Doctoral Dissertation

Data-Informed Learning Habit-Building in K12 Education

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Abstract

Learning habits refer to learners' repetitive behaviors, suggesting the learning patterns of regularity in time, activity, and social interactions. This research focuses on habits that learners learn at a specific time. The regular schedule is valuable in the K12 context since the students can cultivate time management skills at a young age and apply them in the future as autonomous and lifelong learners. Namely, learning habits suggest how learners use their time and affect various aspects of their daily lives. However, giving long-term support for habit-building in educational contexts is challenging due to the lack of continuous tracing of one's behaviors.

On the other hand, ICT tools have been widely spread in schools in recent years. For example, the GIGA school program in Japan allows learners to have their own devices such as tablet computers to learn everywhere. This makes a great volume of learning logs accumulated from daily usage. With Learning Analytics (LA) techniques, researchers use the log data to monitor learners' daily learning activities and analyze their habitual behaviors. Therefore, this research is motivated to explore how data-informed support can be provided to build learning habits with real-time and continuous feedback.

Specifically, this research tackles the problems that learners might encounter regarding time management, as a strategy for learning habit-building. A time management cycle involves goal setting, time awareness/tracking, planning, taking action, and time shifting/adjusting. In other words, regulating habitual behaviors requires learners to plan and monitor their time use. However, learners tend to struggle in the process. First, learners might build less appropriate habits since they are unaware of the time slot when they can learn productively. Second, learners might not take action continuously since they do not stay motivated in their learning.

Regarding the above problems, this research proposes HAbit-Building Informed by Trace data (HABIT), a persuasion mechanism composed of 3 components: detection module, diagnosis module, and recommendation engine. First, the detection module extracts types and stages of learning habits from learners' daily learning logs. Types of learning habits refer to temporal affinity with a specific time slot, such as reading English books in the morning. In addition, each habit type can have its stages, which means different phases of behavior change (i.e., pre-contemplation, contemplation, preparation, action, and maintenance stages). Second, the diagnosis module prescribes different in-

terventions to prompt the transition between stages, aiming to facilitate habit-building processes. Third, the recommendation engine generates the computed recommendations on which habit type to build based on learners' productivity in different time slots from their learning logs.

To explore the potential of data-informed support based on the proposed mechanism, this research surveys learners' perceptions of their learning habits. Overall, the learners recognize the feasibility of integrating data-informed support into their daily learning. However, the comparison between self-report and log data shows that some learners are not aware of their learning habits as the detection from their learning logs. The above findings shed light on the implication of self-regulated learning (SRL) support within adaptive learning systems. Specifically, the recommendation engine can suggest a productive time for learners deciding to build a habit for their focused activities. 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 slot as a feasible cue to automate the target learning behaviors. These enable learners to continuously interact with their goals of habit-building, which leads to successful SRL.

Collectively, this research contributes to adaptive learning and personalization through analytics. While learning habits can be easily assessed by questionnaires with speedy answers, the process of building habits is dynamic. Hence, it is valuable and novel to extract types and stages of learning habits from daily learning logs and provide the visualization and suggestions of the LA dashboard for real-time and continuous feedback. In addition, the proposed mechanism can recommend an optimal time in learning plans and provide learners with a sustainable cue to automate learning behaviors long-term. By building productive learning habits, learners can get more engaged in their studies as well as lead more balanced lives. Regarding the support for building learning habits, this research looks forward to the evidence of its effectiveness at the meso level upon the initial implementation in the Japanese K12 context. Therefore, this research has potential for evidence-based education in the current technology-enhanced teaching-learning era.

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Chapter 1

Introduction

1.1 Supporting learning habit-building using Learning Analytics approach

Learning habits refer to learners' repetitive behaviors, suggesting the learning patterns of regularity in time, activity, and social interactions (Boroujeni & Dillenbourg, 2019). This research focuses on habits that learners learn at a specific time, such as studying in certain time slots, or a particular amount of study time each weekday. Boroujeni et al. (2016) discovered that learners affirming a regular learning schedule could have higher values on their academic achievements. For example, the learners who studied on similar weekdays, over weeks of the course tended to perform better than those who followed the course schedule. Specifically, such a regular schedule is valuable in K12 education since students are more constrained to a timetable than undergraduates.

The students can cultivate time management skills at a young age and apply them in the future as autonomous and lifelong learners (Manso-Vázquez et al., 2016; Ozer & Yukselir, 2023). For instance, building a habit of completing the study work in a specific time slot can make learning a routine and improve learners' academic performance. 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 is essential for mental and physical health (Nguyen et al., 2024). Namely, learning habits suggest how learners use their time and affect various aspects of their daily lives. However, giving long-term support for habit-building in educational contexts is challenging due to the lack of continuous tracing of one's behaviors.

On the other hand, ICT tools have been widely spread in schools in recent years. For example, the GIGA school program in Japan allows learners to have their own devices such as tablet computers to learn everywhere (The Government of Japan, 2021). This makes a great volume of learning logs accumulated from daily usage (Ogata et al., 2018; Raga Jr et al., 2018; Viberg et al., 2020). The logs indicate the data that record one's actions in digital learning environments. With the techniques of Learning Analytics (LA), the accumulated data can be made good use to monitor a learner's daily learning activities and enable fine-grained analysis of different learning behaviors (Isha & Wibawarta, 2023; J. Li et al., 2022; Wen & Song, 2021). This has brought opportunities to support learners to build learning habits with real-time and continuous feedback. Therefore, this research is motivated to explore how to support learning habit-building using the LA approach.

1.2 Current issues on time management to build learning habits

This research tackles the problems that learners might encounter regarding time management, as a strategy for learning habit-building (Cho et al., 2024). A time management cycle involves goal setting, time awareness/tracking, planning, taking action, and time shifting/adjusting (Peng & Kamil, 2018). In other words, regulating habitual behaviors requires learners to plan and monitor their time use. However, learners tend to struggle in the process, as Andrade (2014) and Liborius et al. (2019) indicated.

First, learners get easy to miss time since it is invisible, leading to poor time management. Hence, Watanabe et al. (2023) developed a system, MAI Helper, which allows learners to manage their study time and control their learning activities based on ordinal learning behavior data. Similarly, H. 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 per day and increasing their time awareness. While the researchers confirmed learners' academic performance growth with the system support, little evaluation focused on whether learners' current learning habits involve high learning productivity.

