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Optimizing learning productivity: Personalized recommendations for habit-building through learning analytics

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Abstract

This study investigates the development of productive learning habits through temporal regularity in learning activities. Building effective habits involves self-regulated learning (SRL) strategies, particularly in time management, which are critical for learners to regulate their behaviors and optimize their productivity. While Learning Analytics (LA) techniques have been employed to monitor habitual behaviors and provide long-term support, few of them attended to learners' decisions on which habit to build when they try to find their optimal time for learning. To address this gap, we designed an algorithm that generates personalized recommendations for optimal learning time slots based on learning log data. Our findings reveal that these recommendations can increase learners' awareness of productive time slots, guide them in aligning their behaviors with their goals, and support the development of sustainable learning habits. The study also highlights the implications for K-12 learners who often lack specific time management skills, and educators, who can leverage such tools to provide structured guidance and targeted feedback. By integrating adaptive learning systems and personalized recommendations, this study contributes to advancing SRL support within technology–enhanced learning environments, offering practical insights for improving time management, goal setting, and overall learning productivity.

Keywords: learning habits, learning analytics, learning productivity, time management, recommendation

Introduction

As ICT tools have been widely adopted in educational contexts, Learning Analytics (LA) researchers found it significant to extract learning habits by investigating the regular patterns from the trace data that logs learners' activities. Boroujeni and Dillenbourg (2019) indicated that important learning patterns include regularity in time, activity, and social interactions. In this study, we define learning habits as the temporal regularity of study behaviors—specifically, the tendency to study during certain time slots of the day (morning, afternoon, evening, or night). This definition focuses on when learners study, rather than how they study (e.g., using strategies like highlighting or note-taking). The regular schedule is particularly valuable in the K-12 context since the students can cultivate time management skills at a young age and apply them in the future as autonomous and lifelong learners. For instance, building a habit of completing the study work at a specific time of day can make learning a routine and improve learners' academic performance (Frăsineanu, 2018; Cho et al., 2024). Furthermore, the learners can have more time to explore their interests by participating in extracurricular activities. Meanwhile, they can also lead a balanced life with sufficient exercise and sleep, which are essential for mental and physical health (Nguyen et al., 2024). In this sense, learning habits—understood as regular time-use patterns—can have broad implications for both academic and personal development.

To support time management and habit-building in education, LA researchers monitored learners' use of time and scaffolded them to build learning habits based on their log data. For instance, Boroujeni et al. (2016) measured the time regularity of learning activities and identified learners' habitual behaviors such as studying at certain hours of the day. On the other hand, Hsu et al. (2024a) modeled the process of habit-building into different stages and designed interventions to prompt the transition between habit stages. While the preceding studies presented the potential for providing long-term support in habit-building using continuous logs, few of them attended to learners' decisions on which habit to build when they try to find their optimal time for learning. As Hsu et al. (2024b) discovered, inactive learners without habits could still have a productive learning time. In addition, learners' existing habits could also be changed to improve their learning productivity. Therefore, recommendations regarding the productivity of different time slots can be helpful when learners decide to start a habit or reflect on their current learning status.

This study aims to achieve the above objective and bridge the research gap. First, we target the context of English reading in a Japanese junior high school and model the productivity of different time slots using learning logs to compute the recommended habits for different learners. Second, we survey learners' perceptions of productive learning time and status, which are also compared to the detection from their log data. Third, we conduct an initial evaluation to examine whether the recommendations can support learners in building productive learning habits. We answer the following research questions.

- RQ1: Can the recommendations increase learners' awareness of their learning habits?
- RQ2: Can the recommendations prompt learners to adjust their reading time slots to increase productivity?

Our study considers learners' productivity at different times of the day and has the potential to increase their awareness of learning habits. We focus on learning processes depicted by log data, going beyond the summative evaluation of learners' academic performance. This alleviates their load and makes learning a pleasure. In addition, we contribute to self-regulated learning (SRL) in K-12 education by tackling learners' time management to sustain a preferable habit, which affects long in learners' lives.

Literature Review

Time Management as Strategy for Building Learning Habits

This study considers time management as a strategy to build effective learning habits. As Bourguet (2024) postulated, analyzing learners' study regularity can help identify potential gaps in their time management strategies and increase awareness of their learning habits. Specifically, we focus on the habits learners develop when studying during different time slots (i.e., morning, afternoon, evening, and night). This time-based segmentation is informed by Ricker et al. (2020), who analyzed clickstream data from K-12 learners using these four time periods to assess learning patterns and classify chronotypes. Their work draws from chronobiology, emphasizing the biological basis for variation in learners' performance throughout the day. Time management serves as the foundation for cultivating consistent learning habits, which in turn contribute to better productivity outcomes. Cho et al. (2024) suggested that times of the day serve as more accessible cues for learners than other temporal factors. For instance, these time-based cues are more readily available than days of the week (e.g., weekends) and more flexible than specific clock times (e.g., 1–2 PM). Understanding these cues allows learners to optimize their learning patterns, forming habits that maximize their time use and enhance productivity.

