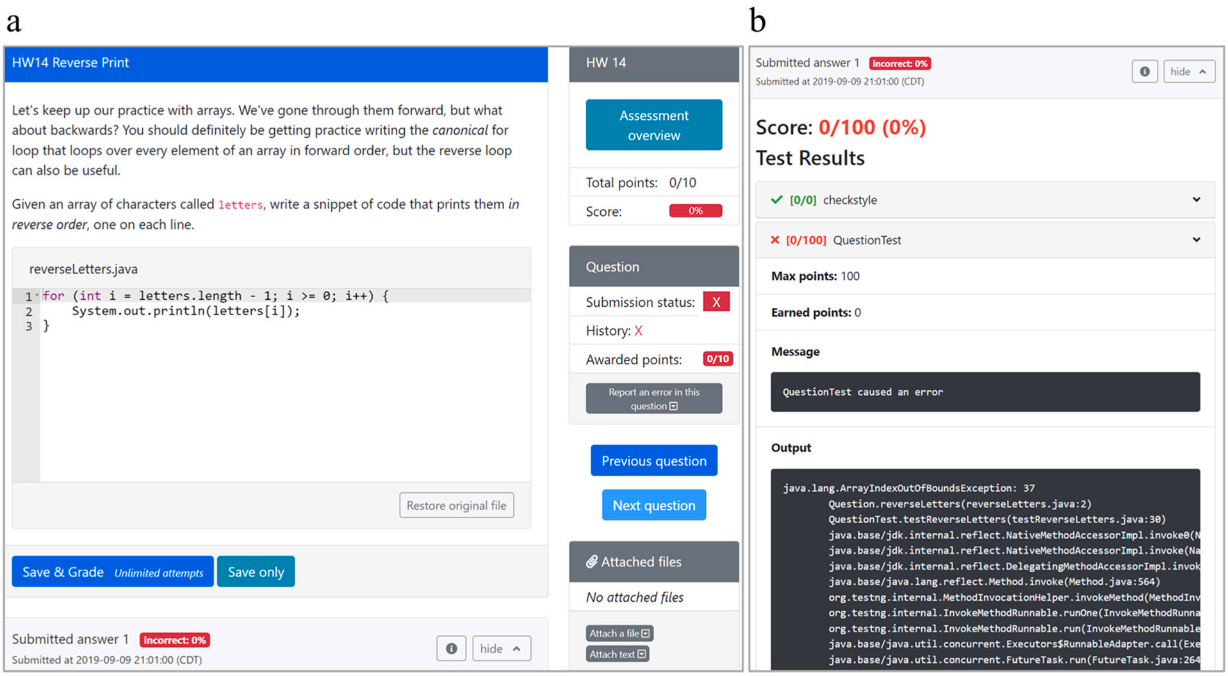

Fig. 1. Screenshots of PrairieLearn.

A quiz was released weekly, and each quiz consisted of multiple-choice and small coding problems. Students were given 1 h to complete the quiz, with unlimited attempts allowed for coding problems and up to two attempts for multiple-choice problems. Prior to the COVID-19 outbreak, students completed quizzes at an on-campus computer-based testing facility during Monday to Wednesday. After the outbreak (in the eighth week of Spring 2020), all classes were held online, and students took quizzes online during class time on Wednesday.

Assignments contributed to 20% of the final grades, while quizzes accounted for 30%. Lecture and lab participation as well as projects accounted for 50%. Students could still practice the problems of assignments and quizzes after the deadline but would not receive course credits. For convenience, we refer to these as non-credit problems. Data in the current study comprised students' submission traces for both credit and non-credit problems, quiz scores, and self-reported prior programming experience collected before the first class.

4.3. Analytic units

This study focused on the temporal change in time management behaviors, so aggregating the data over the entire semester was not appropriate. We are interested in the mutual associations between the behaviors and learning outcomes, the measure of which was quiz performance. Hence, this study used the period between two adjacent quizzes as the analytic unit. In this way, we only utilized time management behaviors after quiz t-1 and before quiz t to predict performance on quiz t, which, in turn, was used to predict only time management behaviors after quiz t and before quiz t+1. Although quizzes were administered every week, the period between two adjacent quizzes did not necessarily align with a calendar week due to students having the flexibility to take quizzes anytime between Monday and Wednesday. Consequently, the duration of the period varied per student per week, with an average of 7.4 days and a standard deviation of 1.90 days. For ease of reference, this paper denotes the period between quizzes t-1 and t as week t.

4.4. Measurements

Table 1 summarizes the definition of the main measurements and related terms. The text below explains each measurement.

Quiz performance. A quiz might involve all the material covered up to that point, with an emphasis on the material covered since the last quiz. Quizzes in weeks 4, 9, and 14 were different from the others as they served as midterms, focusing on the material covered since the last midterm. Thus, quizzes in different weeks involved different programming concepts and skills and might vary in difficulty. To mitigate the potential impact of these differences on the comparability of scores across quizzes, we transformed raw quiz scores to z-scores within each week. A student's quiz z-score in week t indicated how many standard deviations their raw quiz scores in week t deviated from the average score in this week. If a student's quiz z-score was higher in week t than in week t-1, it meant that their quiz performance standing in the class improved between the two weeks, and we may infer that they learned more in week t than week t-1 relative to their classmates.

Self-selected and incentivized spaced practice. Previous studies in real-world settings have operationalized spaced practice as the number of practice sessions (Carvalho et al., 2020; de Barba et al., 2020) or days (Hartwig & Malain, 2022; YeckehZaare et al., 2021). This study adopted the operationalization of practice sessions for two reasons. First, the analytic unit was a period between two adjacent quizzes, limiting the maximum number of study days to nine. The small range of study days resulted in smaller variances compared to practice sessions and suppressed the power of detecting relationships between spaced practice and other variables. Second, students often worked on PrairieLearn at midnight (see Fig. 4). Using the operationalization of practice days would result in unreasonable measurements. For instance, consecutive submissions with a short interval but on different dates (e.g., 23:58 on Monday and 00:01 on Tuesday) would be counted as two practice days, whereas submissions with a long interval but on the same date (e.g., 18:00 and 22:00 on Monday) would be counted as one practice day.

The data did not contain the amount of time that students had worked on a problem before the first submission of a session and the amount of time that students spent after a submission unless there was another submission following it. Thus, it was not possible to determine the exact start and end times of students' practice sessions. However, a reasonable hypothesis is that submissions within a session would be temporally clustered, indicative of a focused period of activity. In contrast, the intervals separating different sessions

Table 1
The primary measurements and related terms.

Terms	Definition
Credit problems	Problems in assignments that were released at 00:00. Students could earn credits by solving them within a 24-h window.
Non-credit problems	Any problem after its deadline.
Quiz performance (t)	The z-scores that were transformed from raw scores of quiz t.
Quiz period (t)	The period between the end of quiz t-1 and the start of quiz t.
Practice session	A period where there was at least one submission, and the interval between consecutive submissions was no more than 15 min.
Incentivized spaced practice (t)	The number of practice sessions on unsolved credit problems in quiz period t, multiplied by $\frac{7}{day_t}$ for normalization. day_t was the number of days in period t.
Self-selected spaced practice (t)	The number of practice sessions on non-credit problems and solved credit problems in quiz period t, multiplied by $\frac{7}{day_t}$.
Procrastination (t)	The average interval between the release of a credit problem and the first submission on it in quiz period t.
#Submissions (t)	The number of submissions on non-credit and credit problems in quiz period t.

were likely to be more variable. Based on this assumption, the current research defined a session as a period marked by at least one submission, where the interval between consecutive submissions was no more than 15 min. The choice of this 15-min threshold stemmed from an observed pattern in submission intervals: the frequency of intervals shorter than the chosen threshold exhibited only a slight increase when extending the threshold beyond 15 min (see figure A1 in the appendix). For instance, as the threshold increased from 15 min to 1 h, the proportion of intervals shorter than the threshold increased slightly from 81.57% to 83.77%. The pattern aligned with the initial assumption: when the threshold is in the typical range of submission intervals during a session, one would expect a rapid increase in the proportion of intervals as the threshold extends; conversely, when the threshold exceeds the typical range, a slower rate of increase in the proportion of intervals is anticipated.

Note that the gap between sessions may influence the spacing effect, but the impact has been widely recognized as relying on the retention interval (e.g., Cepeda et al., 2008; Son & Simon, 2012), which is the interval between a test and the last session before the test. A longer gap leads to better test performance when the retention interval is long. For a retention interval of seven days, a gap of one day may result in the best test performance (Cepeda et al., 2008). In the current study, the mean and median of the retention interval (the interval between the last practice session before a quiz and the time of starting the quiz) were 16.2 and 4.5 h, respectively. With such a short retention interval, the gap between sessions was unlikely to influence quiz performance. Indeed, the association between the session gap and quiz performance was null (see figure A2 in the appendix). Thus, this study did not focus on the session gap.

