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RESEARCH

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Supporting "time awareness" in self-regulated learning: How do students allocate time during exam preparation?

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Abstract

The development of technology enables diverse learning experiences nowadays, which shows the importance of learners' self-regulated skills at the same time. Particularly, the ability to allocate time properly becomes an issue for learners since time is a resource owned by all of them. However, they tend to struggle to manage their time well due to the lack of awareness of its existence. This study, hence, aims to reveal how learners allocate their time and evaluate the effectiveness of the time allocation by examining its effects on learners' performance. We collect the learning logs of 116 seventh-graders from the online learning system implemented in a Japanese public junior high school. We look at the data in the time window of 34 days before the regular exam. Even though clustering techniques as a Learning Analytics method help identify different groups of learners, it is seldom applied to group students' learning patterns with different levels of indicators extracted from their learning process data. In this study, we adopt the method to cluster students' patterns of time allocation and find that better performance can result from the consistency of study time throughout the exam preparation period. Practical suggestions are then proposed for different roles involved in digital learning environments to facilitate students' time management. Collectively, this study is expected to make contributions to smart learning environments supporting self-regulated learning in the digital era.

Keywords: Learning analytics, Time awareness, Time allocation, Self-regulated learning, Time management

Introduction

The digital era enables various learning experiences. Learners nowadays can make use of various resources to achieve different learning objectives. With such flexibility in learning, it also becomes an issue for them to have effective self-regulated learning, which involves the development of learning strategies and the ability to manage available learning resources. That is, self-regulated skill seems to be an essential skill for learners to lead competent and autonomous lives in this era (Manso-Vázquez et al.2016; Ozer & Yukselir, 2021).

Time, in specific, is a common resource owned by everyone. When it comes to making use of time, it indicates the ways how people allocate their time to different activities.

This may determine the effectiveness of one's behavior (Son & Kornell, 2008). In self-regulated learning, time management becomes a skill determining to what extent one can allocate time properly. As indicated by Liborius et al., (2017), learners struggle to develop the good skill of time management in general. Since time is invisible, it gets easy to miss it. To allocate time properly involves one being aware of the proper amounts of time allocated in proper activities at the proper time. When such information does not come into learners' minds, they tend to have poor skill of time management. Namely, learners' awareness of time plays a key role in their time management skills, which has raised concern about learners' time allocation in studies related to self-regulated learning. Huchendorf (1989) explored how students allocate their study time—both concerning which materials they select to study and how long they study them. He et al. (2019) introduced a system, LearnerExp, for both instructors and learners to explore and explain time management intuitively by visualizing the time allocated to learning activities per day. These studies make learners' time allocation visible, increasing time awareness and aiming to facilitate their skills of time management.

Good skill of time management enables learners to maximize the net returns from obtained knowledge with minimized time investment. That is, in addition to showing how learners allocate their time, the relation between time allocation and performance could inform whether such behaviors are effective or not. This specifies the support of learners' time management skills by indicating what is regarded as proper time allocation. Delucchi et al. (1987) examined students' reported total study time, their allocation of that time to specific study activities, and relationships between such allocations and achievement. Dickinson and O'Connell (1990) also investigated the relationship between study time and test scores. The students were required to keep a continuous log of the amount of time that they spent reading, reviewing, and organizing for the course.

In contrast to self-report data, trace data is immediately collected within the actual environment and could not degrade the accuracy and completeness of learners' recall, perceptions, and interpretations of how they learn (Li et al. ; Li et al., 2018). With the rapid development of smartphones and wearable devices, it is more common to track fine-grained, time-stamped data from e-learning activities. Learning Analytics (LA) methods help valid inferences about a learner's learning from the data of massive volume and high rate of velocity (Viberg et al., 2020; Raga et al., 2018). Carlson et al. (2013) used an expectation–maximization approach to extract the error-making and hint-seeking behaviors of each student to characterize their learning strategy. Saint, Gašević, and Pardo (2018) used process mining techniques to identify strategic and tactical learner behaviors and found that certain temporal activity traits relate to performance in the summative assessments attached to the course.

The above studies reflect the core characteristics of LA to generate an understanding of, and support for learners' learning processes, achieved by high-resolution temporal data about various types of actions (Knight et al., 2017; Jivet et al., 2018). Time allocation is a dynamic behavior that occurs over time. Therefore, in this study, we adopt clustering techniques to measure learners' time allocation and examine its relation to their performance in the exam preparation period. The objective is to understand how students allocate their time, and whether their performance is affected by the time allocation. Collectively, these are expected to inform us of practical ways to facilitate learners' skills of time management, leading them to autonomous lives in today's digital environments, and thus contribute to self-regulated learning in this digital era.