Time management in education is closely associated with the theory of self-regulated learning. Cho et al. (2024) state that learning habits involve behavioral regulation. This regulation is addressed in Pintrich's (2000) SRL model, which comprises four phases: (1) Forethought, planning, and activation; (2) Monitoring; (3) Control; and (4) Reaction and reflection. These phases are further applied across four areas of regulation: cognition, motivation/affect, behavior, and context. Behavioral regulation connects time management practices to productive learning outcomes by encouraging deliberate planning and monitoring. That is time management functions as both a mechanism for self-regulation and a driver of productive learning habits.

Understanding the relationship between learning habits, time management, and productivity can inform interventions to improve student learning outcomes. Holili et al. (2024) suggested that efficient time allocation emerged as a key predictor of high productivity. According to Serdyukov and Serdyukova (2012), time-related factors in online learning, such as identifying the best times of the day or week for studying, are associated with time efficiency and learning outcomes. Ahmad et al. (2023) examined the relationship between time management and students' productivity in an online learning context. The results indicated a significant influence of time management skills on productivity levels. These findings highlight that time management enhances learning habits and is critical to improving academic performance.

Data-informed Support for Time Management

Considering time management as a strategy, we attend to learners' decisions on which habit to build when they try to find their optimal time for learning. This assists learners in establishing more concrete learning plans. As Cho et al. (2024) discovered, the specificity of plans suggested learners' time management skills and determined their achievements. Poor time management leads to negative consequences such as missing deadlines to finish the required assignments, failing to keep track of the schedule, and being less productive than others (Raković et al., 2023; Muhlisin & Yatini, 2024). Hence, Al-Janabi et al. (2018) designed a time management recommendation system and provided their students with an effective way to exploit their time based on the web-based questionnaire data regarding the time use of the target participants.

On the other hand, we design recommendations that are adaptive to learners' productivity using their learning logs. Watanabe et al. (2023) also developed a system, MAI Helper, which allows learners to manage their study time and control their learning activities based on ordinal learning behavior data. Furthermore, they confirmed learners' academic performance growth with the system support. Similarly, He et al. (2019) introduced a system, LearnerExp, for instructors and learners to explore and explain time management by visualizing the time allocated to learning activities daily. This makes learners' time allocation visible, increasing time awareness and aiming to facilitate their time management skills.

While the above systems use learning logs, they were implemented in higher education. We consider the importance of SRL in K-12 education, as Ricker et al. (2020) argued. They employed student clickstream data to test whether the time of day a student was most active in a course affected their final course performance. They also generated insights about how and to what degree student activity within a course could help educators provide data-driven support and foster higher engagement and performance. However, our study goes beyond identifying the impact learning time slots may have on academic performance. We investigate learners' productivity at different times of the day, focusing on the learning processes to increase their awareness of learning habits. Table 1 summarizes the comparison between this study and other related works.

Table 1

Related works and their data source, focused achievement, and context

	Al-Janabi et al. (2018)	Watanabe et al. (2023)	He et al. (2019)	This study
Data source	Web-based questionnaire	Learning logs	Learning logs	Learning logs
Focused achievement	Learning productivity	Academic performance	Academic performance	Learning productivity
Context	K-12	Higher education	Higher education	K-12

Designing Recommendations on Habits Considering Productive Learning Time

This section describes how we conceptualize the recommendations regarding learners' productivity at different times of day to support their decisions on which habits to build. First, we select an educational context that values the habit-building of learners. Second, we derive a formula for learning productivity to represent how effectively learners use the time. Third, we write an algorithm that computes learners' most productive time slots to build a habit.

Habit-building of English Reading: K-12 Context of This Study

This study focuses on the habit-building of English reading in a Japanese junior high school. By making reading a routine, learners can expand their vocabulary and improve their English fluency. To achieve these objectives, the school students read as many books as possible in a short time with the support of the LEAF system (Figure 1). Specifically, they have a tablet computer and can access the school's Learning Management System, Moodle. It connects an e-book reader, BookRoll, with over 500 registered English picture books. Via BookRoll, the learners can navigate the e-books and make their learning actions (e.g., read 82 words in a minute) logged in the Learning Record Store (LRS).

On the other hand, Moodle also connects a goal-oriented active learner system, GOAL, which analyzes the BookRoll log data and provides feedback on the learners' status on an LA dashboard (Figure 2). Furthermore, the GOAL system scaffolds the self-regulated learning process and engages the learners in the goal-setting, planning, and self-reflection for English reading activities. To conceptualize the recommendations for building reading habits, we illustrate the potential use scenes within the GOAL system as follows.

- Learner profile 1, one who never reads: The learner decides to start a reading habit, and the system provides the recommendation in the goal-setting phase.
- Learner profile 2, one who reads randomly: The learner plans to maintain a reading habit, and the system provides the recommendation in the planning phase.