We distinguished self-selected spaced practice and incentivized spaced practice. Practice sessions on an assignment before its deadline and prior to the first correct submission were classified as incentivized spaced practice because solving the problem before its deadline could earn credits. The credits might be external motivation that drove the practice. Practice sessions on non-credit problems were counted as self-selected spaced practice. Additionally, practice sessions on a problem before its deadline but after the first correct submission was also considered self-selected spaced practice. This was because practicing a solved assignment would not be awarded extra credits, and such practice sessions were likely driven by intrinsic motivation.

The length of the period between quizzes varied from five to nine days, which might contribute to the variation in the number of practice sessions. To eliminate this effect, we used Equation (1) to transform the number of practice sessions. $session_{kt}$ denoted student k's practice sessions in week t, while day_{kt} denoted the number of days in week t, i.e., the period between the completion of quiz t-1 and the start of quiz t. Multiplying by seven converted $spacing_{kt}$ to represent total practice sessions per week, rather than per day.

$$spacing_{kt} = \frac{session_{kt}}{day_{kt}} * 7. \tag{1}$$

The spacing behaviors occurred naturally, with no restrictions on the amount of study time. Therefore, a high frequency of practice sessions could partially stem from significant effort investment. To address this issue, we used the total number of submissions on problems (regardless of for credits or non-credit purposes) as an indicator of effort investment and controlled for its impact when predicting quiz performance (see Fig. 3), as previous studies have done (Carvalho et al., 2020; Hartwig & Malain, 2022).

Academic procrastination. Academic procrastination was operationalized as the interval between an assignment's release and the timing of the first submission. If students attempted an assignment after its deadline or never attempted it, academic procrastination on the assignment was 24 h. We used the average procrastination across assignments within a week in subsequent analyses. Prior studies have found the interval (or a similar measurement, such as the number of days elapsed since a task released) positively correlated with self-reported procrastination measured by well-established procrastination scales in both the academic and non-academic settings (Beswick et al., 1988; Steel et al., 2001; Zuber et al., 2020). In addition, the positive correlation between the interval and learning outcomes found in prior work (e.g., Aggarwal & Ashok, 2022; Pereira et al., 2021; Zhang, Cunningham, et al., 2022) is in line with the positive correlation between academic procrastination and learning outcomes (Kim & Seo, 2015). The above findings offered evidence supporting the validity of using the interval as a measure of academic procrastination.

Prior programming experience. Prior experience included self-rated programming ability and programming language familiarity. Self-rated ability ranged from one to five, with a higher rating indicating a higher level of proficiency. Programming language familiarity contained four categories: (1) *none* (12.43%), indicating no prior programming experience; (2) *Java* (15.46%), indicating programming exclusively in Java; (3) *others* (27.46%), referring to programming in languages other than Java; (4) *Java and others* (44.65%), indicating programming in both Java and other languages.

4.5. Analyses

The present study utilized two-level dynamic structural equation models (DSEM ; Asparouhov et al., 2018), implemented in Mplus 8.3, to examine the dynamic associations among the variables of interest. DSEM integrates time-series, multilevel modeling, and structural equation modeling and is suitable for analyzing intensive longitudinal data, where there are multiple measurement occasions. To enhance the estimation accuracy, 26 students were excluded from the analyses because they attempted less than half of the quizzes and had fewer than seven measurement occasions. A total of 288 students attempted seven or more but not all quizzes, so their data were unequally distributed in time. Ignoring the issue may cause inaccurate results because DSEM assumes a constant lag effect across measurement occasions. Imagine the first three measurements of a student occurred at weeks 1, 2, and 5. If we regarded the measurements as being collected in occasions 1, 2, and 3, the lag effect for weeks 1–2 would be assumed to be the same as that of weeks 2–5, although the interval between occasions 2 and 3 was three times of that between occasions 1 and 2. We used the *TINTERVAL* statement in Mplus to accommodate the unequally spaced measurement occasions (McNeish et al., 2020). In the above example, using *TINTERVAL* = *week(1)* would automatically code the measurements as collected in occasions 1, 2, and 5 and insert missing values for occasions 3 and 4. In this way, the lag effect for weeks 1–2 would not be the same as that of weeks 2–5.

To address RQ 1, three two-level autoregressive lag-1 (AR1) models (McNeish et al., 2020) were employed, with each model corresponding to a different type of time-management behavior. Fig. 2 illustrates the model for incentivized spaced practice. φ_1 was the autoregressive lag-1 effect. β_1 was the effect of week number on incentivized spaced practice. γ_{11} was the predictive effects of prior programming experience on incentivized spaced practice. Gender, grade, and major were covariates. Semester was also added to the model to account for the potential impact of COVID-19 and first-year students' behavioral differences between their first (Fall 2019) and second (Spring 2020) semesters in college. For instance, they might be adapting to college life in the first semester, but their behaviors might be more stable in the second semester.

To differentiate the within-person and between-person effects and facilitate interpretation, person-mean centering was applied to incentivized spaced practice, i.e., subtracting each student's mean incentivized spaced practice from their weekly raw value. The latent person-mean centering technique in Mplus was used to reduce bias in the estimates (Asparouhov et al., 2018). This is why the student-level incentivized spaced practice was depicted as a latent variable in Fig. 2.

For RQ2, we added the moderation effects of prior programming experience on the relationship between incentivized spaced practice and week number, which was γ_{21} and γ_{22} in Fig. 2.

To investigate RQs 3 and 4, we utilized a two-level vector autoregressive lag-1 model (VAR (1); McNeish et al., 2020), illustrated by Fig. 3 φ_1 to φ_4 represented autoregression effects. β_1, β_2, and β_3 represented the predictive effects of time management behaviors on quiz scores at the week level (RQ 3.2), while β_4, β_5, and β_6 were that at the student level (RQ 3.1). β_7, β_8, and β_9 denoted the predictive effects of quiz scores in the current week on time management behaviors in the subsequent week (RQ 4). The number of submissions was a covariate, and its associations with time management behaviors and quiz scores were not of interest. The same is true for the other covariates.

5. Results

Preliminary analyses were conducted to explore the relationships among student-level variables (see Tables 2 and 3). Quiz scores and self-rated ability had a weak and positive relationship, and both were weakly and negatively related to procrastination, the two types of spaced practice, and the number of submissions. The two types of spaced practice were weakly and positively related to each other, and both were moderately related to the number of submissions. Procrastination was weakly and negatively related to incentivized spaced practice but positively related to self-selected spaced practice. Students with different programming language familiarity showed differences in quiz scores and time management behaviors. Disparities in the variables also occurred between students with different majors, between male and female students, and between freshmen and not-freshmen.

5.1. RQs 1 and 2: the changes in time management behaviors over time and the moderation effect of prior programming experience

Fig. 4 displays the weekly change in time management behaviors throughout a semester. The incentivized spacing behavior generally declined over time. The AR1 model yielded an effect of the week number at −0.13 (see Table 4), indicating that, on average, the number of practice sessions for credits diminished by 0.13 from week *t-1* to week *t*. In contrast, self-selected spaced practice increased over the semester. On average, the number of non-credit practice sessions increased by 0.03 from week *t*-1 to week *t*. In addition to the general trend, a dramatic decrease in incentivized spaced practice and a dramatic decrease in self-selected spaced practice occurred during week 4 (which coincided with the first midterm exam). An abrupt increase during week 10 and an abrupt decrease during week 13 also occurred in incentivized spaced practice.

Students procrastinated more and more over the semester. For example, the proportion of students commencing assignments after 20 h since the release of the assignments escalated from 5.6% in week 1 to 40.1% in week 14. The effect of the week number was 0.31 in the AR1 model (see Table 4), meaning a delay of 0.31 h in starting assignments from week *t*-1 to week *t*. In line with Tables 2 and 3, prior programming experience and gender influenced the time management behavior. Table 4 also provides information on the autoregressive effects of time management behaviors, all of which were positive. Students who engaged in more practice sessions in

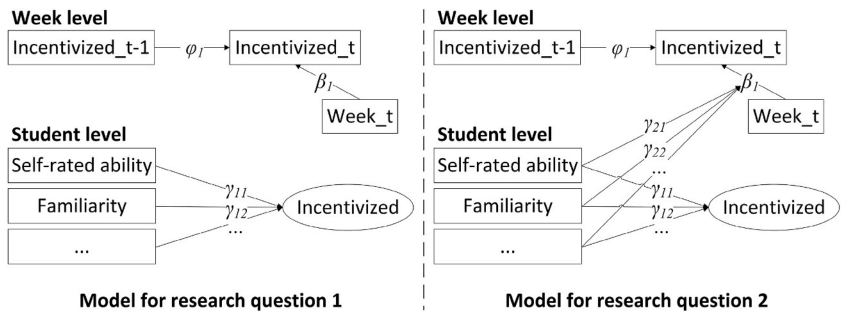

Fig. 2. The two-level AR1 models for the change in incentivized spaced practice
Note. Incentivized_t: Incentivized spaced practice in week *t*. Week: week number. Familiarity: language familiarity. Rectangles indicate observed variables, while ellipses indicate latent variables.