Two research questions are: (RQ1) How do students allocate their study time in digital environments during the period of exam preparation? (RQ2) What effects can different ways of time allocation have on students' exam performance? To answer the research questions, we collect students' learning logs in a digital environment implemented in a Japanese junior high school, design time allocation indicators, and then use them to find the association with students' exam performance.

Literature review

The idea of how people allocate time during study rooted before the cognitive revolution and the derived research topics are key points in various educational psychology literature (Son & Kornell, 2008). Students' allocation of study time is regarded as a kind of investment (Huchendorf, 1989). Serving as the effects of the investment, students get concerned about how to allocate their time to achieve the best performance. Therefore, there were several discussions on the relationship between time allocation and performance (Nonis & Hudson, 2010).

When it comes to learners' allocation of study time, studies first look into their total study time, which can be considered as course efforts. In the test of the inventory model of student time allocation, total study time was found to have a positive and significant effect on the demand for economic knowledge (Huchendorf, 1989). Beyond total study time, some studies consider learners' time allocation from different perspectives. Dolton et al. (2003) divided the study time into the allocation of formal study (lectures and classes) and self-study. Recognizing that students adopt specific study habits for exams, Brown et al. (2017) also administered a survey to characterize how students envisioned spending time during class as well as what activities they expected to complete outside of class in preparation for exams. Similarly, Bratti and Staffolani (2013) investigated the effect of lecture attendance and self-study on undergraduate students' academic performance. The results indicated that there might be bias in estimates of the elasticity of student performance if considering the study time from only one aspect. Another aspect such as time allocated in specific learning activities could be measured as students' engagement with effortful study strategies (Jenifer et al., 2022). The study of Delucchi et al. (1987) showed that the total time indices with achievement did not show significant correlations. In the study of Dickinson and O'Connell (1990), weak relationships with test scores were found for total study time and time spent reviewing. A much stronger relationship was found for time spent organizing the course content.

The previous works can be organized as groups about the inconsistent relationship between time allocation and performance (Nonis & Hudson, 2010). This may result from potential factors which affect students' behavior, such as the difficulty of items, limited time to study, and so on. Wang et al. (2016) investigated factors influencing the study time allocation of Chinese junior high school students and the age difference in the effect of habitual responding. Results indicated that agenda and habitual responding have a combined effect on study time allocation and that the contribution of agenda is greater than that of habitual responding. Dunlosky and Ariel (2011) considered the effect of item difficulty in their study. Students often spend more time studying items difficult to learn (vs. less difficult ones), unless little time is available for study or the reward for the correct recall is higher for the less difficult items. In the latter contexts, this shift to focusing on easier items is an effective strategy, and notably, students do not always make this shift when doing so would be effective.

Being at different phases, students tend to change their time allocation in different activities considering the optimization of the achievement. The investigation of Konradt et al. (2021) revealed four distinct pacing style patterns that correspond to the allocation of effort over time during exam preparation: effort investment is allocated towards the deadline, steady, inverted U-shaped, and U-shaped. This emphasizes the importance of investigating the time allocation in students' learning processes (Liboriusa et al., 2017). The educational production function is one of the accepted techniques for modeling the process of exam performance. Dolton et al. (2003) modeled the existence of a university production function based on individual student data relating to examination performance. Krohn and O'Connor (2005) extended the standard education production function and student time allocation analysis to focus on the interactions between student effort and performance over the semester. The results suggested that students respond to higher midterm scores by reducing the number of hours they subsequently allocate to studying for the course, and that contrary to results based on semester totals, class attendance is not related to examination scores throughout the semester. Bensnes (2016) investigated what is in effect random variation in students' preparation time before high-stakes exams. The study found that 5 extra days of preparation time increases exam scores.