As Al-Janabi et al. (2018) indicated, the high productivity that results from proper time management can help avoid work stress in learners' lives and make learning a pleasure. Liu et al. (2022) suggested that time of day can affect memory, interest, motivation, and achievement. Specifically, the circadian rhythms in cognitive processes affect school-related activities such as executive functions, which refer to the ability to program or regulate behavior and are essential for problem-solving. Continuously working at non-optimal times could lead to chronic circadian rhythm disruption and deteriorate physical and mental health (Clarizio & Gill, 2022). Therefore, it is important to cater aspects of everyday learning to an individual's optimal time of day.

Second, learners might not take action continuously since they do not stay motivated in their learning. As Gardner et al. (2020) argued, habit-building is a process whereby a stimulus generates an impulse to change behavior. Regarding behavioral changes, the transtheoretical model (TTM) suggests that people proceed through 5 linear phases: pre-contemplation, contemplation, preparation, action, and maintenance stages. For instance, people in the contemplation stage may still feel ambivalent toward changing their behavior. On the other hand, people can also achieve the maintenance stage but relapse and become stuck. This might be because they recognize the pros of changing their behavior and take action. However, the emphasis on the pros might still be equal to the cons (Grimley et al., 1994). Therefore, habit-building has been promoted as a mechanism for sustaining behavioral change when conscious motivation erodes.

To support the process, the stages can motivate different intervention designs. In the medical field, Jimmy and Martin (2005) evaluated the patients' answers to a questionnaire and provided feedback regarding their current stage of change related to health-enhancing physical activity. Specifically, they presented varied benefits to the precontemplators without intending to become active. In addition, the contemplators forming an intention to become active were provided leaflets with further information on how to become active. Namely, understanding how habits develop is important to promote, foster, and maintain them (Gardner & Lally, 2018). While past studies focused on behavior change in contexts such as physical activity or diet (G. He et al., 2023; Lee et al., 2017; Merz & Steinherr, 2022), few studies have addressed its support in the educational field.

1.3 Dissertation proposal and overview

Regarding the above problems, this research proposes to extract learning habits from daily learning logs and design data-informed support for habit-building in K12 education. This makes it possible to evaluate learning habits not simply at a specific time but automatically trace their processes. Learners can also build learning habits based on evidence derived from learning logs. Specifically, learning habits are operationalized in 3 constructs: types, productivity, and stages. First, types of learning habits refer to temporal affinity with a specific time slot, such as reading English books in the morning. Second, habit productivity involves effectiveness, efficiency, and effortlessness in different learning time slots. Third, each habit type has its stages, which means different phases of behavior change (i.e., pre-contemplation, contemplation, preparation, action, and maintenance).

Based on the constructs of learning habits, this research further proposes HAbit-Building Informed by Trace data (HABIT), a system-generated persuasion mechanism composed of 3 components: detection module, diagnosis module, and recommendation engine. The mechanism refers to the Persuasive System Design (PSD) model, guiding the process of behavior change. First, the detection module extracts types and stages of learning habits from learners' daily learning logs. Second, the diagnosis module prescribes different interventions to prompt the transition between stages, aiming to facilitate habit-building processes. Third, the recommendation engine generates the computed recommendations on which habit type to build based on learners' productivity in different time slots from their learning logs. To explore the potential of data-informed support based on the proposed mechanism, this research surveys learners' perceptions of their learning habits and performs a comparative analysis of discrepancies between self-report and log data. The following main research questions are tackled in this dissertation.

- RQ1: What types of learning habits can be extracted from learning logs?
- RQ2: How can stages of learning habits be extracted from learning logs?
- RQ3: What intervention can be provided to build learning habits in digital learning environments?

Figure 1.1 summarizes the structure of this dissertation, consisting of the chapters as follows. Chapter 2 provides the theoretical foundation from both learning and behavior science perspectives. Practical system design principles are also reviewed. Chapter 3 describes the research methodology, including the system infrastructure, study contexts, and data processing. From Chapter 4 to 6, empirical studies are presented to illustrate how the research objectives are achieved. Chapter 7 concludes this dissertation with the research summary, contribution, and implications. Finally, a couple of limitations and future works are discussed.

main issue	Difficulties in tracing one's behaviors for long-term support of habit-building in K12 education		
solution	Leverage LA techniques to provide real-time and continuous feedback		
objectives	Mining learning habits from daily learning logs		Designing data-informed support for building learning habits
sub issues	Lack of awareness of how to regulate the time use	Decreasing motivation to learn continuously	Little guidance in the process of behavior change
proposals	What **habit types** can be extracted? • Extract patterns of time allocation in long-term and short-term time windows • Evaluate habit productivity in different learning time slots	How can **habit stages** be extracted? • Develop a stage extraction data model to trace the process of habit-building and understand learners' behaviors in different stages	What **intervention** can be provided? • Propose a system-generated persuasion mechanism to inform productive patterns of time allocation and prescribe personalized intervention based on stage
chapters	4. Study 1 (SLE; ICCE[a]; ECTEL)	5. Study 2 (ET&S)	6. Study 3 (RPTEL; ICCE[b])

Figure 1.1: Dissertation overview

Chapter 2

Literature Review

2.1 Learning habits and time management

In this research, time management serves as a strategy to build learning habits. As Bourguet (2024) postulated, presenting learners' study regularity can indicate the potential gaps in their strategies of time management and increase the awareness of their learning habits. Specifically, this research focuses on the learning habits that learners learn at different time slots (i.e., morning, afternoon, evening, and night). Cho et al. (2024) suggested that times of the day are more accessible cues than other temporal factors. For instance, they are available more often than days of the week (e.g., weekends) and more flexible than a clock time (e.g., 1–2 PM). Therefore, the present research proposal provides sustainable cues essential to build a long-term learning habits.

Furthermore, this research facilitates learners' self-regulated learning (SRL). Cho et al. (2024) indicated that learning habits involve behavioral regulation in time management. Such regulation was uniquely analyzed in Pintrich (2000)'s SRL model, compounded by 4 phases (i.e., Forethought, planning and activation; Monitoring; Control; Reaction and reflection) and 4 areas for regulation (i.e., cognition, motivation/affect, behavior, and context). Specifically, the regulation of behavior requires learners to plan and monitor their use of time. The present research proposal aims to support learners in these significant SRL processes.