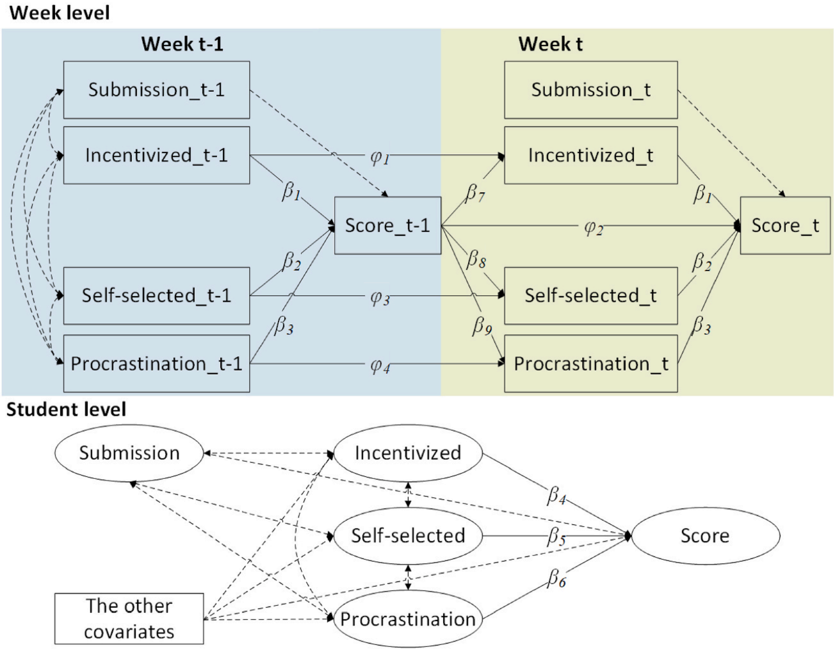

Fig. 3. Two-level VAR1 model for the associations among spaced practice, procrastination, and quiz scores
Note. Rectangles indicate observed variables, while ellipses indicate latent variables. Single-headed arrows are regression, while double-headed arrows are correlation. The dashed lines are for controlling the covariates and are not of interest. For clarity, the correlations in week *t* are not displayed.

week *t-1* were inclined to maintain similar levels of practice sessions in week *t*, a pattern also observed in procrastination behaviors.

Programming experience moderated the change rate of all time management behaviors (Table 5). For self-rated ability, students rating their ability at level five showed a 0.12 (0.03*4) higher change rate in incentivized spaced practice than students rating their ability at level one. Students familiar with at least one programming language had a 0.05 to 0.08 higher change rate in both incentivized and self-selected spaced practice than those unfamiliar with any language. Also, students familiar with only Java showed a growth rate in procrastination 0.13 higher than those unfamiliar with any language.

Gender, grade, and major did not moderate the change rate of time management behaviors. Students in Spring 2020 showed a 0.04 lower change rate in self-selected spaced practice and a 0.14 higher change rate in procrastination than those in Fall 2019.

5.2. RQs 3 and 4: relationships between time management behaviors and quiz performance

Fig. 5 displays the results of the two-level VAR1 model. Regarding the prediction of time management behaviors on quiz performance (RQ3), at the week level (RQ3.1), both incentivized and self-selected spaced practice showed a statistically significant positive effect on quiz performance, while academic procrastination had a statistically significant negative effect. On average, a student's quiz performance increased by 0.01 standard deviations if they practiced one more session, regardless of credit or non-credit purpose and decreased by 0.02 standard deviations if they started the homework assignment 1 h later. The three types of behaviors explained 5% of the variances in quiz performances at the week-level (i.e., within-person variances), derived by comparing the two-level VAR1 model with its variant without the time management behaviors.

At the student level (RQ3.2), the prediction of self-selected spaced practice and procrastination on quiz performance was consistent with that at the week level. A student's overall quiz performance was 0.08 standard deviations higher than another student who practiced one fewer session for non-credit purposes each week. Students starting assignments later had quiz scores 0.14 standard deviations lower than those starting the assignments 1 h earlier. However, the prediction of incentivized spaced practice on quiz performance was negative, contrary to the week-level finding. A student's overall quiz performance was 0.50 standard deviations lower than another student who practiced one fewer session for credits. The three types of behaviors explained 48.90% of the variances in quiz performances at the student level (i.e., between-person variances), derived by comparing the two-level VAR1 model with its variant without the time management behaviors.

Interestingly, the quiz performance in week *t*-1 predicted students' time management behaviors in week *t* (RQ4). A student with quiz performance one standard deviation higher at the current week tended to practice 0.17 more sessions for credits, 0.21 fewer sessions for non-credit purposes, and initiated assignments 0.47 h earlier in the subsequent week. Quiz performance explained 0.68%, 2.10%, and 2.10% of the variances in incentivized spaced practice, self-selected spaced practice, and procrastination, respectively.

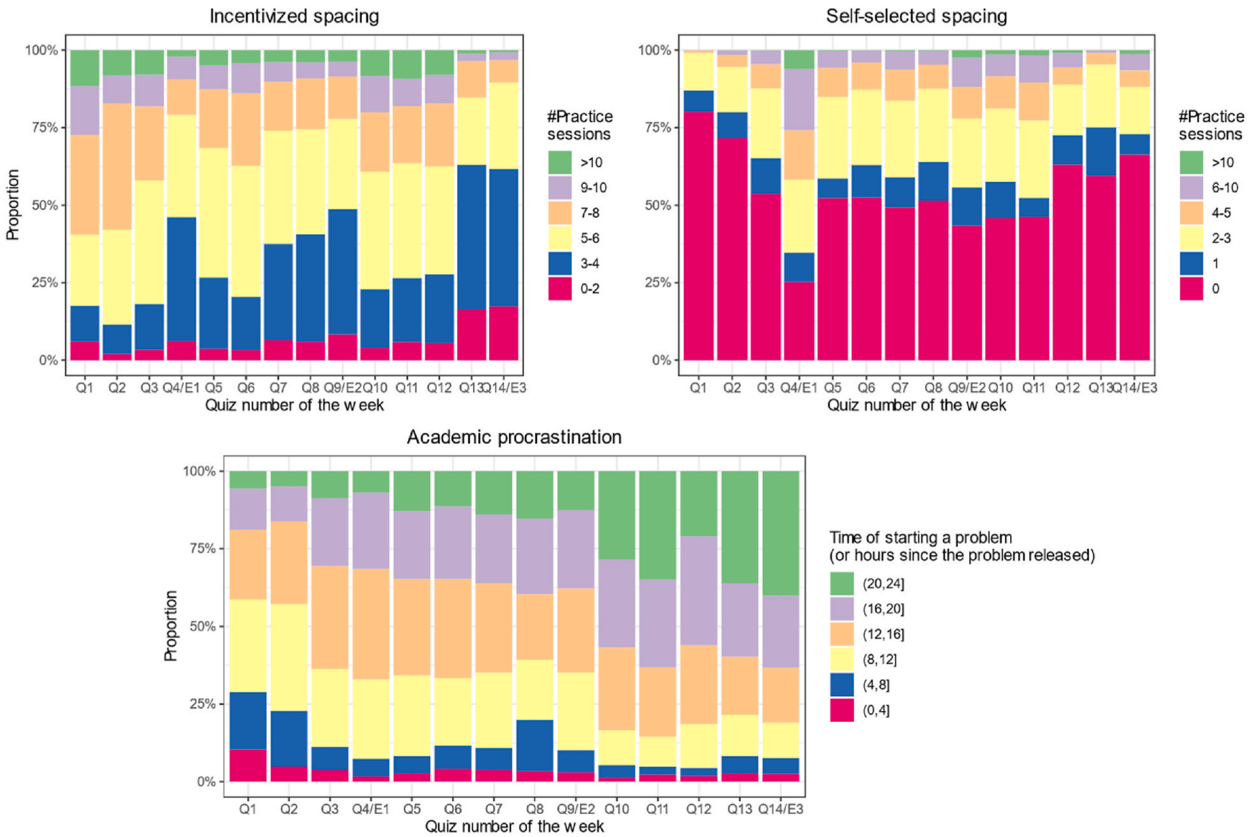

Fig. 4. Binned time management behaviors in each week.

Table 2
Binary Kendall correlation at the student level.

	Quiz scores	1	2	3	4
1. Incentivized spaced practice	−0.14***				
2. Self-selected spaced practice	−0.15***	0.26***			
3. Procrastination	−0.34***	−0.24***	0.04*		
4. #Submissions	−0.21***	0.48***	0.50***	−0.05	
5. Self-rated ability	0.21***	−0.09*	−0.28***	−0.18***	−0.23***

Note. Holm correction was applied to control the family-wise error rate.