Figure 1 summarizes the aspects of time allocation which were investigated in the above studies. In this study, we consider students' time allocation in three aspects: (1) total study time, showing total efforts put in courses; (2) study time in different types of materials, dealing with the effects of different learning activities; (3) study time in different phases ahead of the exam, dealing with the effects of different timing during a period. Based on the literature review, it is known that time allocation could be considered in different aspects, and would lead to different results of the effects on performance. In

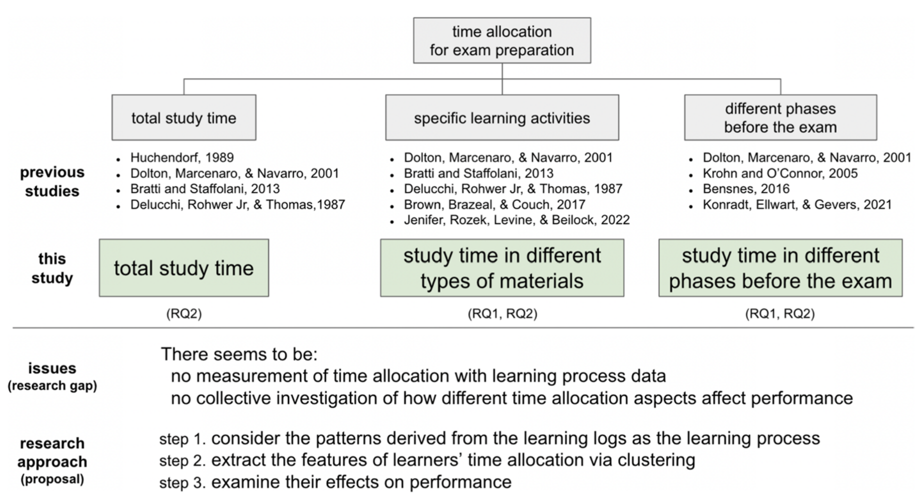

Fig. 1 Aspects of investigated time allocation and approach to bridge the research gap

addition, time allocation was measured as a summative value among these aspects. There seems to be a research gap where time allocation is measured with learning process data and the effects of each aspect on performance are collectively investigated. In terms of the research gap, this study considers the patterns derived from the learning logs as the learning process, extracts the features of learners' time allocation via clustering, and examines their effects on performance. We expect to bridge the research gap from the literature with this approach and show the significance of this study.

Methods

Research design

In this study, we conduct two analyses to answer the research questions as Fig. 2 shows. Analysis 1 finds groups of patterns to show how students allocate their study time in digital environments during the period of exam preparation, aimed to answer RQ1. Analysis 2 compares the performance between patterns to show the effects of different ways of time allocation on students' exam performance, aimed to answer RQ2. The following details how the analyses are conducted.

Analysis 1 We conduct time series clustering to find groups of patterns in terms of both study time in different types of materials and study time in different phases ahead of the exam.

Analysis 2 We first look into the relationship between students' total study time and performance. Then, we compare the performance between groups clustered in terms of study time in different types of materials and study time in different phases ahead of the exam via tests for mean comparison.

Participants and study context

We follow the purposive sampling strategy and include all the students from a Japanese public junior high school who provided consent as the participants of this study. The participants cover 116 seventh-graders with an average age of 13 years old. The school has implemented an online learning system and offered basic courses such as math, English, and Japanese on that platform. During the preliminary investigation of the collected

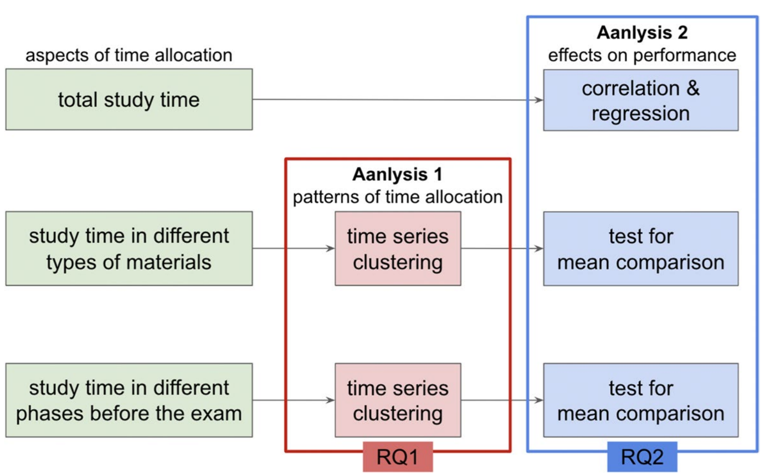

Fig. 2 Research design

learning logs, we find that the participants were active in the math course. Hence, we select the math course in this study to extract their learning processes.