- Learner profile 3, one who reads regularly: The learner intends to examine their current habits, and the system provides the recommendation in the self-reflection phase.

Figure 1

English reading within Learning and Evidence Analytics Framework (LEAF)

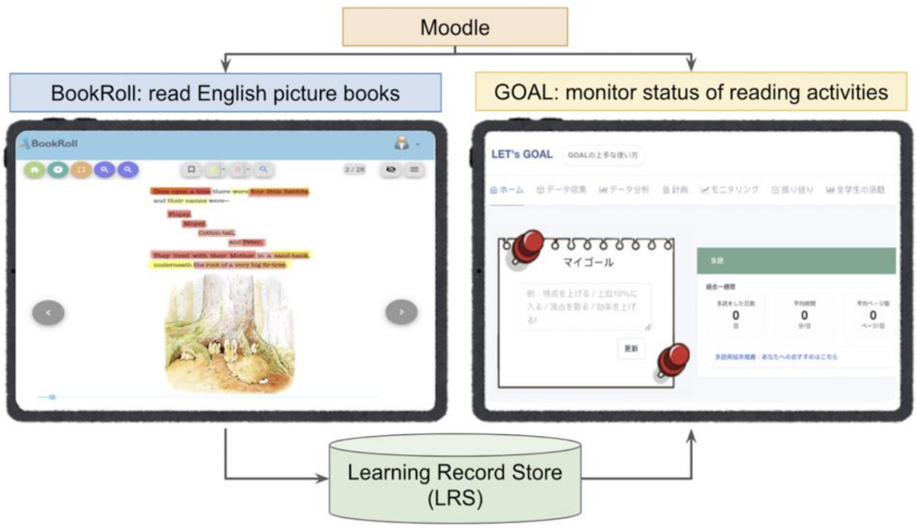
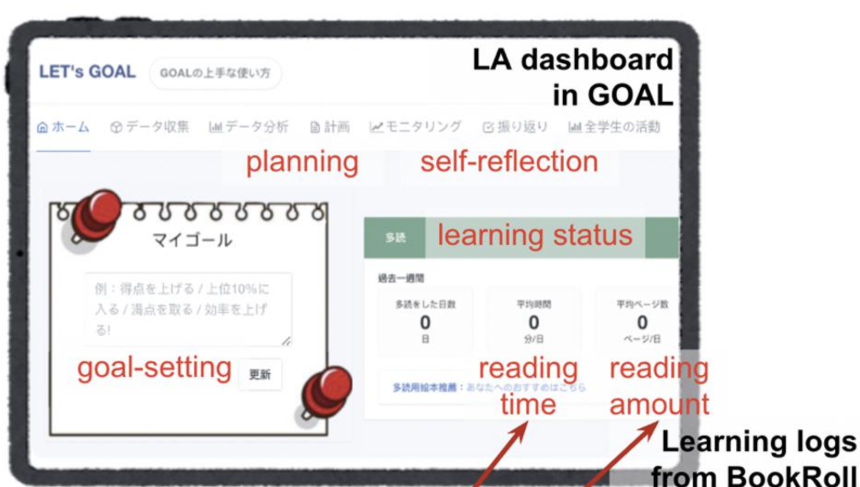


Figure 2

Learning logs from BookRoll and LA dashboard in GOAL



user_id	content_id	operation_name	difftime	page_no	operation_date
S001	cc70903297f	OPEN	1	1	2020-05-04 09:01:35
S001	cc70903297f	NEXT	18	1	2020-05-04 09:01:53
S001	cc70903297f	PREV	7	2	2020-05-04 09:02:00
S001	cc70903297f	PAGE_JUMP	32	1	2020-05-04 09:02:32
S001	cc70903297f	CLOSE	1	5	2020-05-04 09:02:33

In this study, we focus on two cohorts of the junior high school students. With the first cohort (2021-2023), we model learning productivity using their log data and investigate their awareness of learning habits; with the second cohort (2024), we implement the recommendations in an initial evaluation and examine their impact on learners' productivity. The experiment with the 2024 cohort was conducted during the summer vacation period, when learners are not bound by their regular school timetable and are expected to independently manage their learning time. This setting was intentionally chosen to ensure that learners had sufficient flexibility to act on the system's recommendations, making it more appropriate for evaluating self-regulated learning behaviors, particularly time management.

Modeling Productivity of Different Learning Time Slots

In terms of the above scenes, this study considers informing the learners of their most productive learning time of day and delivering recommendations when they set goals, make plans, or reflect on their learning in the GOAL system. We operationalize productivity as how effectively, efficiently, and effortlessly a learner uses time and focus on the quantity produced in the learning session. This aligns with Lakein's (1991) concept of time management and allows us to compare the productivity of different time slots based on trace data. The following defines the practical time management factors.

- Effectiveness: Methods that are used to achieve the desired goals.
- Efficiency: The lowest cost of losing time to achieve the goals.
- Effortlessness: Accomplishing the desired goals comfortably instead of feeling psychological or physical stress when dealing with time.