Table 3
Distributions of the variables of interest in different groups.

Mean (SD)		Raw quiz scores	Incentivized spacing	Self-selected spacing	Procrastination
Language familiarity	Java and others	86.35 (8.05)	1.01 (1.17)	5.53 (1.17)	13.69 (3.83)
	Java	86.29 (8.85)	1.31 (1.35)	5.56 (1.16)	14.17 (3.47)
	Others	81.79 (9.52)	1.49 (1.35)	5.87 (1.53)	15.36 (3.46)
	None	78.60 (9.39)	2.10 (1.56)	5.94 (1.47)	16.36 (3.14)
Major	CS	87.49 (8.27)	5.72 (1.24)	1.08 (0.96)	12.96 (3.66)
	CS+	85.70 (8.07)	5.54 (1.17)	1.48 (1.48)	14.25 (4.04)
	Others	83.17 (9.46)	5.71 (1.37)	1.32 (1.36)	14.89 (3.57)
Gender	Female	82.75 (9.54)	5.95 (1.32)	1.76 (1.45)	14.59 (3.88)
	Male	84.65 (9.04)	5.58 (1.31)	1.15 (1.26)	14.54 (3.66)
Grade	First year	85.16 (8.53)	5.64 (1.30)	1.29 (1.37)	14.27 (3.80)
	Not first year	80.34 (10.55)	5.81 (1.42)	1.43 (1.26)	15.58 (3.22)
Semester	Fall 2019	84.70 (9.48)	5.64 (1.24)	1.44 (1.47)	14.45 (3.75)
	Spring 2020	83.05 (8.60)	5.76 (1.47)	1.1 (1.05)	14.75 (3.66)

Table 4
The effect of the week number on time management behavior.

Estimates and 95% confidence intervals	Incentivized spaced practice [d]	Self-selected spaced practice [d]	Procrastination
Fixed effect			
Intercept	6.19 [5.88, 6.51]	1.16 [0.91, 1.44]	16.76 [15.95, 17.59]
Week [a]	**−0.13 [-0.14, -0.12]**	**0.03 [0.02, 0.04]**	**0.31 [0.28, 0.33]**
Autoregression	**0.10 [0.07, 0.12]**	**0.25 [0.23, 0.28]**	**0.26 [0.23, 0.28]**
Self-rated ability	**−0.14 [-0.25, -0.03]**	**−0.35 [-0.44, -0.25]**	**−0.55 [-0.88, -0.28]**
Java and others [b]	**−0.15 [-0.48, 0.20]**	**−0.39 [-0.67, -0.10]**	**−1.55 [-2.46, -0.64]**
Java [b]	**−0.16 [-0.51, 0.19]**	**−0.40 [-0.68, -0.09]**	**−1.48 [-2.37, -0.50]**
Others [b]	0.06 [-0.25, 0.37]	−0.16 [-0.43, 0.11]	−0.52 [-1.38, 0.28]
Female	**0.26 [0.10, 0.41]**	**0.34 [0.20, 0.50]**	0.19 [-0.27, 0.54]
First year	−0.08 [-0.30, 0.13]	−0.06 [-0.26, 0.11]	−0.52 [-1.12, 0.02]
CS [c]	0.20 [-0.12, 0.48]	−0.23 [-0.48, 0.03]	**−1.24 [-2.04, -0.47]**
CS + [c]	0.03 [-0.22, 0.26]	0.16 [-0.06, 0.37]	−0.01 [-0.65, 0.65]
Spring 2020	−0.08 [-0.29, 0.1]	−0.33 [-0.49, −0.15]	−0.40 [-0.94, 0.10]
Random effect			
Intercept	1.15	0.50	10.15
Week	0.00	0.00	0.03

Note. The estimates in bold were statistically significant at 0.05 level. a: To ease the interpretation on the estimates, we subtracted one from the week number so that it started at zero. The intercept was time management behaviors in the first week, and the main effects of student-level covariates were behavioral differences in the first week. b: Students unfamiliar with any language were the reference. c: Students majoring in a program unrelated to CS were the reference. d: Due to the abrupt change in practice sessions in week 4, we excluded observations in this week in the AR1 model for incentivize and self-selected spaced practice.

Table 5
The moderation effect of programming experience on the change of behavior.

Estimates and 95% confidence intervals	Incentivized spaced practice [d]	Self-selected spaced practice [d]	Procrastination
Fixed effect			
… … (The main effect of each variable was omitted for simplicity)			
Self-rated ability:Week	**0.03 [0.01, 0.04]**	−0.01 [-0.02, 0.01]	−0.02 [-0.05, 0.00]
Java and others:Week	**0.06 [0.03, 0.10]**	**0.07 [0.03, 0.10]**	0.06 [-0.01, 0.14]
Java:Week	**0.05 [0.01, 0.10]**	**0.08 [0.04, 0.11]**	**0.13 [0.05, 0.20]**
Others:Week	**0.06 [0.03, 0.10]**	**0.06 [0.03, 0.09]**	0.00 [-0.07, 0.06]
Female:Week	−0.01 [-0.03, 0.00]	0.00 [-0.01, 0.02]	0.00 [-0.03, 0.04]
Freshman:Week	0.00 [-0.03, 0.03]	0.01 [-0.01, 0.03]	−0.02 [-0.06, 0.04]
CS:Week	0.01 [-0.03, 0.06]	0.01 [-0.02, 0.03]	−0.06 [-0.12, 0.00]
CS+:Week	0.00 [-0.03, 0.02]	0.01 [-0.02, 0.03]	0.01 [-0.04, 0.06]
Spring 2020:Week	0.02 [-0.01, 0.05]	**−0.04 [-0.06, -0.01]**	**0.14 [0.09, 0.18]**
Random effect			
Intercept	1.02	0.52	9.21
Week	0.00	0.00	0.03

Note. The estimates in bold were statistically significant at 0.05 level.

6. Discussion

This investigation explored the temporal changes of undergraduates' time management behaviors in an online programming problem system (RQ1), factors related to the changes (RQ2), the within-person (RQ3.1) and between-person (RQ3.2) associations between the behaviors and learning outcome, as well as the within-person prediction of learning outcomes on the behaviors (RQ4). We applied a set of two-level DSEM to analyze submission traces, quiz results, and self-reported data to answer these questions.

6.1. RQs 1 and 2: the change in time management behaviors over time and the moderation effect of prior programming experience

In response to RQ1, an upward trend in academic procrastination was observed, which aligns with prior studies (Allevato & Edwards, 2013; Leinonen et al., 2021). The increase may be attributed to the growing complexity of the computing concepts and skills covered in the later assignments. Students tend to procrastinate more in complex tasks than simple tasks (Sun & Kim, 2022). Additionally, the initial flexibility in students' schedules during the beginning of the semester may gradually diminish as their academic and other obligations accumulate, leading to some students struggling with time management.

The increasingly busy schedule may also account for the decline in incentivized spaced practice, given that previous research found a negative association between spaced practice and the number of academic commitments (Susser & McCabe, 2013). Distributing practice requires effortful control and brings challenges to learners, particularly on assignments for credits where students had only a 24-h timeframe to earn the credits. As the schedule became more packed, the difficulty of distributing study time likely grew. The decrease in incentivized spaced practice was also related to increasing procrastination. Beginning an assignment later left students less

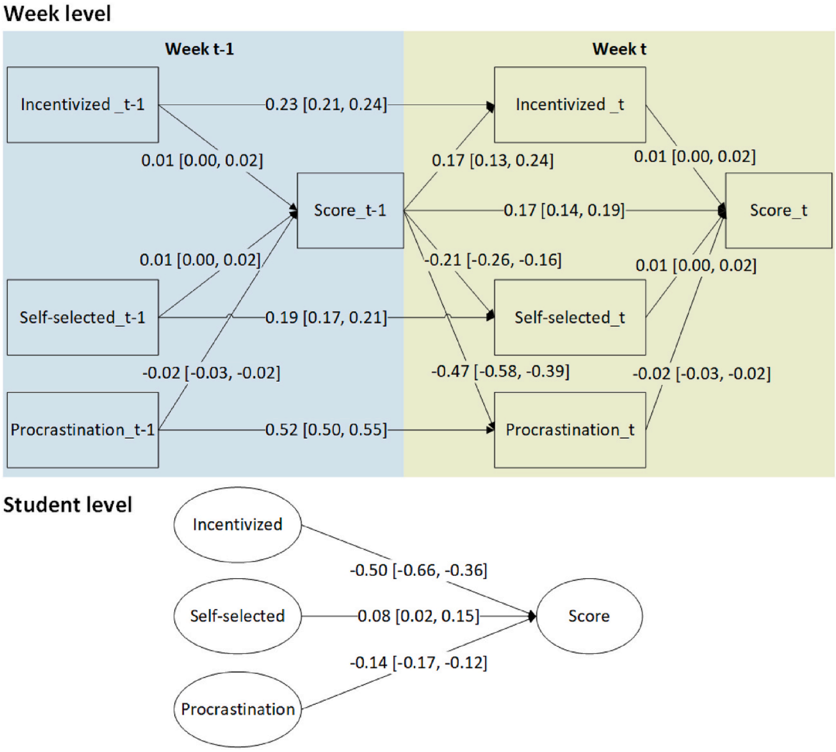

Fig. 5. The unstandardized coefficients and 95% confidence intervals in the two-level VAR1 model
Note. The *p*-values of all coefficients were smaller than 0.01. Rectangles indicate observed variables, while ellipses indicate latent variables. For clarity, the figure does not show covariates and correlations.

flexibility to distribute the study time if they aim to complete it before the deadline, as evidenced by the negative association between incentivized spaced practice and procrastination in the current and other studies (Zhang, Cunningham, et al., 2022).