Data collection and processing

The data logged are from the participants' daily learning activities conducted in the online learning system implemented in the school, i.e., the Learning & Evidence Analytics Framework (LEAF) (Ogata et al., 2018, 2022). Figure 3.a shows the architecture of LEAF, which consists of a Learning Management System (LMS), an e-book reader (BookRoll), a Learning Analytics Dashboard (LAD), and a Learning Record Store (LRS). The LMS serves as the access point to BookRoll, which includes various learning materials, and enables different reading interactions. The interaction log data are stored in the LRS and then processed into learning feedback on the LAD.

In the target course, learning materials in BookRoll include three types: textbook, exercises, and answers. Via personal tablets, students access these materials both at school and at home. In this study, we consider the hours out of school as the time of students' self-regulated learning. Therefore, the reading logs are limited to the data from 6 p.m. to 8 a.m. the next day. Based on the research objective, we look at the data in the time window of 34 days before the regular exam, taking place on Oct. 1, 2020. We mark the time 3/2/1/ week(s) before the exam as different phases of the period considering students were reminded in that way on the school calendar. The data from 116 seventh-graders are collected and analyzed (Fig. 3b).

Measures

The objective of this study is to reveal students' time allocation during the period of exam preparation and its effects on their performance. With the log data collected from the digital learning environment, we measure students' time allocation based on Total Reading Time (TRT), Daily Reading Time (DRT), and Daily Progress (DP). On the other hand, we consider Performance Scores (PS) as students' performance (Fig. 3.c). The following describes the definition of each measure.

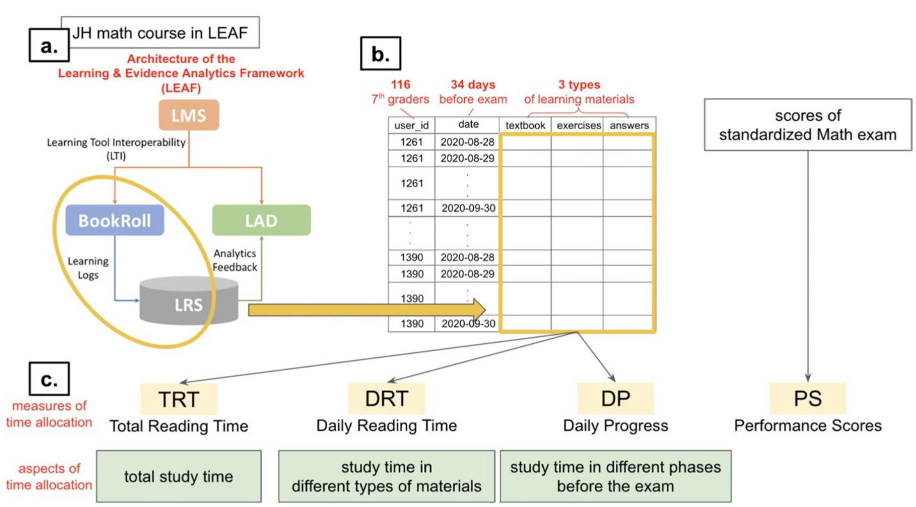

Fig. 3 Extracting learning data from architecture of the learning & evidence analytics framework (LEAF)