2.2 Data-informed support for time management

Considering time management as a strategy, this research attends 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' skills of time management 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. 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 questionnaire data regarding the time use of the target participants.

On the other hand, this research designs recommendations 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' growth of academic performance with the system support. Similarly, H. 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 per day. This makes learners' time allocation visible, increasing time awareness and aiming to facilitate their time management skills. The system was also equipped with a grade point prediction module that predicts the probability of each learner's grade points based on the pre-trained model.

While the above systems used learning logs, they were implemented in higher education. This research considers the importance of SRL in K12 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, this research goes beyond identifying the impact learning time slots may have on academic performance. This research investigates learners' productivity at different times of the day, focusing on the learning processes to increase their awareness of learning habits. Table 2.1 summarizes the comparison between this research and other related works.

Table 2.1: Related works and their data source, focused achievement, and context

	Al-Janabi et al. (2018)	**Watanabe et al. (2023)**	**He et al. (2019)**	**This research**
Data Source	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

2.3 Habit-building and models of behavior change

A core hypothesis within habit theory is that it is a process whereby a stimulus generates an impulse to act because of a learned stimulus-response association (Gardner, 2015; Gardner et al., 2020). This has prompted interest in habit formation as a mechanism for sustaining behavioral change when conscious motivation erodes. Therefore, understanding how habits develop is important to promote, foster, and maintain them (Gardner & Lally, 2018).

Concerning habitual behavior, the transtheoretical model (TTM) suggests that people's behavioral changes proceed through 5 linear stages (Grimley et al., 1994). The 5 stages are defined below.

- Precontemplation: In this stage, one does not take action to change behavior within the next 6 months.
- Contemplation: In this stage, one takes action to change behavior within the next 6 months.
- Preparation: In this stage, one takes action to change behavior within the next 30 days.
- Action: In this stage, one takes action to change behavior within the last 6 months.
- Maintenance: In this stage, one takes action to change behavior for more than 6 months.

To support learners in building learning habits–a change of behavior, this research refers to the design of a Behavior Change Support Systems (BCSS), which is an information system designed with behavioral outcomes that people comply to form, alter, or reinforce their behaviors without being coerced or deceived (Steinherr, 2021). When developing BCSSs, designers often refer to the Persuasive System Design (PSD) Model and carry out the 3 generic steps as follows (Oinas-Kukkonen & Harjumaa, 2009).

- Step 1: Analyzing the persuasion context.
- Step 2: Selecting design principles.
- Step 3: Defining the software requirements and implementing the system.

Specifically, selecting the design principles of the PSD model plays a critical role since it bridges the persuasion context and the support implementation. Oinas-Kukkonen and Harjumaa (2009) integrated 28 design principles into the following categories. First, in the primary task category, the design principles (e.g., Reduction, Tunneling, Self-monitoring, etc.) support users in carrying out the primary task. Second, in the dialogue support category, the design principles (e.g., Praise, Reminders, Suggestion, etc.) help users keep moving toward their goal or target behavior. Third, in the system credibility category, the design principles (e.g., Trustworthiness, Expertise, Surface credibility, etc.) describe how to design a more credible and persuasive system. Fourth, in the social support category, the design principles (e.g., Social learning, Social comparison, Normative influence, etc.) describe how to design a system that motivates users by leveraging social influence.

Furthermore, Oinas-Kukkonen and Harjumaa (2009) also demonstrated how the PSD model can be applied by giving an example of a running system–Nike+–and discussing several design principles incorporated into its functionality. For instance, the Nike+ system supported users' primary tasks with the design principle of reduction, which suggests a system should reduce complex behavior into simple tasks to help users perform the target behavior. Therefore, the system reduced the complexity of planning the exercises by suggesting training programs according to the runner's goals.

Similarly, following the PSD model, Steinherr (2021) selected the design principle of tunneling and presented LANA, a BCSS towards self-regulated learning (SRL) of university students. Considering the principle instructs the system to guide users through a process, the students were supported in finding suitable starting points to improve their learning behavior without losing track or overwhelming themselves. For example, the students' successes in mastered tasks are shown, and they can reflect on their learning repeatedly, which paves the way for further SRL implementation. Overall, the students shared a positive attitude in a questionnaire toward their experience with LANA.

Table 2.2 summarizes the research fields, target behaviors, and data sources of the aforementioned examples. The PSD model is considered suitable for this research since it is a widely adopted model in public health interventions and can be a useful reference to design education interventions on learning habit-building with a behavioral science approach, also argued by Cho and Kizilcec (2021). This research focuses on the K12 context, in which learners need support of self-regulated learning. The developed system leverages the characteristics of LA approach to provide interventions adaptive to individual learning status. In other words, the roles of self-regulation and individualization are tackled in the goal attainment of building learning habits. On the other hand, the public health interventions also target such target goal-oriented behaviors and require a long-term commitment to achieve goals (Cho & Kizilcec, 2021). Hence, the PSD model can appropriately guide the habit-building interventions in education as well from the behavioral science perspective.

Table 2.2: Existing applications of the PSD model in health and educational fields

	Nike+ (Oinas-Kukkonen & Harjumaa, 2009)	**LANA (Steinherr, 2021)**	**This research**
Research field	Health	Education	Education
Target behavior	Running regularly	Using strategies of self-regulated learning	Learning regularly
Data source	Sensors	Questionnaire	Learning logs

The comparison of the present approach with the related works is performed to position this research in the existing designs that applied the PSD model to support behavior change. First, even though LANA is an application in the educational field, it aims to change the behavior of using metacognitive strategies of SRL, such as goal setting and planning. Additionally, it relies on the self-reported data of its users from the questionnaire. In contrast, our research uses learning logs to provide data-informed support for building learning habits–changing behavior–of reading regularly. This is close to the design of Nike+, which aims to support its users to build running habits using the data collected by the sensors equipped with the running shoes. However, Nike+ is a health application. Therefore, this research can bridge the gap in the educational field related to support for habit-building based on the PSD model.