Contrary to the decrease in incentivized spaced practice, self-selected spaced practice increased over time. The most plausible explanation is that students had increasing opportunities to practice non-credit problems because such problems gradually accumulated. Furthermore, certain computing concepts and skills taught later in the course relied on mastery of knowledge taught earlier. For instance, an understanding of iteration requires knowledge of conditionals (Rogalski & Samurçay, 1990). Such sequential connections among knowledge components may have compelled students to practice non-credit problems to reinforce their understanding of previously taught material. Additionally, the course design, which advocated persistent practices by releasing a new assignment each day, may have contributed to the rise in self-selected spaced practice. Experiencing a learning strategy affects learners' beliefs about it, and the belief plays a critical role in the utilization of the strategy (McDaniel & Einstein, 2020). As students gained more experience with the course design, they likely developed a better understanding of the benefits of spaced study and engaged accordingly. It is worth noting that the increase of self-selected spaced practice over time was small. Further investigations are necessary to explore such behavioral changes over time.

Regarding RQ2, programming experience moderated the change in time management behaviors. To some extent, the moderation effect might be related to the main effect of programming experience. Students with programming experience generally practiced fewer sessions and procrastinated less in the first week, leaving more room for growth practice sessions and procrastination. The most prominent pattern was that students familiar with at least one programming language exhibited less initial usage of the spacing strategy than those unfamiliar with any language, but the former showed a higher growth rate in the usage as the course progressed. This pattern may be attributed to that students were already familiar with the learning material covered at the beginning of the course and did not feel the need to practice non-credit problems. However, as the course advanced, the learning material became less familiar, so they had to exercise the problems. Studies have found that prior domain knowledge facilitates SRL behaviors and the increase in such behaviors, as prior knowledge may enable them to allocate more working memory capacity to regulate behaviors (Taub & Azevedo, 2019; Zhang, Cunningham, et al., 2022). Programming language familiarity was indicative of prior knowledge; and thus, it might facilitate the growth rate in spacing behaviors.

Interestingly, students familiar with Java showed a higher growth rate in procrastination than those unfamiliar with any language, although this effect was not statistically significant in those familiar with both Java and other languages. A relevant and interesting result is that those familiar with Java started assignments (2.21 and 2.53 h) earlier than those unfamiliar with any language during the first week. These findings may be explained by the positive association between task complexity and procrastination (Sun & Kim, 2022). Students familiar with Java might perceive the early problems as simple. However, as the course progressed and the assignments became more complex, maintaining low-level procrastination might become more challenging.

6.2. RQs 3 and 4: relationships between time management behaviors and quiz performance

For RQ3, this study found that quiz performance was predicted negatively by procrastination and positively by self-selected spaced practice at both the week and student levels. These findings were in line with the expectations and prior studies (Li et al., 2021; Martin et al., 2015). Surprisingly, incentivized spaced practice predicted quiz performance positively at the week level but negatively at the student level. One possible explanation is that incentivized spaced practice was negatively related to prior domain knowledge (as suggested by Tables 1–3), and certain prior knowledge factors were not measured in this study. Consequently, the student-level prediction of incentivized spaced practice on quiz performance might be strongly confounded with the prior knowledge factors and be negative. The week-level prediction did not suffer this issue because a student's prior knowledge remained consistent throughout the course. These findings highlight the challenge in measuring spaced study using log data from real-world settings, particularly in obtaining an uncontaminated measure of spacing behavior in a digital learning environment without experimental control. For future investigation in such a context, we resonate with previous research (Hartwig & Malain, 2022; Yeckehzaare et al., 2022) and suggest controlling potential confounding variables to ensure unbiased findings, such as the effort or time investment.

The results showed a negative correlation between the time of submission and quiz scores, suggesting that later submissions tended to result in lower scores. However, we do not advocate staying up late to do the assignment. Further analysis revealed that the advantages of beginning assignments early were most pronounced between noon and midnight, as detailed in figure A3of the appendix. Specifically, the quiz-z scores not only had a higher mean but a smaller variance in the cases of starting problems before noon (12:00) than those starting problems after noon. Moreover, and the negative correlation between the time of submission and scores was significantly weaker before noon than after noon. Thus, initiating assignments early can enhance learning outcome, but it should not come at the expense of sacrificing sleep until after midnight.

For RQ4, quiz performance in the current week predicted time management behaviors in the next week. This aligns with our expectations. According to Wolters and Brady's (2021) theory about time and SRL, after completing a task, learners reflect on performance- and time-related outcomes. The learner may utilize the reflection to update time-related knowledge and belief, which impact time management behaviors in future tasks. Considering that spaced practice and procrastination influenced the quiz performance in the current week, after the quiz, students might reflect on their time management strategies and adjust the strategies in the next week. Therefore, higher quiz performance in the current week was associated with less procrastination and more incentivized spaced practice in the next week. It is unclear why higher quiz performance was related to less self-selected spaced practice, which warrants further investigation. Overall, these findings support Wolters and Brady's (2021) theory. Nevertheless, it is important to note that the prediction effect of quiz performance on time management was weak in this study, suggesting the need for further exploration.

6.3. Educational implications

This study demonstrated that both procrastination and spaced practice significantly predicted quiz performance with a small within-person effect size and a large between-person effect size (0.05 and 0.49 R^2, respectively). The findings highlight the significance of time management behaviors in introductory programming learning and call on scaffolding time management in online programming problem systems. The course in this study already used a problem schedule which encouraged students to distribute study time by releasing a problem and requiring solving it within a day to earn credits. However, students with prior programming experiences were less inclined to distribute practices on the problems. This does not imply that the students with limited experience were more motivated by the problem schedule to distribute study time than those with more experience. Instead, the reason may be that students with experience could solve the problem within a single session, but those with limited experience could not. In another CS1 study with a comparable problem system, students could earn additional credits by completing a few simple problems (e.g., multiple-choice questions) per day, and they distributed practices evenly throughout the course rather than massing before exams (YeckehZaare et al., 2019). Combining these findings, rewarding credits for a few attempts on programming problems per day may be more effective in promoting spaced study in programming than rewarding credits for solving a single problem per day.

A direct approach to mitigating procrastination may be rewarding students for commencing assignments early (but not staying up). However, this approach may not be effective and could potentially be counterproductive. As Allevato and Edwards (2013) noted, such rewarding may only benefit students already good at time management. Furthermore, the finding in this study suggests that such rewards may benefit those with prior experience, given that both self-reported programming ability and language familiarity were negatively related to procrastination. Therefore, it may be more effective to combat procrastination via alternative approaches, such as communicating peers' assignment progress (Edwards et al., 2015; Huang et al., 2021) and improving the psychological antecedents of procrastination (e.g., task aversiveness and fear of failure; Steel, 2007).

Prior knowledge and demographics are important factors that learning systems may adapt to (Plass & Pawar, 2020). However, of the three demographic variables examined, only gender displayed a weak relation with incentivized and self-selected spaced practice and did not moderate behavioral changes. In contrast, prior experience predicted all types of time management behaviors and moderated the changes. The finding does not imply that the demographic variables are not important in adaptive learning systems. But for time management in online programming learning, it may be more effective to tailor scaffolding based on learners' prior knowledge instead of these demographics. Specifically, at the beginning of the course, students with lower prior knowledge need more support to combat procrastination and less support to apply the spacing strategy. As the course progresses, they need more scaffolding on spaced study, while students with higher prior knowledge need more support in overcoming procrastination.

The current research corroborates the value of intensive longitudinal approaches in the fields of learning analytics and SRL by capturing the dynamic learning process (Hilpert et al., 2023). The action logs and other process data, which naturally accumulate in digital environments and are frequently used by learning analytics research, can be converted into intensive longitudinal data through careful segmentation. Despite calls for temporal analyses in learning (Knight et al., 2017; Molenaar & Wise, 2022), only a few studies have adopted an intensive longitudinal approach to understanding learning. One possible reason is that the intensive longitudinal method leans towards variable-centered approaches, while temporal analysis techniques focus on event-centered approaches (Molenaar & Wise, 2022). Indeed, in two recent review articles about temporally focused analytics in SRL and collaborative learning (Lämsä et al., 2021; Saint et al., 2022), the categories of analysis techniques do not even include longitudinal analysis. Intensive longitudinal methods can reveal both the within-person and between-person variation in learning and relevant factors, which may provide better explanations for learning and guidance for interventions (Saqr, 2023). Given that the potential of the methods has not yet been realized, future exploration is necessary to harness the methods in conjunction with event-centered approaches to close the loop of learning analytics (Wise et al., 2021).