In our previous study (Hsu et al., 2024b), we explored how to calculate productivity from learning logs as shown in Formula (1). High productivity P indicates learner j can achieve more effective results r in learning object i efficiently and effortlessly with less time t and load l in terms of the total N objects to learn. While we validated the formula for measuring math learning productivity with log data, the study context differs in this present work. Hence, we further operationalize the measurement into two steps, which makes the formula applicable in various learning contexts. First, learning indicators should be selected to represent effectiveness, efficiency, and effortlessness, respectively. Second, the correlation between the indicators should be tested to ensure their independence and validate the measurement of learning productivity.

$$P_{ij} = \frac{1}{N}\sum_{i=1}^{N} r_{ij} \times \frac{1}{t_{ij}} \times l_{ij} \quad (1)$$

Based on the above steps, we identify the potential indicators from the English reading context, such as reading amount, reading time, and reading speed. First, the reading amount indicates the effectiveness of how many pages a learner reads. Second, reading time indicates the efficiency of how much time a learner spends. Third, reading speed indicates the effortlessness of how many words a learner reads per minute. Learners with higher reading productivity can read more pages in less time with a higher speed. The variables in Formula (1) are defined as follows.

- N = Total number of books
- r_{ij} = The pages read in book *i* by learner *j*
- t_{ij} = The minutes spent by learner *j* on book *i*
- l_{ij} = The words read per minute by learner *j* in book *i*

To ensure the independence of the variables, we examine their correlation using 32-month learning logs of the cohort (2021-2023)–96 ninth-grade learners, with an average age of 15. Table 2 summarizes their descriptive statistics and correlation. The variables were tested to represent a low correlation between each other. Namely, we validated the measurement of learning productivity using log data of English reading.

Table 2

The descriptive statistics of productivity variables and their correlation for cohort (2021-2023)

	Mean	SD	Effectiveness	Efficiency	Effortlessness
Effectiveness	19.91	14.93	1		
Efficiency	14.53	12.53	-0.22	1	
Effortlessness	150.34	158.47	0.20	-0.04	1

Computing Recommendations for Learners to Start a Habit

To recommend the most productive time to the learners in the above scenes, we designed Algorithm 1 in the GOAL system to generate the feedback based on their BookRoll reading logs stored in the LRS. We consider both conditions with and without data logged. First, the learners never read, and thus no logs can be used to calculate the learning productivity. In this case, the recommendation suggests that learners first read in their free time and introduces the idea that the system can further diagnose their productivity when detecting their reading logs in different slots. Second, the learners read randomly or regularly, and the system can compare their productivity between times of day. For this case, we illustrate how the recommendation works by presenting the following example of a learner's status from the cohort (2021-2023) (Figure 3). The day was segmented into four time slots—morning, afternoon, evening, and night—based on the framework proposed by Ricker et al. (2020), which has been applied to analyze time-of-day learning patterns in the K-12 context.

Algorithm 1

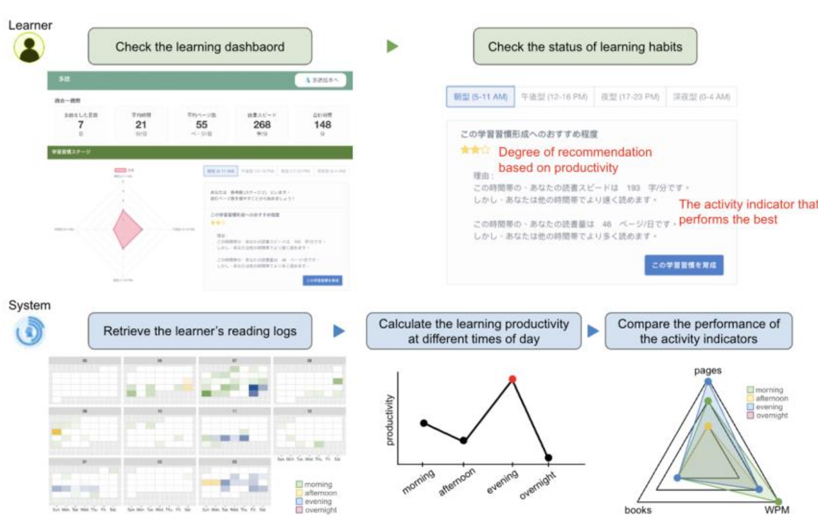
Computing recommended learning habits considering productivity

```
Input: query q for learner s; LRS, the Learning Record Store.
Output: F feedback regarding the most productive time, reason optimal activity indicators.
df ← filter(LRS,uuid = q.uuid)
if len(df)=0 then
print "Let's read in your free time! I can further diagnose your productivity when
    detecting your reading logs in different slots."
else
  P ← sort(df, productivity)
  P' ← P.head
  F ← "In/at" + P'.slot + "you can read the most productively."
end if
indicator ← []
for i in P,P' do
  indicator.append(i) if max(P.i) = P'.i
end for
reason ← "Specifically, the indicator (" + indicator + ")outperforms other times of day."
return F,reason
```