2.4 Summary: Research position and novelty

This research is positioned at the intersections of Learning Analytics, Time Management, and Behavior Change. From the preceding studies, the research gaps are identified as follows. First, few studies have addressed the effectiveness of time use in the learning processes of the K12 contexts. Second, few studies have addressed data-informed support of behavior change in the educational field. These imply the novelty and significance of this research, which realizes data-informed learning habit-building with trace data and intervention based on the PSD model (Figure 2.1). On the other hand, the preceding studies valued the role of learning habits. However, they relied on survey data and did not always tackle how the support can be provided. The proposed data-informed learning habit-building evaluates learning habits not simply at a specific time but automatically trace their processes. Learners can also build learning habits based on evidence derived from learning logs.

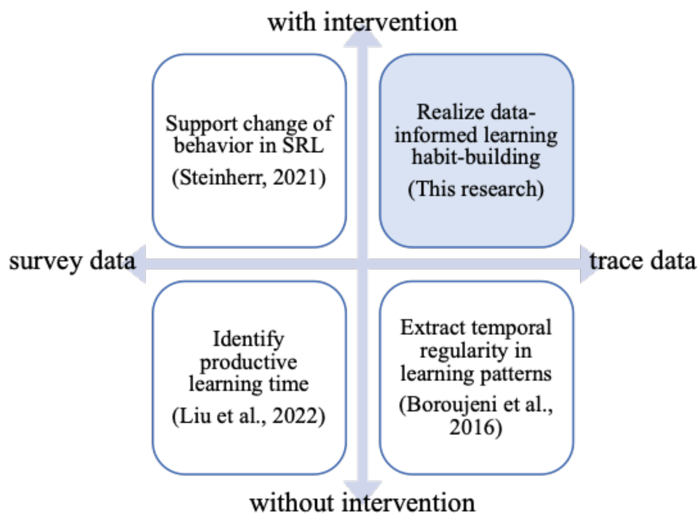


Figure 2.1: Research position and novelty

Chapter 3

Research Methodology

3.1 Learning and Evidence Analytics Framework (LEAF)

This research collects data from a Japanese junior high school, which has been implementing the Learning Analytics and Evidence Framework (LEAF) (Ogata et al., 2018) in daily learning activities for more than 3 years. Figure 3.1 shows the architecture of LEAF. It is a digital learning environment composed of a Learning Management System (LMS), several behavior sensors, and a Learning Record Store (LRS). From the LMS, learners can access the behavior sensors, BookRoll (Ogata et al., 2015) and GOAL (H. Li et al., 2021), working on different learning activities with equipped tablet computers.

BookRoll is an e-book reader and registers various materials in PDF files. Learners can do math exercises with digital pens or read more than 500 digital picture books in English. Their actions during the learning activities are traced in the LRS. Figure 3.2 shows the interface of BookRoll with the labeled elements that the operations are logged when the learner clicks. Table 3.1 presents the fields of the log data.

GOAL is a self-directed learning scaffolding system, which engages learners in the goal-setting, planning, and self-reflection of their learning. Learners also record their weekly math test scores in the system. GOAL aggregates the BookRoll activities and presents learners' learning time and test scores on the Learning Analytics (LA) dashboard (Figure 3.3).

3.2 Daily learning with long-term use of LEAF

The target school has adopted the LEAF system and offered basic courses such as math, English, and Japanese on that platform. During the preliminary investigation of the

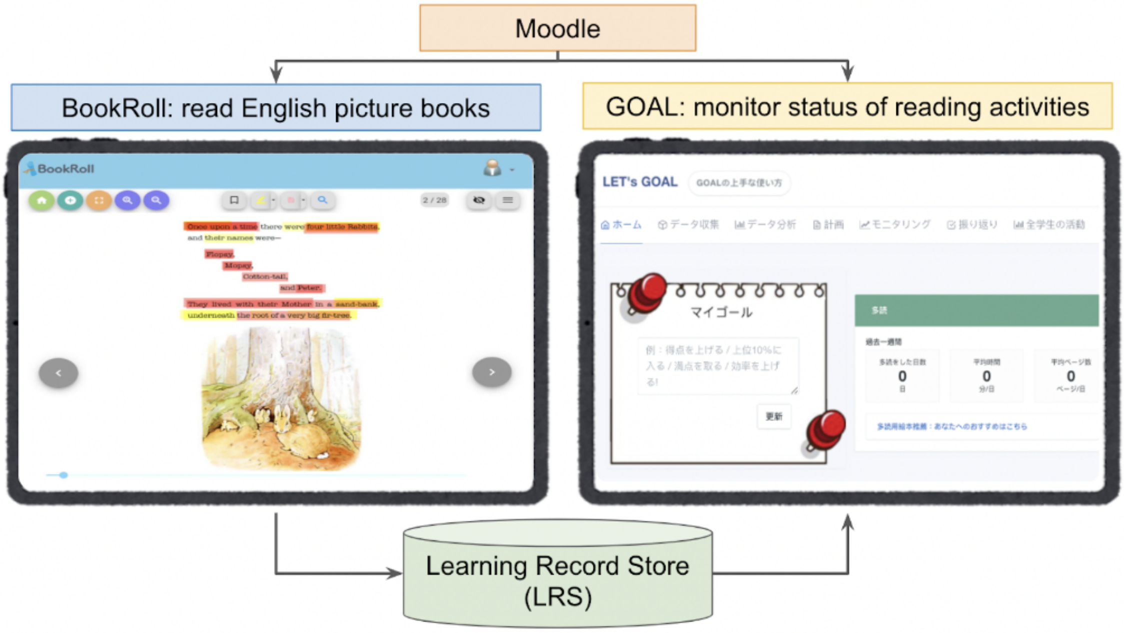
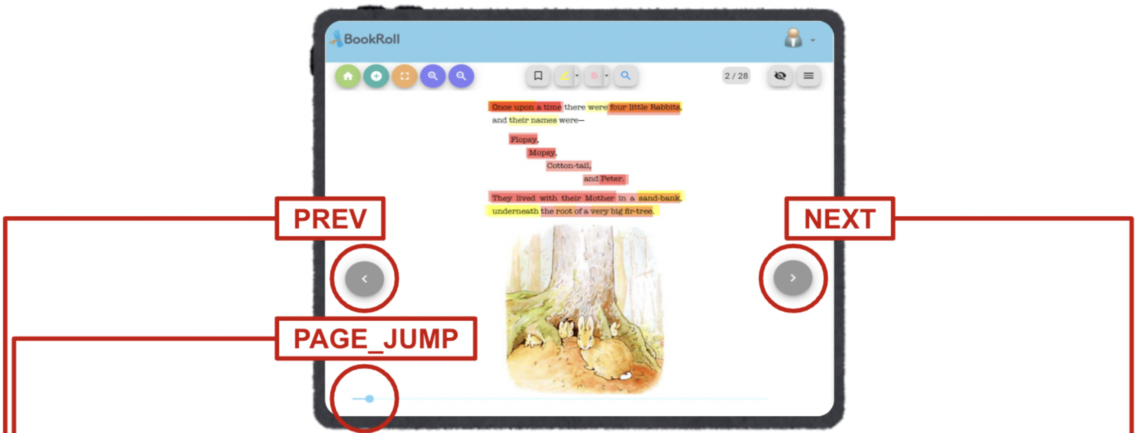