6.4. Limitations and future research

Inevitably, the course design and learning environment impact students' learning behaviors (Hartwig & Malain, 2022), and this may restrict the generalizability of the results in the current research. For instance, task characteristics are important antecedents of procrastination (Steel, 2007; Sun & Kim, 2022). If the assignments are fewer but more complex, and students have one week to solve each assignment for credits, procrastination may exhibit a pattern of change different from this study. Similarly, in a course focusing on declarative knowledge with limited exercises, it may be difficult to differentiate between incentivized and self-selected spaced practice because it is unclear whether a study session is mainly for credits or mastering skills. So do the associations between these spacing behaviors and learning outcomes. In addition, the schedules of assignments and quizzes in this study caused short retention intervals (the interval between the last practice session before a quiz and the time of starting the quiz). The short retention intervals might be the reason that the gap between practice sessions was not related to the quiz performance. Future studies may explore the relationship between the spacing gap, the number of practice sessions, and quiz (or test) performance in a learning environment with larger retention intervals.

At the week level, the relationships between time management behaviors and quiz performance were weak. The reason may be that the quizzes in different weeks varied in programming concepts and skills as well as difficulty. The impact of these variations on quiz performance was only partially controlled through the z-score transformation and may lead to an underestimation of the week-level associations. To address this issue, future research can apply equating and linking techniques (Kolen & Brennan, 2014) to transform the scores on different quizzes to the same scale.

The interval between the release of a credit problem and the first submission on it was not a perfect measurement of academic procrastination because strategic delay might lead to a large interval (Klingsieck, 2013). Nevertheless, the overall effect of strategic delay on the interval was likely small. Otherwise, the current work would find a positive or null relationship between the interval and quiz performance, given that strategic delay has been found positively related to learning outcomes across studies (Kim & Seo, 2015). Future research may cross-validate the current findings using a more robust and rigorous measurement of academic procrastination.

The current study did not measure motivation and affect, which are critical components of SRL and adaptive learning systems (Wolters & Brady, 2021). Subsequent studies may measure these factors on multiple occasions and align them with action logs. By combining these data, researchers can investigate the dynamic associations among motivation, affect, and time management to deepen the understanding of procrastination and spaced study as well as SRL in online environments.

6.5. Conclusion

This study investigated undergraduates' time management behaviors in an online programming problem system. The results revealed an increasing trend in academic procrastination over time, possibly influenced by task complexity and packed schedules. Incentivized spaced practice decreased, while self-selected spaced practice increased. Programming experience moderated the change rate of spacing behaviors. Consistent with previous research, this study established relationships between time management behaviors and quiz performance. However, the prediction of incentivized spaced practice on performance was inconsistent between the week and student levels, highlighting the challenge of measuring spaced study in real-world settings. Quiz performance in the current week predicted time management behaviors in the subsequent week, supporting the claim in Wolters and Brady's (2021) SRL theory that learners reflect on task performance and adapt behaviors in future tasks. Overall, these findings underscore the significance of time management behaviors in online programming learning and call for tailored scaffolding to reduce procrastination and promote spaced practice. Additionally, the study highlights the value of intensive longitudinal approaches in understanding the temporality of learning and encourages future exploration of combining event-centered and variable-centered analytics.

Declaration of interest

None.

Funding

This work was supported by National Science Foundation [grant numbers 1561676].

CRediT authorship contribution statement

Yingbin Zhang: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Luc Paquette:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Xiaoyong Hu:** Writing – review & editing, Supervision, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to polish the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data availability

The authors do not have permission to share data.

Appendix

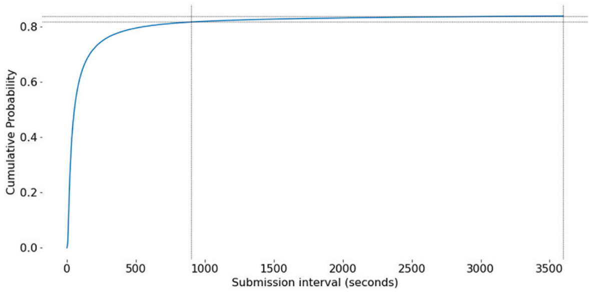

Figure A1. The distribution of intervals between successive submissions

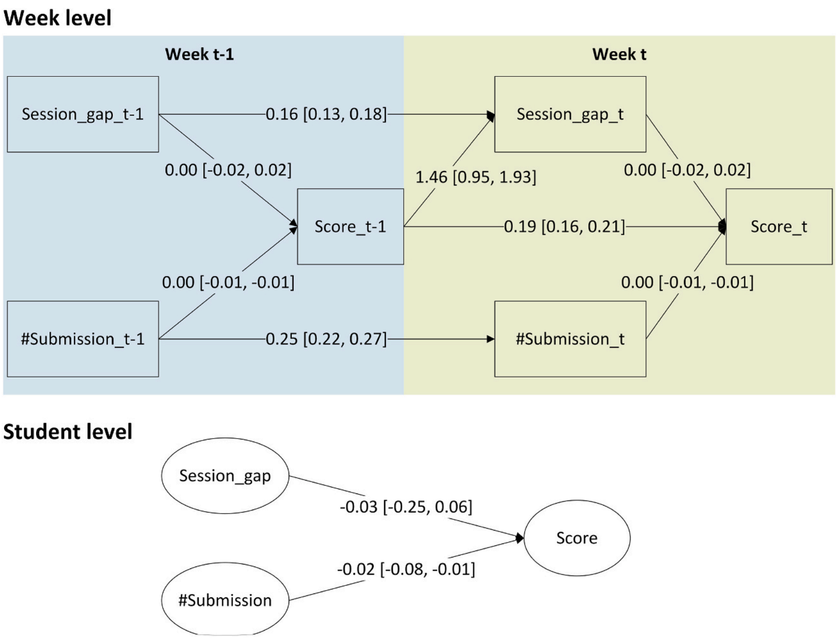

Figure A2. The associations among session spacing gap and quiz performance

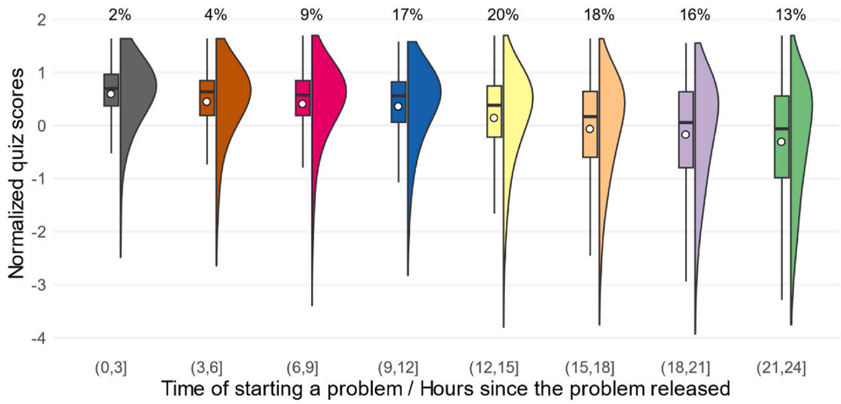

Figure A3. The distribution of quiz-z scores within each window of starting a problem
Note. The black line in the box indicates the mean value. The white circle is the median. The shape beside the box is the density plot. Numbers in the top are the percentages of students starting a problem in each window.

References

Aggarwal, A., & Ashok, A. (2022). Exploring the differences in students' behavioral engagement with quizzes and its impact on their performance in a flipped CS1 course. In I. Jormanainen, & A. Petersen (Eds.), *Proceedings of the 22nd Koli calling international conference on computing education research* (pp. 1–11). https://doi.org/10.1145/3564721.3564740. New York, NY, USA.