Learner S010 has been engaged in English reading activities for 32 months. With the reading logs collected during this period, the system calculates the learning productivity at different times of day as follows: 1260 in the morning (i.e., 05:00–11:59), 587 in the afternoon (i.e., 12:00–16:59), 1886 in the evening (i.e., 17:00–23:59), and 0 at night (i.e., 00:00–04:59). The result shows that Learner S010 could learn the most productively in the evening. In addition, the system outputs the recommendation indicators (i.e., number of books, number of pages, and words per minute) that perform the best in that time slot as the reason for the recommendation. In the case of Learner S010, he or she will receive the feedback, "In the evening, you can read the most productively. Specifically, the indicator (number of pages: 23) outperforms other times of day."

Figure 3

Workflow of how system computes and learners receive recommendations



Learners’ Awareness of Learning Habits (RQ1)

This section investigates the potential of the proposed recommendation for assisting learners in building productive learning habits. We compute recommendations for the cohort (2021-2023) using their learning logs. Meanwhile, we probe their perceptions regarding habit-building in a questionnaire. From these two data sources, we investigate the difference between the detected and perceived productive learning time. In addition, we also examine whether learners identify their learning status at a time of day as the log data detects.

The Difference between Detected and Perceived Productive Learning Time Slot

In the questionnaire, the learners indicated their intended time slot for building reading habits. We compared the response with the productive time detected from their learning logs, as summarized in Table 3.

The log data presents that 29, 33, 33, and 1 learner(s) could learn productively in the 4 slots (i.e., morning, afternoon, evening, and night). Compared to their perceptions, 35 learners intended to read in the same slot as detected with the highest productivity–7 in the morning, 5 in the afternoon, and 23 in the evening. In addition, many learners (n=64, 67%) intended to read in the evening even though 22 and 18 learners could learn more productively in the morning and afternoon, as shown from their logs.

Table 3

Comparison between the detected and perceived productive learning time

		Detection				Total
		Morning	Afternoon	Evening	Night	
Perception	Morning	7	6	7	0	20
	Afternoon	0	5	2	0	7
	Evening	22	18	23	1	64
	Night	0	4	1	0	5
Total		29	33	33	1	96
Consistency with detection		24%	15%	70%	0%	36%

The Difference between Detected and Perceived Learning Status

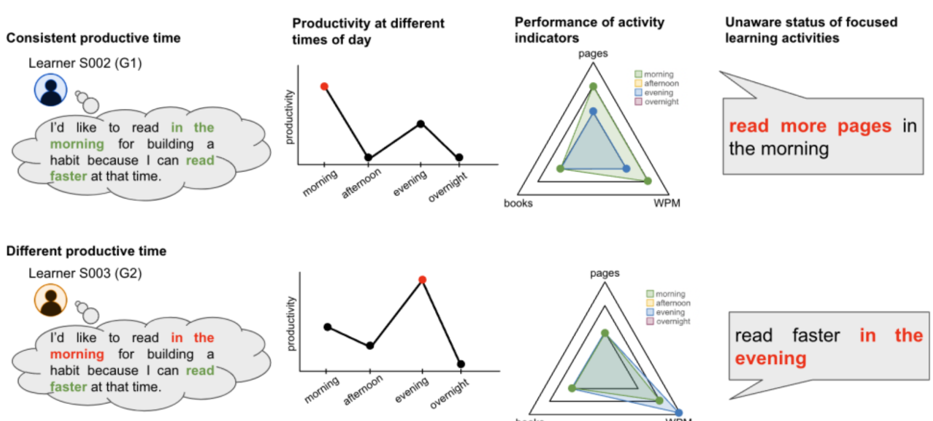
On the other hand, the learners also selected the reading activity indicators (i.e., number of books, number of pages, and words per minute) that were perceived to outperform others in their intended learning time. For instance, the learners may claim they can read the most pages in the morning. Based on the response, we examined whether learners identify their learning status at a time of day as the log data detects, as Figure 4 illustrates.

First, we divided the learners into G1, who reported a productive learning time consistent with the detection from log data, and G2, who indicated a different slot from the detection from log data. Second, we investigated the unaware learning status of their focused learning activities. For instance, Learner S002 in G1 acknowledged reading faster in the morning. However, the log data detected that he or she could further read more pages in that time slot. On the other hand, Learner S003 in G2 also acknowledged reading faster in the morning. However, the log data detected that he or she could actually read faster in the evening. Third, we aggregated the number of learners situated in the above cases among the 2 groups. The result shows that 29 of 35 (83%) G1 learners and 52 of 61 (85%) G2 learners identified their learning status differently from what the log data detected.

While some learners reported a productive learning time consistent with the detection from log data, some indicated a different slot. In brief, the learning logs of most learners uncovered the unaware learning status of their focused activities. For instance, they thought they could learn productively in the evening. However, their learning logs uncovered the high productivity in the morning.