Figure 3.1: English reading within Learning and Evidence Analytics Framework (LEAF)



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

Figure 3.2: BookRoll interface and its learning logs

Table 3.1: Example fields of BookRoll log data

Fields	Description	Example
operation_name	Include OPEN, CLOSE, NEXT, PREV, PAGE_JUMP, ADD_HW_MEMO, and ANSWER_CORRECT. OPEN and CLOSE indicate the learner opens or closes a PDF file. • NEXT and PREV indicate the learner turns to the next or previous page in a PDF file. • PAGE_JUMP indicates the learner jumps to a certain page in a PDF file. • ADD_HW_MEMO indicates the learner adds a pen stroke in a PDF file with a digital pen. • ANSWER_CORRECT indicates whether the learner answers the question correctly.	ADD_HW_MEMO
memo_text	Record a single pen stroke in a comma-separated format: Pen color, Multiple UNIX time: x-coordinate: y-coordinate. • The pen color is recorded in RGB format. • UNIX time is the time stamp when the data is recorded.. • x-coordinate and y-coordinate express where the pen is at that particular time.	0.5rgb(0, 0, 0),1649738139686:238.927714:239.183035,1649738139887:236.903618:240.191537, …

collected learning logs, learners are found to be active in the math and English courses. Hence, this research selects the following contexts to extract datasets for analysis.

Regular math exam preparation

In this context, learning materials in BookRoll include three types: textbook, exercises,

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

Figure 3.3: Learning logs from BookRoll and LA dashbaord in GOAL

and answers. Via personal tablets, learners access these materials both at school and at home. They are also reminded of the exam day 3/2/1/ week(s) ahead, as presented in the school calendar. To reveal how learners allocate their time and evaluate the effectiveness of the time allocation, this research considers the hours out of school as the time of learners' self-regulated learning. Therefore, the learning logs are limited to the data from 6 PM to 8 AM the next day.

Weekly math test exercises

This context involves the learning of practicing and testing math exercises. Figure 3.4 shows the workflow of the learning activities. On a tablet computer, learners practice exercises of a math concept for a week and then take a test of the same concept on the

Monday in the following week. After the test, learners check the answers and score the test with their peers by exchanging each other's tablets. Finally, learners record the score they get and the full score of the test. This workflow was implemented repeatedly on a weekly basis.

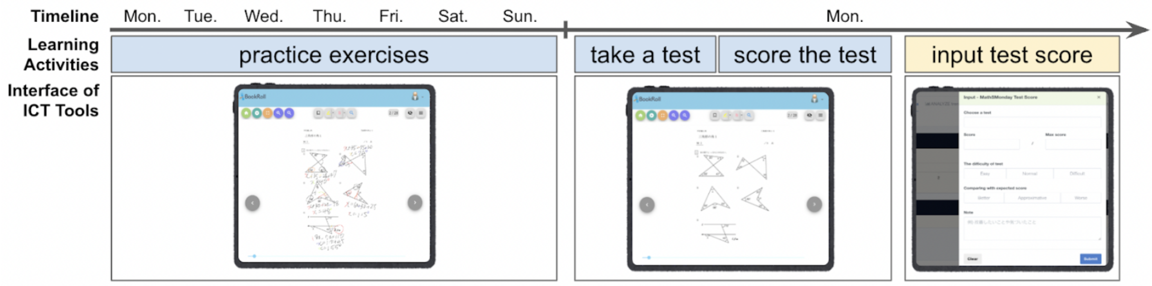


Figure 3.4: Workflow of weekly math learning in study context of junior high school

English extensive reading

In this context, learners read as many books as possible in a short time with the support of the LEAF system. By making reading a routine, learners can not only expand their vocabulary but also improve their English fluency. Thus, they plan their reading schedule along with the target set by themselves in GOAL (e.g., reading for 20 minutes per day) and carry out their plan by reading the picture books in BookRoll. Table 3.2 summarizes the important indicators in the context and their descriptions.

Table 3.2: Learning indicators from log data and their descriptive statistics

Indicators	**Definition**
Reading time	Total minutes a learner reads in an hour
Reading speed	The number of words a learner reads in a minute
Reading categories	The number of books a learner reads
Reading amount	The number of pages a learner reads

3.3 Defining learning indicators to operationalize habit constructs

To extract learning habits from daily learning logs and design data-informed support for habit-building in K12 education, this research further defines indicators to operationalize the 3 constructs of learning habits: types, productivity, and stages (Figure 3.5).

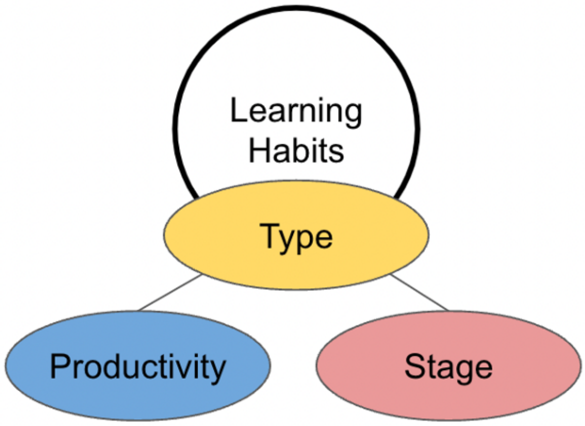


Figure 3.5: Habit constructs operationalized by this research

Temporal affinity: related to types of learning habits

Different types of learning habits can be represented by the extracted patterns of regularity from the learning logs that record the time and duration of learners' activities (Ricker et al., 2020). For instance, Boroujeni et al. (2016) considered the following 6 patterns of regularity in time.