Allevato, A., & Edwards, S. H. (2013). The effects of extra credit opportunities on student procrastination. In *Proceedings of 2013 IEEE frontiers in education conference* (pp. 1831–1836). https://doi.org/10.1109/FIE.2013.6685154

Asparouhov, T., Hamaker, E. L., & Muthén, B. (2018). Dynamic structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 25*(3), 359–388. https://doi.org/10.1080/10705511.2017.1406803

Benjamin, A. S., & Bird, R. D. (2006). Metacognitive control of the spacing of study repetitions. *Journal of Memory and Language, 55*(1), 126–137. https://doi.org/10.1016/j.jml.2006.02.003

Bjork, R. A., Dunlosky, J., & Kornell, N. (2013). Self-regulated learning: Beliefs, techniques, and illusions. *Annual Review of Psychology, 64*, 417–444. https://doi.org/10.1146/annurev-psych-113011-143823

Carvalho, P. F., McLaughlin, E. A., & Koedinger, K. R. (2022). Varied practice testing is associated with better learning outcomes in self-regulated online learning. *Journal of Educational Psychology, 114*, 1723–1742. https://doi.org/10.1037/edu0000754

Carvalho, P. F., Sana, F., & Yan, V. X. (2020). Self-regulated spacing in a massive open online course is related to better learning. *Npj Science of Learning, 5*(1), 2. https://doi.org/10.1038/s41539-020-0061-1

Cepeda, N. J., Vul, E., Rohrer, D., Wixted, J. T., & Pashler, H. (2008). Spacing effects in learning: A temporal ridgeline of optimal retention. *Psychological Science, 19*(11), 1095–1102. https://doi.org/10.1111/j.1467-9280.2008.0220

Cheang, B., Kurnia, A., Lim, A., & Oon, W. (2003). On automated grading of programming assignments in an academic institution. *Computers & Education, 41*(2), 121–131. https://doi.org/10.1016/S0360-1315(03)00030-7

Cheng, S., & Xie, K. (2021). Why college students procrastinate in online courses: A self-regulated learning perspective. *The Internet and Higher Education, 50*, Article 100807. https://doi.org/10.1016/j.iheduc.2021.100807

Chowdhury, S. F., & Pychyl, T. A. (2018). A critique of the construct validity of active procrastination. *Personality and Individual Differences, 120*, 7–12. https://doi.org/10.1016/j.paid.2017.08.016

Chu, A. H. C., & Choi, J. N. (2005). Rethinking procrastination: Positive effects of "active" procrastination behavior on attitudes and performance. *The Journal of Social Psychology, 145*(3), 245–264. https://doi.org/10.3200/SOCP.145.3.245-264

de Barba, P. G., Malekian, D., Oliveira, E. A., Bailey, J., Ryan, T., & Kennedy, G. (2020). The importance and meaning of session behaviour in a MOOC. *Computers and Education, 146*, Article 103772. https://doi.org/10.1016/j.compedu.2019.103772

Edwards, S. H., Martin, J., & Shaffer, C. A. (2015). Examining classroom interventions to reduce procrastination. In *Proceedings of the 2015 ACM conference on innovation and technology in computer science education* (pp. 254–259). https://doi.org/10.1145/2729094.2742632. Vilnius, Lithuania.

Edwards, S. H., Snyder, J., Pérez-Quiñones, M. A., Allevato, A., Kim, D., & Tretola, B. (2009). Comparing effective and ineffective behaviors of student programmers. In *Proceedings of the fifth international workshop on computing education research workshop* (pp. 3–14). https://doi.org/10.1145/1584322.1584325. Berkeley, CA, USA.

Fouh, E., Breakiron, D. A., Hamouda, S., Farghally, M. F., & Shaffer, C. A. (2014). Exploring students learning behavior with an interactive etextbook in computer science courses. *Computers in Human Behavior, 41*, 478–485. https://doi.org/10.1016/j.chb.2014.09.061

Garcia, D. D., Campbell, J., DeNero, J., Dorf, M. L., & Reges, S. (2016). CS10K teachers by 2017? Try CS1K+ students NOW! Coping with the largest CS1 courses in history. In *Proceedings of the 47th ACM technical symposium on computing science education* (pp. 396–397). USA: Memphis, Tennessee. https://doi.org/10.1145/2839509.2844660.

Garcia, R., Falkner, K., & Vivian, R. (2018). Systematic literature review: Self-regulated learning strategies using e-learning tools for computer science. *Computers & Education, 123*, 150–163. https://doi.org/10.1016/j.compedu.2018.05.006

Greene, J. A., Plumley, R. D., Urban, C. J., Bernacki, M. L., Gates, K. M., Hogan, K. A., Demetriou, C., & Panter, A. T. (2021). Modeling temporal self-regulatory processing in a higher education biology course. *Learning and Instruction, 72*, Article 101201. https://doi.org/10.1016/j.learninstruc.2019.04.002

Hartwig, M. K., & Malain, E. D. (2022). Do students space their course study? Those who do earn higher grades. *Learning and Instruction, 77*, Article 101538. https://doi.org/10.1016/j.learninstruc.2021.101538

Hensley, L. C. (2014). Reconsidering active procrastination: Relations to motivation and achievement in college anatomy. *Learning and Individual Differences, 36*, 157–164. https://doi.org/10.1016/j.lindif.2014.10.012

Hilpert, J. C., Greene, J. A., & Bernacki, M. (2023). Leveraging complexity frameworks to refine theories of engagement: Advancing self-regulated learning in the age of artificial intelligence. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13340

Hong, J., Lee, Y., & Ye, J. (2021). Procrastination predicts online self-regulated learning and online learning ineffectiveness during the coronavirus lockdown. *Personality and Individual Differences, 174*, Article 110673. https://doi.org/10.1016/j.paid.2021.110673

Huang, N., Zhang, J., Burtch, G., Li, X., & Chen, P. (2021). Combating procrastination on massive online open courses via optimal calls to action. *Information Systems Research, 32*(2), 301–317. https://doi.org/10.1287/isre.2020.0974

Keuning, H., Jeuring, J., & Heeren, B. (2018). A systematic literature review of automated feedback generation for programming exercises. *ACM Transactions on Computing Education, 19*(1), 3. https://doi.org/10.1145/3231711

Kim, K. R., & Seo, E. H. (2015). The relationship between procrastination and academic performance: A meta-analysis. *Personality and Individual Differences, 82*, 26–33. https://doi.org/10.1016/j.paid.2015.02.038

Klingsieck, K. B. (2013). Procrastination. *European Psychologist, 18*(1), 24–34. https://doi.org/10.1027/1016-9040/a000138

Knight, S., Wise, A. F., & Chen, B. (2017). Time for change: Why learning analytics needs temporal analysis. *Journal of Learning Analytics, 4*(3), 7–17. https://doi.org/10.18608/jla.2017.43.2

Kolen, M. J., & Brennan, R. L. (2014). *Test equating, scaling, and linking* (3rd ed.). Springer.

Lämsä, J., Hämäläinen, R., Koskinen, P., Viiri, J., & Lampi, E. (2021). What do we do when we analyse the temporal aspects of computer-supported collaborative learning? A systematic literature review. *Educational Research Review, 33*, Article 100387. https://doi.org/10.1016/j.edurev.2021.100387

Le, N., & Pinkwart, N. (2011). Incom: A web-based homework coaching system for logic programming. In *Proceedings of the IADIS international conference on cognition and exploratory learning in digital age 2011* (pp. 43–50). Rio de Janeiro, Brazil.

Leinonen, J., Castro, F. E. V., & Hellas, A. (2021). Does the early bird catch the worm? Earliness of students' work and its relationship with course outcomes. In *Proceedings of the 26th ACM conference on innovation and technology in computer science education* (pp. 373–379). https://doi.org/10.1145/3430665.3456383. Virtual Event, Germany.

Leppänen, L., Leinonen, J., & Hellas, A. (2016). Pauses and spacing in learning to program. In *Proceedings of the 16th Koli calling international conference on computing education research* (pp. 41–50). Koli, Finland. https://doi.org/10.1145/2999541.2999549.

Li, L., Gao, H., & Xu, Y. (2020). The mediating and buffering effect of academic self-efficacy on the relationship between smartphone addiction and academic procrastination. *Computers & Education, 159*, Article 104001. https://doi.org/10.1016/j.compedu.2020.104001

Li, B., Ning, F., Zhang, L., Yang, B., & Zhang, L. (2021). Evaluation of a practice system supporting distributed practice for novice programming students. *Journal of Pacific Rim Psychology, 15*, Article 83197192. https://doi.org/10.1177/18344909211008264

Liao, S. N., Valstar, S., Thai, K., Alvarado, C., Zingaro, D., Griswold, W. G., & Porter, L. (2019). Behaviors of higher and lower performing students in CS1. In *Proceedings of the 2019 ACM conference on innovation and technology in computer science education* (pp. 196–202). Scotland UK: Aberdeen. https://doi.org/10.1145/3304221.3319740.

Loksa, D., Margulieux, L., Becker, B. A., Craig, M., Denny, P., Pettit, R., & Prather, J. (2021). Metacognition and self-regulation in programming education: Theories and exemplars of use. *ACM Transactions on Computing Education, 22*(4), 39. https://doi.org/10.1145/3487050

Lorås, M., Sindre, G., Trætteberg, H., & Aalberg, T. (2021). Study behavior in computing education—a systematic literature review. *ACM Transactions on Computing Education, 22*(1), 9. https://doi.org/10.1145/3469129

Martin, J., Edwards, S. H., & Shaffer, C. A. (2015). The effects of procrastination interventions on programming project success. In *Proceedings of the 11th annual international conference on international computing education research* (pp. 3–11). USA: Omaha, Nebraska. https://doi.org/10.1145/2787622.2787730.