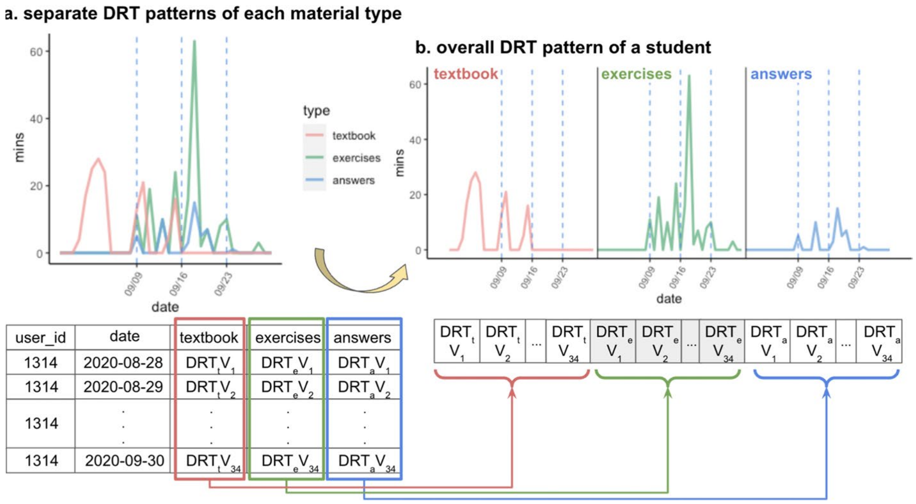

Fig. 4 Patterns of daily reading time (DRT) across material types

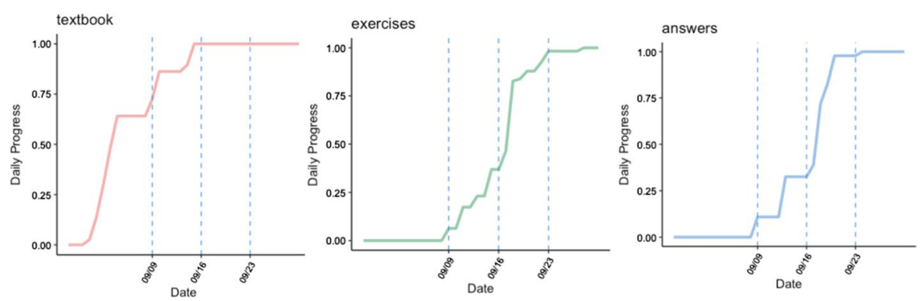

Fig. 5 Patterns of daily progress (DP) for each material type

Total reading time (TRT) TRT indicates the sum of the reading time in the whole period of exam preparation. TRT of each material type is calculated separately. On average, students read the textbook for 140.83 min (SD = 58.68), did the exercises for 256.76 min (SD = 130.41), and referred to the answers for 44.01 min (SD = 65.73) in total during the whole period.

Daily reading time (DRT) DRT indicates the sum of the reading time in a day. It forms patterns of the reading time students spent every day during the period. DRT of each material type is calculated separately. From each student's reading logs, we derive separate DRT patterns for each material type (Fig. 4.a). Then, we consider the patterns as an overall DRT pattern of a student (Fig. 4.b).

Daily progress (DP) DP indicates the ratio of the accumulated DRT in a day to TRT of the period. It forms patterns of the progress students complete every day during the period. We calculate DP of each material type separately. From each student's reading logs, we derive separate patterns of DP in each material type (Fig. 5).

Performance scores (PS) PS indicates students' scores on the final standardized Math exam administered by the school, which were measured on a 100-point scale. On average, students got 43.84 points (SD = 14.13).

Results

Students' time allocation patterns before exam

We conduct time series clustering to find groups of patterns in terms of both the overall DRT patterns in the period and the separate patterns of DP in each material type. For each clustering, two is shown as the optimal number of clusters via the Silhouette Analysis Method.

Figure 6 shows the difference in the DRT patterns between the two clusters. In the beginning, (a) both spent time on textbooks, but (b) cluster 1 also spent time doing exercises. 3 weeks before the exam, (c) both spent time on textbooks and exercises. After 2 weeks before the exam, (d) both focused on doing exercise, and cluster 1 spent more time than cluster 2. Also, (e) cluster 1 studied the example answers at the same time. From such patterns, we identified that (f) the students in cluster 1 tend to do exercises and refer to answers throughout the period, which implies the drill-and-practice strategy for math learning.

Table 1 compares the means of total DRT of each material type in different phases before the exam between the two clusters. It shows that cluster 1 has significantly higher means of total DRT in most of the material types across the period than cluster 2. Therefore, we label cluster 1 as active learners (N = 14), while cluster 2 is labeled as inactive learners (N = 102).

Figure 7 shows the difference in the DP patterns between the two clusters. Considering the slope where students' daily progress changes, we label students as learners with the following features studying each material type. The numbers of learners regarding the textbook and answers were not 116 because there were no logs for some learners who did not read the textbook or answers during the period of focus in our analysis.

Textbook The early learners (N = 79) are those who complete over half of the progress before the mid of the beginning, while the late learners (N = 35) are those who complete over half of the progress after the mid of the beginning.

Exercises The quick learners (N = 66) are those who keep a higher percentage of progress throughout the period, while the slow learners (N = 50) are those who keep a lower percentage of progress.