- Pattern 1 (P1): Studying on certain hours of the day.
- Pattern 2 (P2): Studying on certain day(s) of the week.
- Pattern 3 (P3): Studying on similar weekdays, over weeks of the course.
- Pattern 4 (P4): Same distribution of study time among weekdays, over weeks of the course.
- Pattern 5 (P5): Particular amount of study time on each weekday, over weeks of the course.

- Pattern 6 (P6): Following the schedule of the course.

This research uses clustering analysis and presents the patterns by the clusters such as the learners who study on weekday mornings (P1 and P2) or the learners who study consistently throughout exam preparation (P6). Figure 3.6 illustrates how learning patterns are extracted from log data by the example of P1 and P2.

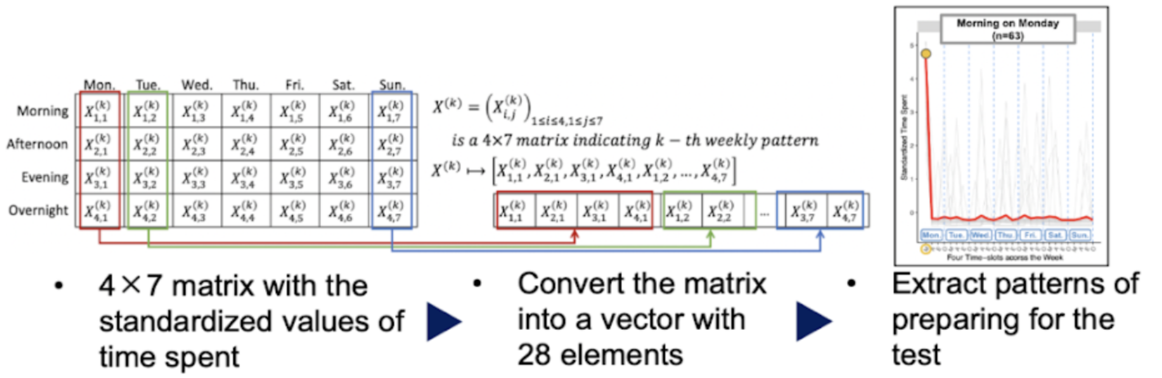


Figure 3.6: Extracting learning patterns from log data

First, this research divides the hours within a day into 4 time slots: morning (05:00–11:59), afternoon (12:00–16:59), evening (17:00–23:59), and overnight (00:00–04:59). Second, this research sums up the time spent in each slot and makes a 4×7 matrix with the standardized values of the time spent by a learner in the 4 time slots from Monday to Sunday. Third, this research converts the matrix into a vector with 28 elements and regards it as the weekly pattern of the learner. Fourth, the patterns are labeled into 4 groups: morning on weekdays, evening on weekdays, afternoon on weekends, and mixed (i.e., learning in multiple slots of the day). The clusters are considered potential habit types of learners.

Phases of behavior change: related to stages of learning habits

This research operationalizes how learners build learning habits based on the transtheoretical model (Grimley et al., 1994). Previous studies indicated that habit-building can be considered a behavioral change that usually takes 4 months (Gardner & Lally, 2018; Lally et al., 2010). Based on this definition, Table 3.3 describes the stages of learning habits. The temporally defined details (e.g., within the next 30 days, within the last 4 months, for more than 4 months, etc.) distinguish the stages from each other. For instance, the action stage refers to the phase wherein learners read within the last 4 months and have not built reading habits. On the other hand, the maintenance stage refers to the phase wherein learners read for more than 4 months and sustain reading habits. Dependent on the learning activities, the action like *read* can be replaced with the one in the specific activity.

Table 3.3: Definition of self-directed extensive reading habit stages

Stages	**Definition**
Stage 1: precontemplation	Learners do not read to build reading habits within the next four months.
Stage 2: contemplation	Learners read to build reading habits within the next four months.
Stage 3: preparation	Learners read to build reading habits within the next thirty days.
Stage 4: action	Learners read to build reading habits within the last four months.
Stage 5: maintenance	Learners read to build reading habits for more than four months.

Using learning logs, this research measures the stages with monthly frequency type and sequence of monthly frequency types. The monthly frequency indicates how frequently learners learn in a given month and is categorized as follows: They did not learn at all (Frequency A), learned in random weeks (Frequency B), or learned every week (Frequency C). The sequence of the monthly frequency types indicates the sequence whereby the monthly frequency types occur. It presents which type comes first and which type comes next. As the stages are defined by whether one intends to take action on a monthly basis, this research considers that the frequency type indicates whether one takes action and that the sequence of frequency type indicates one's intention.

To continuously measure which stage a learner stays at when the month ends and trace whether the learner proceeds to the subsequent stage or returns to an earlier stage in the latest learning activities, the stage of the first month is measured as follows. If the monthly frequency type is Frequency A, the learner is in precontemplation stage because of not taking action. If the monthly frequency type is Frequency B or Frequency C, the learner is in contemplation stage, indicating that he or she has taken action. Based on the stage of the first month, this research considers the sequence of the monthly frequency types to measure the stages in the following months, as presented in Table 3.4.

Table 3.4: Measurement of stages after the first month

Stages	**Case**	**Sequence of Monthly Frequency Types**
Stage 1: precontemplation	Consecutive Frequency A comes after the first month with Frequency A	**A**-A
	Consecutive Frequency A for more than 4 months comes after a month without Frequency A	B-A-A-A-A C-A-A-A-A
Stage 2: contemplation	Frequency B	B
	A sequence of Frequency C after Frequency A	A-C
	A sequence of consecutive Frequency A within 3 months after Frequency B or C	B-A B-A-A B-A-A-A
Stage 3: preparation	A sequence of Frequency C after Frequency B	B-C
	The second Frequency C in a consecutive sequence after Frequency A	A-C-C
Stage 4: action	The second Frequency C in a consecutive sequence after Frequency B	B-C-C
	The third Frequency C in a consecutive sequence after Frequency A	A-C-C-C
Stage 5: maintenance	Consecutive Frequency C for more than 3 months after Frequency B	B-C-C-C
	Consecutive Frequency C for more than 4 months after Frequency A	A-C-C-C-C

Note. Frequency A = not learn at all. *Frequency B* = learn in random weeks. *Frequency C* = learn every week.
The underlined letter shows the frequency type of the measured month. The **bold** letter shows the frequency type of the first month.