Figure 4

Example cases of unaware learning status detected from log data

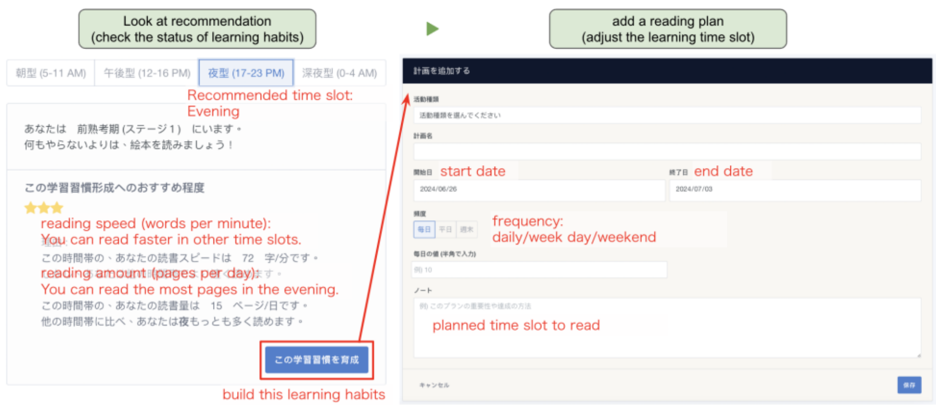


Learning Time Adjustment According to Recommendations (RQ2)

This section investigates whether the recommendation prompted learners to adjust their reading time slots to increase productivity. We conducted a 5-week initial evaluation with the cohort (2024)–94 seventh-graders, aged 13 on average. In week 1-2, the learners read at their preferred time. In week 3-5, the learners received the recommendations suggesting their most productive learning time slot based on the log data of the previous 2 weeks. After checking the messages, learners clicked a button to add a plan and indicated they would adjust to read in the recommended time slots (Figure 5). Using the learning logs, we first examine whether learners increased their overall learning productivity after checking the recommendations. Then, we investigate whether learners read more productively in the adjusted learning time slots according to the recommendations.

Figure 5

Workflow of how learners check recommendations and add reading plans



Change of Overall Learning Productivity after Receiving Recommendations

Regardless of learning time slots, we calculate learners' overall productivity in week 1-2 and week 3-5 using Formula (1). The learners are further divided into check or not-check groups based on whether they clicked the recommendation messages in the interface. In terms of the 2 groups, we compare the difference in their overall learning productivity between the 2 periods respectively.

Descriptive statistics reveal observable trends in productivity changes between week 1-2 and week 3-5. Learners who checked the recommendations showed an increase in productivity from a mean of 5.61 to 6.06. In contrast, those who did not check the recommendations exhibited a slight decrease in productivity, with the mean dropping from 4.84 to 4.21. The paired-samples t-test is conducted to assess the significance of these differences. The analysis indicates that the changes in productivity for both groups were not statistically significant (Table 4). Further analysis using ANCOVA reveals that the groups did not have a significant effect on the difference in productivity between the 2 periods ($F = 0.32$, $p = 0.574$, $\eta^2 = 0.002$).

Table 4

Paired-samples t-test of overall productivity between week 1-2 and week 3-5

group	period	N	M	SD	Range	p	Cohen's d
Check	week 1-2	22	5.61	2.54	9.21	0.477	0.15
	week 3-5	22	6.06	2.38	8.88		
Not-check	week 1-2	72	4.84	3.10	10.96	0.337	-0.11
	week 3-5	72	4.21	3.43	12.47		

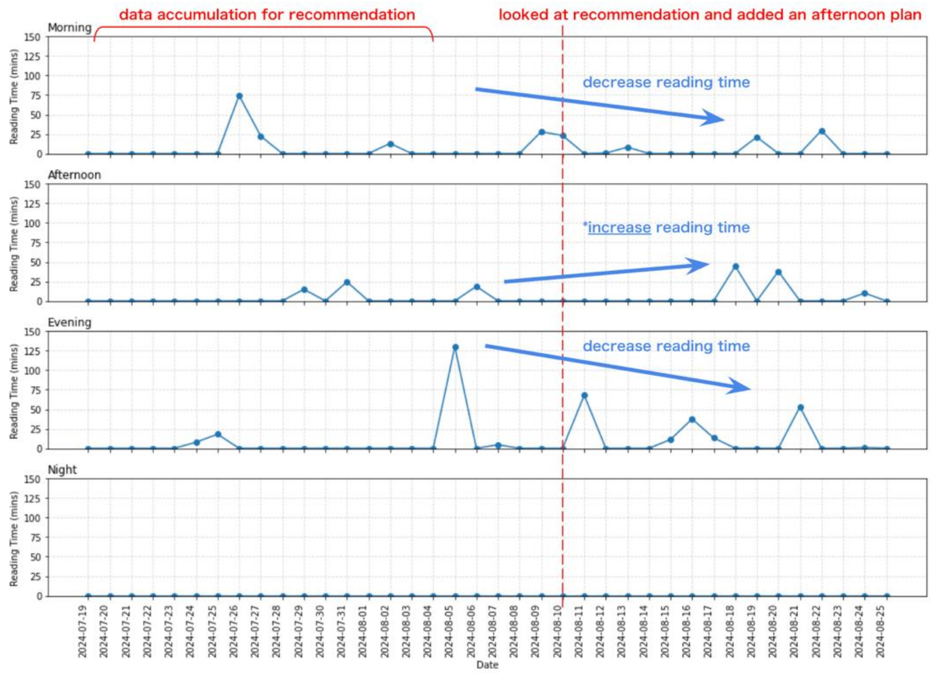
Productivity in Adjusted Learning Time Slots Based on Recommendations