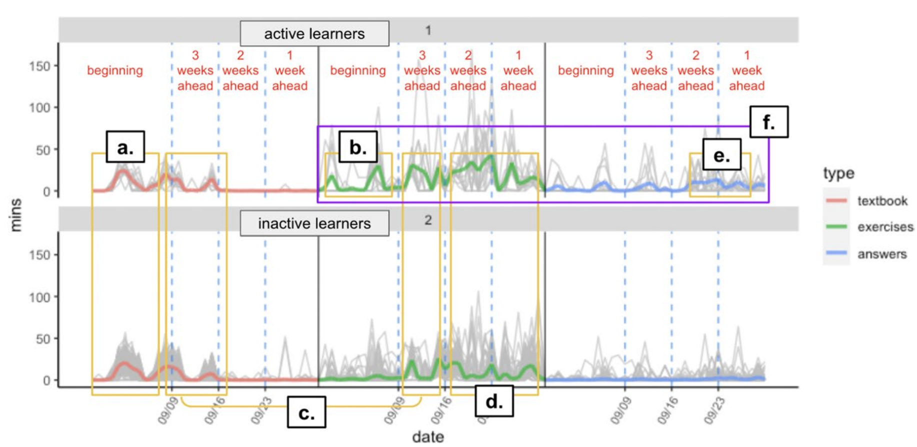

Fig. 6 Clusters of patterns of daily reading time (DRT)

Table 1 Total DRT of each Material Type in 4 Phases

	Beginning			3 weeks ahead			2 weeks ahead			1 week ahead		
	Mean			Mean			Mean			Mean		
	Active learner (cluster1)	Inactive learner (cluster2)	t *p*	Active learner (cluster1)	Inactive learner (cluster2)	t *p*	Active learner (cluster1)	Inactive learners(cluster2)	t *p*	Active learners (cluster1)	Inactive learners(cluster2)	t *p*
Textbook	105.14	94.46	1.06 .30	47.36	41.79	1.32 .20	1.00	0.78	0.49 .63	0.71	1.95	− 1.28 .20
Exercises	84.79	21.42	3.06 < .01	117.43	61.19	2.49 < .05	174.50	70.54	6.38 < .001	136.57	68.40	3.80 < .01
Answers	30.50	5.09	2.02 .06	23.71	4.36	2.11 .05	44.57	4.05	3.85 < .01	56.93	15.18	4.16 < .01

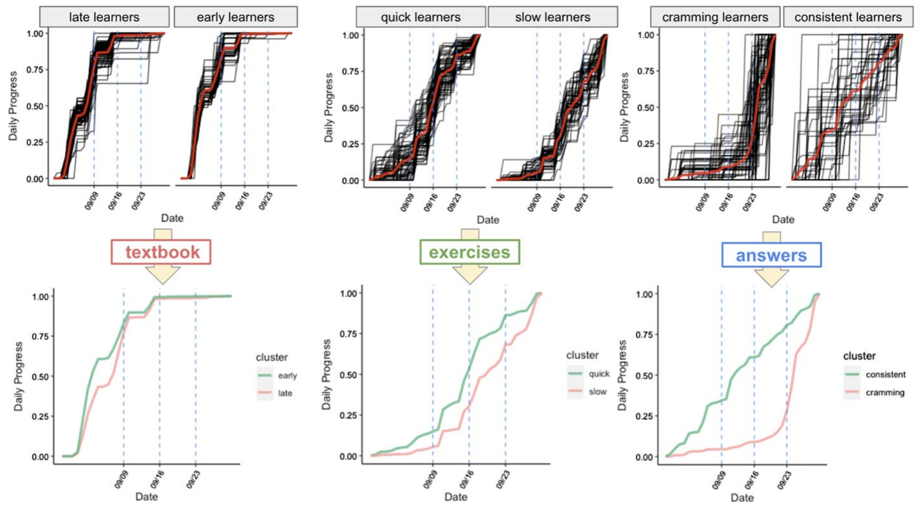

Fig. 7 Clusters of patterns of daily progress (DP)

Table 2 Difference between DRT Clusters on Performance

	M	SD	t	*p*
Active learners	41.00	14.02	− 0.81	.43
Inactive learners	44.24	14.17		

Answers The consistent learners (N = 71) are those who complete half of the progress 2 weeks ahead of the exam (half of the preparation period) and complete the other 50% in the last half of the period, while the cramming learners (N = 39) are those who complete less than 25% of the progress 1 week ahead of the exam and increase their study time at the end of the period.

Performance difference between clusters

We look into the correlation between TRT of each material type and PS separately. As the effects of single TRT on students' exam performance, TRT in each material type is found to be insignificantly correlated to PS. The respective correlation coefficients are r_t $(114) = -0.09$, $p = 0.34$, r_e $(114) = -0.02$, $p = 0.83$, and r_a $(114) = 0.06$, $p = 0.50$, ordered by textbook, exercises, and answers.