Habit outcome: related to productivity of learning habits

Productivity of learning habits involves how effectively a learner uses time. This research refers to Lakein (1991)'s factors of effective time management and derives Equation (3.1) for calculating the productivity of different time slots from learning logs. The following defines the effective time management factors. 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.

- 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.

$$P_{ij} = \frac{1}{N} \sum_{i=1}^{N} r_{ij} \times \frac{1}{t_{ij}} \times \frac{1}{l_{ij}} \tag{3.1}$$

This research further operationalizes the measurement into 2 steps, making 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. Based on the above steps, Table 3.5 summarizes the potential indicators identified from math and English contexts.

Table 3.5: Indicators of time management in math and English contexts

Factors	**Variables**	**Indicators**	
		math	**English**
Effectiveness	r_{ij}	accuracy rate of attempts	number of pages
Efficiency	$\frac{1}{t_{ij}}$	1/time spent	1/time spent
Effortlessness	$\frac{1}{l_{ij}}$	1/sensible pause counts	words per minute

Chapter 4

Study 1: Extracting and recommending types of learning habits

4.1 Overview

This study aims to extract and evaluate types of learning habits. By applying different sizes of sliding window to the time series data of learning logs, long-term and short-term habit types are extracted.

Regarding long-term learning habits, this study looks at the data in the time window of 34 days before the exam, taking place on Oct. 1, 2020. The participants cover 116 seventh-graders with an average age of 13 years old. First, groups of patterns depict students' time allocation of exam preparation. Then, the patterns are compared to reveal their effects on the exam performance. The following sub-RQs are answered.

- SRQ 1.1: How do students allocate their study time in digital environments during the period of exam preparation?
- SRQ 1.2: What effects can different ways of time allocation have on students' exam performance?

As for short-term learning habits, this study focuses on the self-directed learning of doing math exercises along with weekly tests to examine the learning effects. The window size is set as one week ahead of the tests. For analyses, this study targets the dataset of 114 ninth graders at the age of 15 on average from Apr. 2022 to Feb. 2023. The learners had 31 weekly tests in total. First, clusters from the learning patterns represents learners' chronotypes of learning habits. Then, the existing habit types are examined whether to involve high learning productivity. The following sub-RQs are further answered.

- SRQ 1.3: What clusters of learning patterns can be extracted from the daily logs of math learning?
- SRQ 1.4: Can learners with learning habits learn productively?
- SRQ 1.5: Is there potential for recommending learners to build a more productive habit?

4.2 Related works

In the educational context, the wide spread of ICT tools has motivated researchers to identify learning habits using the techniques of Learning Analytics (LA). For instance, Boroujeni et al. (2016) introduced measures to calculate the entropy of the histogram of the learners' activities over time to identify whether their activities were concentrated around a particular hour of the day or a particular day of the week.

Furthermore, 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 (Liborius et al., 2019). Students tend to change their time allocation in different activities at different phases considering the optimization of the achievement. Hence, the educational production function is one of the accepted techniques for modeling the process of exam preparation.

The above works measured time allocation as a summative value. There seems to be lack of measurement of time allocation with learning process data. 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.

4.3 Habit types of 3 weeks before a regular math exam

4.3.1 SRQ 1.1: Students' time allocation of exam preparation

With the log data collected from the digital learning environment, students' time allocation is measured based on Total Reading Time (TRT), Daily Reading Time (DRT), and Daily Progress (DP). On the other hand, Performance Scores (PS) is considered as students' performance. The following describes the definition of each measure (Figure 4.1).

- 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 minutes (SD = 58.68), did the exercises for 256.76 minutes (SD = 130.41), and referred to the answers for 44.01 minutes (SD = 65.73) in total during the whole period.

- 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.

- 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. This study calculates DP of each material type separately. From each student's reading logs, this study derives separate patterns of DP in each material type (Figure 4.2).

- 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).

This study conducts time series clustering to find groups of patterns in terms of the separate patterns of DP in each material type. Figure 4.3 shows the difference in the DP patterns between the 2 clusters, as the optimal number of clusters via the Silhouette Analysis Method. Considering the slope where students' daily progress changes, students are labeled 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.

- 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.

- 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).