McDaniel, M. A., & Einstein, G. O. (2020). Training learning strategies to promote self-regulation and transfer: The knowledge, belief, commitment, and planning framework. *Perspectives on Psychological Science, 15*(6), 1363–1381. https://doi.org/10.1177/1745691620920723

McNeish, D., Hamaker, E. L., & Steinley, D. (2020). A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus. *Psychological Methods, 25*(5), 610–635. https://doi.org/10.1037/met0000250

Molenaar, I., & Järvelä, S. (2014). Sequential and temporal characteristics of self and socially regulated learning. *Metacognition and Learning, 9*(2), 75–85. https://doi.org/10.1007/s11409-014-9114-2

Molenaar, I., & Wise, A. F. (2022). Temporal aspects of learning analytics - grounding analyses in concepts of time. In C. Lang, G. Siemens, A. F. Wise, D. Gašević, & A. Merceron (Eds.), *The handbook of learning analytics* (2nd ed., pp. 66–76). https://doi.org/10.18608/hla22.007 SoLAR.

Paiva, J. C., Leal, J. P., & Figueira, Á. (2022). Automated assessment in computer science education: A state-of-the-art review. *ACM Transactions on Computing Education, 22*(3), 34. https://doi.org/10.1145/3513140

Pereira, F. D., Oliveira, E. H. T., Oliveira, D. B. F., Cristea, A. I., Carvalho, L. S. G., Fonseca, S. C., Toda, A., & Isotani, S. (2020). Using learning analytics in the amazonas: Understanding students' behaviour in introductory programming. *British Journal of Educational Technology, 51*(4), 955–972. https://doi.org/10.1111/bjet.12953

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning Questionnaire (MSLQ). *Educational and Psychological Measurement, 53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Plass, J. L., & Pawar, S. (2020). Toward a taxonomy of adaptivity for learning. *Journal of Research on Technology in Education, 52*(3), 275–300. https://doi.org/10.1080/15391523.2020.1719943

Riel, J., Lawless, K. A., & Brown, S. W. (2018). Timing matters: Approaches for measuring and visualizing behaviours of timing and spacing of work in self-paced online teacher professional development courses. *Journal of Learning Analytics, 5*(1), 25–40. https://doi.org/10.18608/jla.2018.51.3

Rogalski, J., & Samurçay, R. (1990). Acquisition of programming knowledge and skills. In J. M. Hoc, T. R. G. Green, R. Samurçay, & D. J. Gilmore (Eds.), *Psychology of programming* (pp. 157–174). Academic Press. https://doi.org/10.1016/B978-0-12-350772-3.50015-X.

Roth, A., Ogrin, S., & Schmitz, B. (2016). Assessing self-regulated learning in higher education: A systematic literature review of self-report instruments. *Educational Assessment, Evaluation and Accountability, 28*(3), 225–250. https://doi.org/10.1007/s11092-015-9229-2

Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2022). Temporally-focused analytics of self-regulated learning: A systematic review of literature. *Computers and Education: Artificial Intelligence, 3*. https://doi.org/10.1016/j.caeai.2022.100060

Saqr, M. (2023). Modelling within-person idiographic variance could help explain and individualize learning. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13309. *n/a*(n/a).

Schraw, G., Wadkins, T., & Olafson, L. (2007). Doing the things we do: A grounded theory of academic procrastination. *Journal of Educational Psychology, 99*(1), 12–25. https://doi.org/10.1037/0022-0663.99.1.12

Son, L. K. (2010). Metacognitive control and the spacing effect. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 36*(1), 255–262. https://doi.org/10.1037/a0017892

Son, L. K., & Simon, D. A. (2012). Distributed learning: Data, metacognition, and educational implications. *Educational Psychology Review, 24*(3), 379–399. https://doi.org/10.1007/s10648-012-9206-y

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin, 133*(1), 65. https://doi.org/10.1037/0033-2909.133.1.65

Suárez-Perdomo, A., Ruiz-Alfonso, Z., & Garcés-Delgado, Y. (2022). Profiles of undergraduates' networks addiction: Difference in academic procrastination and performance. *Computers & Education, 181*, Article 104459. https://doi.org/10.1016/j.compedu.2022.104459

Sun, T., & Kim, J. (2022). The effects of online learning and task complexity on students' procrastination and academic performance. *International Journal of Human-Computer Interaction, 39*(13), 2656–2662. https://doi.org/10.1080/10447318.2022.2083462

Susser, J. A., & McCabe, J. (2013). From the lab to the dorm room: Metacognitive awareness and use of spaced study. *Instructional Science, 41*(2), 345–363. https://doi.org/10.1007/s11251-012-9231-8

Taub, M., & Azevedo, R. (2019). How does prior knowledge influence eye fixations and sequences of cognitive and metacognitive SRL processes during learning with an Intelligent Tutoring System? *International Journal of Artificial Intelligence in Education, 29*(1), 1–28. s40593-018-0165-4.

Tekin, E. (2022). Can learners allocate their study time effectively? It is complicated. *Educational Psychology Review, 34*(2), 717–748. https://doi.org/10.1007/s10648-021-09645-2

van der Meer, J., Jansen, E., & Torenbeek, M. (2010). It's almost a mindset that teachers need to change. *First-year students' need to be inducted into time management. Studies in Higher Education, 35*(7), 777–791. https://doi.org/10.1080/03075070903383211

Wang, T., Su, X., Ma, P., Wang, Y., & Wang, K. (2011). Ability-training-oriented automated assessment in introductory programming course. *Computers & Education, 56*(1), 220–226. https://doi.org/10.1016/j.compedu.2010.08.003

West, M., Herman, G. L., & Zilles, C. (2015). PrairieLearn: Mastery-based online problem solving with adaptive scoring and recommendations driven by machine learning. In *Proceedings of ASEE annual conference & exposition* (pp. 26–1238). Washington: Seattle. https://doi.org/10.18260/p.24575.

Wise, A. F., Knight, S., & Ochoa, X. (2021). What makes learning analytics research matter. *Journal of Learning Analytics, 8*(3), 1–9. https://doi.org/10.18608/jla.2021.7647

Wolters, C. A. (2003). Understanding procrastination from a self-regulated learning perspective. *Journal of Educational Psychology, 95*(1), 179–187. https://doi.org/10.1037/0022-0663.95.1.179

Wolters, C. A., & Brady, A. C. (2021). College students' time management: A self-regulated learning perspective. *Educational Psychology Review, 33*(4), 1319–1351. https://doi.org/10.1007/s10648-020-09519-z

Wolters, C. A., Won, S., & Hussain, M. (2017). Examining the relations of time management and procrastination within a model of self-regulated learning. *Metacognition and Learning, 12*(3), 381–399. https://doi.org/10.1007/s11409-017-9174-1

YeckehZaare, I., Fox, E., Grot, G., Chen, S., Walkosak, C., Kwon, K., Hofmann, A., Steir, J., McGeough, O., & Silverstein, N. (2021). Incentivized spacing and gender in computer science education. In *Proceedings of the 17th ACM conference on international computing education research* (pp. 18–28). USA: Virtual Event. https://doi.org/10.1145/3446871.3469760.

Yeckehzaare, I., Mulligan, V., Ramstad, G., & Resnick, P. (2022). Semester-level spacing but not procrastination affected student exam performance. In *Proceedings of the 12th international conference on learning analytics and knowledge* (pp. 304–314). https://doi.org/10.1145/3506860.3506907. Online, USA.

YeckehZaare, I., Resnick, P., & Ericson, B. (2019). A spaced, interleaved retrieval practice tool that is motivating and effective. In *Proceedings of the 15th ACM conference on international computing education research* (pp. 71–79). Toronto ON: Canada. https://doi.org/10.1145/3291279.3339411.

Zhang, J., Cunningham, T., Iyer, R., Baker, R., & Fouh, E. (2022). Exploring the impact of voluntary practice and procrastination in an introductory programming course. In *Proceedings of the 53rd ACM technical symposium on computer science education* (pp. 356–361). https://doi.org/10.1145/3478431.3499350. Providence, RI, USA.

Zhang, L., Li, B., Zhang, Q., & Hsiao, I. (2020). Does a distributed practice strategy for multiple choice questions help novices learn programming? *International Journal of Emerging Technologies in Learning, 15*(18), 234–250. https://doi.org/10.3991/ijet.v15i18.10567

Zhang, Y., Paquette, L., Bosch, N., Ocumpaugh, J., Biswas, G., Hutt, S., & Baker, R. S. (2022). The evolution of metacognitive strategy use in an open-ended learning environment: Do prior domain knowledge and motivation play a role? *Contemporary Educational Psychology, 69*, Article 102064. https://doi.org/10.1016/j.cedpsych.2022.102064

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7, 783.