We then compare the performance between the 2 groups clustered in terms of the overall DRT patterns in the period and the separate patterns of DP in each material type via independent samples t-test. The result does not show a significant difference between the performance of active learners and the others (Table 2).

Table 3 summarizes the results of the t-test, comparing the performance between clusters of patterns derived from DP. The results show that consistent learners perform significantly better than cramming learners in the case of referring to answers. The students (early learners) completing over half of the progress on reading the textbook before the mid of the beginning do not have a significantly different performance from those who complete after that (later learners). Similar results show in the performance between quick learners and slow learners doing exercises.

Table 3 Difference between DP clusters on performance

	M	SD	t	*p*
Textbook				
Early learners	42.22	13.33	− 1.59	.12
Late learners	46.71	14.20		
Exercises				
Quick learners	46.00	12.65	1.86	.07
Slow learners	41.00	15.55		
Answers				
Consistent learners	46.95	14.48	2.02	< .05
Cramming learners	41.31	13.18		

Discussion

Key findings

Different study time allocation patterns before the exam We consider students' time allocation in three aspects. In terms of the whole period, students allocated their time mainly to doing exercises, followed by reading the textbook and referring to answers. In terms of the tendency of time allocation in material types across the period, students allocated their time to read the textbook in the early phases and do exercises and refer to answers across the period. In such a pattern, some students tended to allocate more time to doing exercises and referring to answers than others. In terms of the phases during the period, learners with different learning features could be identified from students' time allocation in each material type.

The findings show that doing exercises plays a main role in students' math learning. This echoes the strategies indicated by Verschaffel et al. (2019). By practicing, students got more skillful. The findings of the tendency indicate students' potential strategies for exam preparation. As indicated by Andergassen et al. (2014), students tended to understand the concepts first by reading the textbook and then doing exercises to strengthen their understanding. By referring to answers, students review their understanding (Higgins et al., 2019). We also identify learners with specific features echoing students' behaviors indicated by Chung and Hsiao (2020). Considering the approaching of the exam, students might increase their study time to enhance the effects of learning, which is regarded as cramming behavior.

Effects of different study time allocations on exam performance We compare students' performance between different ways of time allocation. In terms of phases in the period, consistent learners referring to answers performed significantly better than those clustered as cramming learners, while no significant difference shows between the performance of early and late learners in the cases of reading the textbook or quick and slow learners in the cases of doing exercises. The performance between students' tendencies of allocating time in different material types across the phases does not show a significant difference. Finally, in terms of the whole period, the time students allocated to each material type is not significantly correlated to their exam performance.

We do not find a correlation between the time allocated in the material types and exam performance. The findings echo what was indicated in previous studies. There have been inconsistent results regarding the relationship between students' total study time and performance since other potential factors, such as the limited amount of time, or the difficulties of the items, might be affecting the relation (Dunlosky & Ariel, 2011; Nonis & Hudson, 2010). In this study, we also consider other factors. We find the results of performance comparison between different learning features in the case of each material type are inconsistent. This indicates that the types of learning materials might have different effects on the relationship between time allocation and performance (Jenifer et al., 2022). We find no significant difference between the performance of students with the time allocation of different tendencies. This implies that the tendencies might not affect students' performance. As previous studies suggested, students can have their learning. There is no common strategy applied to all students, but a strategy suitable for a certain group of students (Schmeck, 1988; Tian et al., 2007; Parra, 2016). This can be the reason why we did not find a significant difference between the performance.

Implications

Research Implications In this study, we measure how students allocate time with their learning processes data collected from a digital environment. The clustering technique helps extract different levels of indicators that indicate different aspects of students' time allocation. Past studies tend to consider learners' time allocation from a single perspective, either the time allocated in certain activities or the time allocated in certain phases. That is, learners' time allocation is regarded as a summative value. On the other hand, this study implies that learning process data with LA methods enable multiple perspectives on learners' time allocation. In addition to a summative value, we consider time allocation as a pattern that informs how much time is allocated in what activity at which time point collectively. This not only enables understanding of learners' time allocation but also implies another way to assess the skill of time management. Therefore, in terms of research on time allocation, LA methods could be the approach helping expand into the unknown. Finally, in terms of the derived patterns, we label the clusters with qualitative interpretation. Future research can focus on representing the patterns with quantitative statistics, such as variance or coefficients, and conducting clustering analysis with these variables. Then, an examination of whether the results are consistent with this study can be done to triangulate the features of students' learning.