We identified 10 learners—constituting 45% of the check group—who added reading plans and adjusted their study time in accordance with the recommendations. To illustrate behavioral changes in response to the recommendations, Figure 6 presents the reading activity of one learner (Learner S034) over time as example, segmented by time slot (morning, afternoon, evening, and night). A vertical line marks the point at which the learner created a plan, and annotations highlight changes in reading time. To evaluate the impact of this adjustment, we compared the learner's productivity in the newly selected time slot with the mean productivity in their other time slots.

Descriptive statistics revealed that the mean productivity was slightly higher for those in the recommended time slot (M = 6.66) compared to other time slots (M = 6.39). However, the Wilcoxon signed-rank test indicated that the observed difference was not statistically significant (p = 0.557). This suggests that while there is a small observed increase in productivity during the recommended time slot, the difference may need further exploration with a larger sample size.

Figure 6

Reading activity of an example learner (Learner S034) over time, segmented by time slot (morning, afternoon, evening, night)



Discussion

Key Findings

This study designed recommendations for productive learning habit-building considering the effects of times of the day on learners' activities from learning logs. Comparing learners' perceptions and conducting an initial evaluation, we identified the following potential of the proposed recommendations.

- The recommendations can help increase learners' awareness by making them reflect on the gap between their perceptions and actual learning behaviors (RQ1). Among the 96 learners, 35 reported the same productive time slot as detected from their log data (G1), while 61 reported a different slot (G2). Further analysis showed that 83% learners in G1 and 85% learners in G2 can become aware of productive learning behaviors that differed from or exceeded their initial perceptions.
- The recommendation may prompt learners to adjust their reading time slots to increase productivity (RQ2). While the statistical analysis did not yield significant results, observable trends indicate that learners who reviewed the recommendations were more likely to show increases in productivity compared to those who did not. Notably, nearly half (45%) of the learners who viewed the

recommendations made explicit adjustments by adding reading plans in the suggested time slots. Their productivity in these slots was slightly higher than in others, suggesting that aligning study schedules with personalized recommendations may support more effective time use.

The first finding indicates that learners may not fully understand their learning productivity patterns or accurately assess their status at different times of the day. For those whose reported productive times align with the log data, this lack of awareness is more subtle, as they may be unaware of specific activities where they exceeded their expectations. For others whose self-reported productive times differ from the log data, the discrepancy highlights challenges with self-regulation. Andrade (2014) argued that learners often struggle to intuitively regulate their learning effectively, while Choi et al. (2023) suggested that learners tend to describe their idealized selves rather than their actual behaviors. This tendency may explain the misalignment between self-reported and observed behaviors.

The second finding suggests that recommendations can encourage learners to adjust their study schedules, leading to potential productivity gains by addressing how learners utilize their time slots. Checking recommendations aligns with self-monitoring and self-evaluation, as highlighted in previous studies as critical self-regulation processes. Zuo et al. (2024) emphasized that self-monitoring involves observing and tracking one's use of learning time slots and the outcomes of those sessions, offering real-time insights into productive and unproductive periods. Similarly, Holili et al. (2024) highlighted the complementary role of self-evaluation in this process. It allows learners to assess the effectiveness of their time management strategies, helping them identify productive and unproductive time slots and refine their strategies. These processes align with our findings, as learners who check recommendations can better understand their learning habits and adjust their time use accordingly. In addition, adding plans provides a proactive layer of time management, aligning with Cho et al.'s (2024) emphasis on planning and goal setting. Creating detailed plans and setting clear goals help learners select and organize time slots based on their most productive periods, ensuring their efforts are purposeful and aligned with their objectives.

Implications

This study demonstrates that learners, particularly secondary school students, often face challenges in managing their time effectively, especially when trying to identify the most productive periods for learning. Secondary school students may struggle to set specific, measurable, and time-based goals, which are essential for efficient time management (Serdyukova & Serdyukov, 2010; Zuo et al., 2024). By incorporating personalized recommendations through adaptive learning systems, students can gain greater awareness of their optimal learning times. For learners examining their current habits, the recommendations can inform them of the activity where they perform beyond their awareness. For learners planning for a new habit, the recommendations can suggest a specific time as a feasible cue to automate the target learning behaviors. These recommendations can guide them in aligning their learning activities with these periods, helping them build productive habits.