Practical Implications Based on the clustering analysis, we identify groups of time allocation patterns and determine their effectiveness, which may also suggest learners' skills in time management. That is, to facilitate the skill, some potential practice could be implied by the derived effectiveness. In this study, we find the patterns of students' study time have more effects on performance than the amount of time allocated. This implies different suggestions for different roles involved in a digital learning environment. For learners, developing learning habits and studying consistently become crucial for effective learning. For instructors, in terms of performance, keeping students studying seems to be more effective than informing them how much time they spend. They can guide them to set goals at the beginning so that the learning patterns would be given meaning. For designers of learning systems, the findings also consolidate the importance of visualizing students' learning patterns and providing timely interventions in the learning processes. For example, when a student is identified to show a pattern that might lead to low performance, the system can send a reminder message to make them closer to the pattern with better effects. With these practices, learners are enabled to develop the skill of time management.

Contribution, limitation, and future work

Based on the above discussion, we get an insight into learners' time allocation extracted from a digital learning environment, proving that LA methods help understand how learners allocate time in their learning processes. Different ways of time allocation are shown and found to be consistent with the results of different past studies. This implies the contribution of this study to reveal the variety of time allocation via a research design with LA methods. On the other hand, this study shows significance in expanding the use of LA methods to understand students' behaviors in math learning, which was discussed in the study of Li et al. (2021a, 2021b) as well. Practically, the visualization of time allocation not only enables learners to be aware of their time use but also inspires the design of interventions motivating them to study consistently (Manso-Vázquez et al., 2016; He et al., 2019). That is, this study can contribute to the support for developing learners' time management skills in practice. Collectively, we expect this study to contribute to the establishment of smart learning environments in which learners' self-regulated learning can be facilitated.

On the other hand, some limitations may underlie the research design. First, in this study, we extract data from the period of a certain exam. If data are retrieved from a broader window, namely periods of multiple exams, it would be possible to compose an effective sequence of learning patterns. For example, a sequence of pattern A, effective in period A, and pattern B, effective in period B, could be a recommendation so that learners' learning could be supported from a long-term perspective. Second, we analyze students' time allocation and then examine its effects on their performance. It indicates that different patterns can be categorized based on the effects on performance. However, another way for the analysis can be dividing students into groups based on their performance and then looking into the patterns of the groups. As Nonis and Hudson (2010) pointed out, personal study habits, such as taking notes, scheduling, and the ability to concentrate, could be related to students' performance. The mentioned analysis design emphasizes the extraction of learning patterns with personal characteristics, which enables personalized recommendations.

Conclusion

This study is aimed to measure learners' time allocation in digital environments and determine the effectiveness of such behaviors. We collect learners' learning process data and adopt clustering techniques and relationship mining to reveal how learners allocate their time and whether it affects their performance. We find that: (1) Learners' time allocation can be considered in terms of the total time allocated in a specific period, the time allocated in different phases of the period, and the time tended to be allocated in a specific activity. (2) The phases in which time is allocated could show a difference in the performance depending on the types of learning materials, while neither the total study time nor the tendency to certain activities has effects on learners' performance.

The findings imply that LA methods help understand time allocation by enabling the extraction of different levels of indicators. Practical suggestions aiming to maintain the consistency of study time could also be provided to learners, instructors, and system designers respectively. The contribution of this study lies in the support for self-regulated learning taking place in digital learning environments by visualizing learners' time allocation and evaluating its effectiveness.

The research design limits the possibility of concrete proposals on the possible design of the intervention. The results from different analysis designs enable different implications to support learners' learning. Therefore, future works can look into learners' time allocation from other perspectives with different research designs to enable more possible solutions to facilitate learners' skills of time management, helping them with effective self-regulated learning in smart learning environments.

Abbreviations

LA	Learning analytics
LEAF	Learning & evidence analytics framework
LMS	Learning management system
LAD	Learning analytics dashboard
LRS	Learning record store
TRT	Total reading time
DRT	Daily reading time
DP	Daily progress
PS	Performance scores

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Author contributions
CH performed the data analysis and drafted the manuscript. IH, HL, RM and HO provided insights and reviewed the manuscript. RM and HO acquired funding for the research. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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