For educators, this study highlights the significant role they play in helping students develop effective time management and SRL skills. Personalized recommendations can provide educators with valuable insights into students' learning habits. Specifically, educators can use data from adaptive learning systems to identify discrepancies between students' self-reported learning behaviors and their actual learning patterns, ensuring that students receive the guidance they need to develop better self-regulation skills (Choi et al., 2023; Nguyen et al., 2024). In addition, active learning methods, such as problem-based learning, can further support students by providing them with structured opportunities to practice time management, goal setting, and task prioritization (Chaerunnisa et al., 2024). Through continuous feedback and structured guidance, educators can help students understand the importance of managing their learning time effectively, fostering academic success and lifelong skills for time management in everyday life.

Collectively, this study highlights the potential of integrating technology–particularly adaptive learning systems and personalized recommendations–into the learning process, offering significant support for both secondary school students and educators in fostering self-regulated learning. For students, such technology helps them become more aware of their most productive learning times, facilitating the development of consistent and effective learning habits. For educators, it provides valuable tools for offering personalized guidance and feedback, helping to enhance the learning experience. As Andrade (2014) underscored, technological interventions can enable learners to continuously engage with their goals and build habits that drive successful SRL. By incorporating these tools into the learning environment, students and educators alike can enhance time management, goal-setting, and overall learning productivity. This reinforces the importance of adaptive learning systems as a powerful means to support students in aligning their learning behaviors with their goals, ultimately promoting greater academic success.

Limitations and Future Work

While this study provides valuable insights into the role of personalized recommendations in supporting learners' time management and productivity, several limitations highlight areas for further investigation.

- Operationalization of Learning Productivity. Our definition of productivity focused solely on the quantity of learning (e.g., time spent for reading), which, while useful for capturing time-use efficiency, does not reflect the quality of learning outcomes such as comprehension or retention. To provide a more complete picture of learning productivity, future work should incorporate multiple data sources, including comprehension tests, quiz results, and learner reflections.

- Sample Size and Generalizability. The small sample sizes in key subgroups—particularly the 10 learners who actively followed the recommendations—limited the statistical power of our analyses and the generalizability of the findings. Additionally, the initial evaluation involved only 22 learners in the check group, which further constrained the reliability of observed effects. Future studies should involve larger and more diverse learner populations to enable more robust statistical analysis and broader applicability across learning contexts.
- Evaluation Period. The intervention was conducted over a relatively short period of three weeks, which may not have been sufficient for learners to internalize the recommendations, reflect on their learning habits, and make meaningful adjustments. This limited duration could be one reason why statistically significant changes in productivity were not observed. As time management and self-regulation typically require sustained reinforcement and iterative practice, future research should consider longitudinal designs to better capture delayed or cumulative effects on learner behavior and productivity.
- Complexity of SRL Research. Self-regulated learning involves complex and interrelated processes, including time management, motivation, metacognition, and environmental influences. Isolating the effects of a single component—such as time-based recommendations—while accounting for these dynamic interactions is inherently challenging. Future research should adopt multi-method approaches and incorporate motivational indicators (e.g., learner-reported goals or interest levels) as well as follow-up qualitative or survey data to examine how recommendations influence learners' self-perception and study behavior. These efforts will support a more comprehensive understanding of SRL mechanisms.

Building on these findings and limitations, future work will aim to (1) expand the study to a larger and more diverse sample, (2) extend the intervention period to enable longer-term behavior tracking, and (3) combine log-based analytics with qualitative feedback to better capture learners' motivation, awareness, and self-regulation strategies. These enhancements will allow for a more comprehensive evaluation of how personalized recommendations support productive learning habits.

Conclusion

This study introduced a novel approach to supporting habit-building by recommending productive learning times based on learners' log data. Analyzing optimal learning statuses at different times of the day provides insights tailored to individual learning patterns. This advances SRL analytics and learner satisfaction with personalized support in digital learning environments. For instance, our recommendations have the potential to assist learners in planning and scheduling their studies with timely and constructive feedback. In addition, we uncovered the lack of learners' awareness of their learning habits. Therefore, the actionable and serendipitous insights empower learners to make informed choices about their learning strategies for time management.

In conclusion, this study provides sustainable and actionable recommendations that support habit-building and SRL processes. The interplay between time management and learning habits forms a reinforcing cycle: effective time management fosters productive habits, which further improve learners' ability to manage time efficiently. Future longitudinal research can deepen our understanding of the sustained impact of these recommendations, potentially driving long-term academic success and improvements in learning behaviors.

Abbreviations

LA: Learning Analytics; LRS: Learning Record Store; SRL: Self-Regulated Learning.

Author's contributions

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

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Availability of data and materials

Not applicable.

Declarations

Competing interests

The authors declare that they have no competing interests.

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