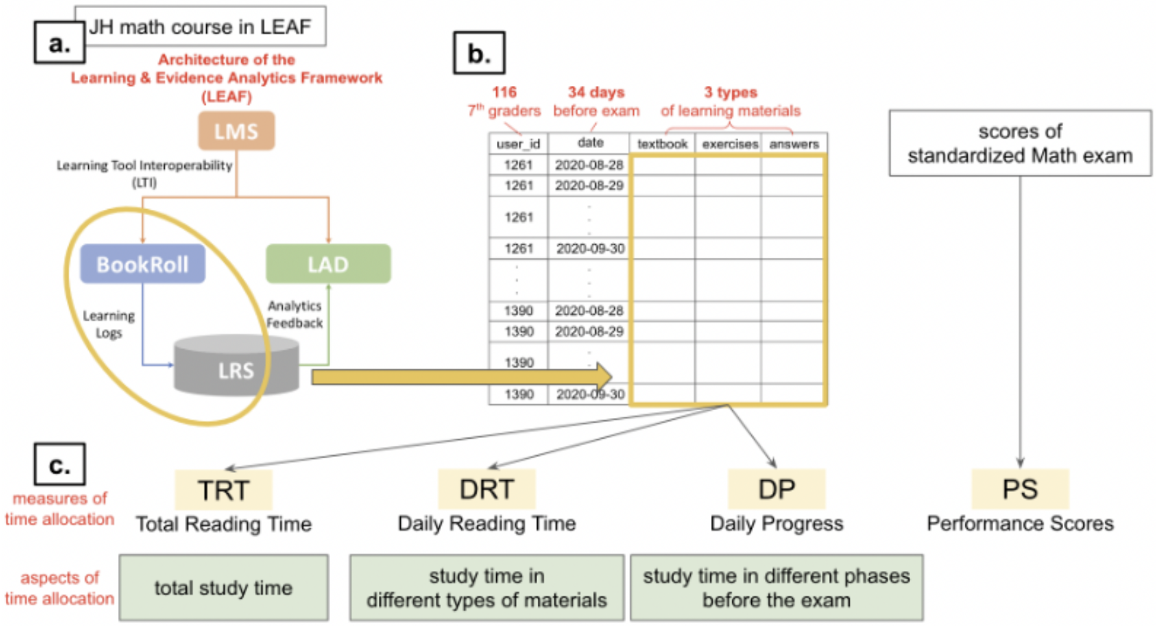


Figure 4.1: Extracting learning data from architecture of the Learning & Evidence Analytics Framework (LEAF)

4.3.2 SRQ 1.2: Performance difference between time allocation patterns

This study compares the performance between the 2 groups clustered in terms of the separate patterns of DP in each material type via independent samples t-test. Table 4.1 summarizes the results, presenting that consistent learners perform significantly better than cramming learners in the case of referring to answers. The students (early learners)

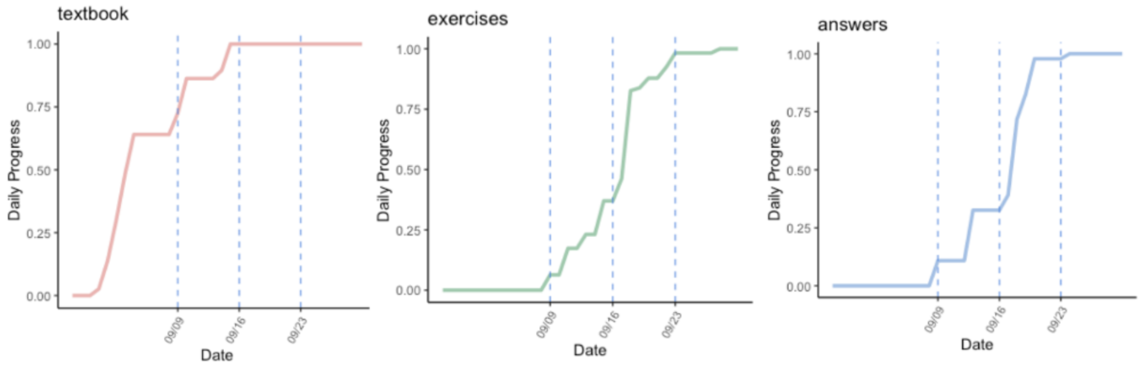


Figure 4.2: Patterns of Daily Progress (DP) for each material type

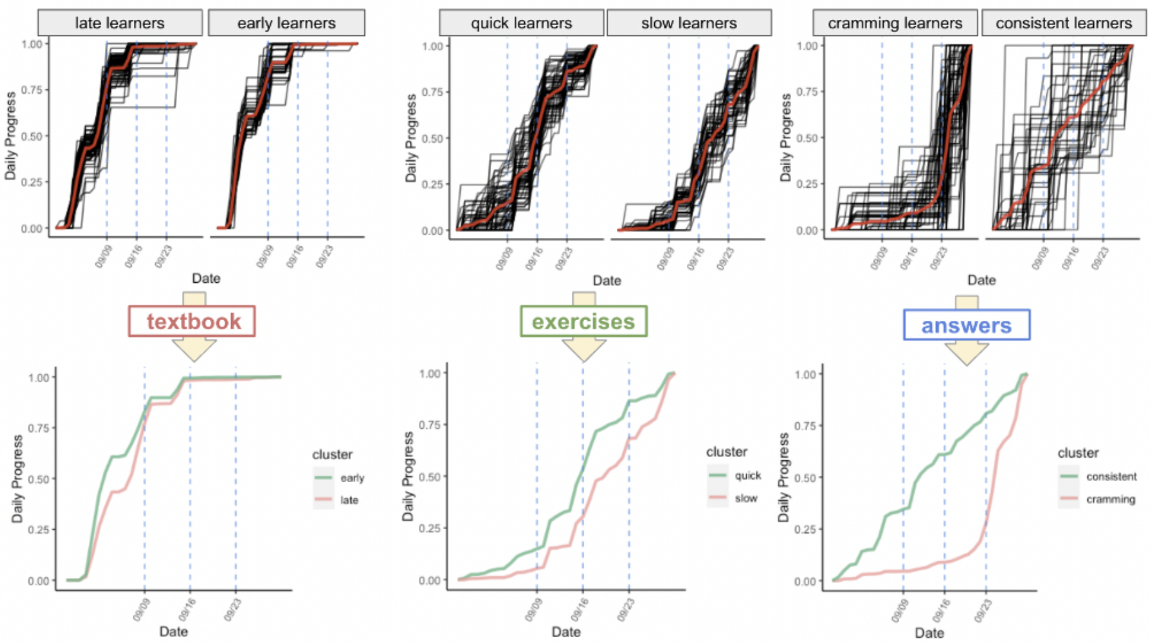


Figure 4.3: Clusters of patterns of Daily Progress (DP)

completing over half of the progress on reading the textbook before the mid of beginning do not have significantly different performance with those who complete after that (later learners). Similar results show in the performance between quick learners and slow learners doing exercises.

Table 4.1: 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		

4.4 Chronotypes of math learning habits and their productivity

4.4.1 SRQ 1.3: Clusters from weekly patterns of practicing before tests

The weekly pattern is indicated by the time spent within the week before a test day. Specifically, this study makes a vector with 28 elements with the time spent values x by the learner in the four times lots from Monday to Sunday (i.e, morning, afternoon, evening, and overnight). $x_{i,j}^{k}$ is the z-score of the time spent. i indicates the time slot, while j indicates the day of the week. k indicates the matrix of the k_{th} week. Figure 4.4 visualizes the pattern based on the vector.

Then, 723 vectors are input for K-means Cluster Analysis. The Average Silhouette Method presents 10 as the optimal number of clusters with the greatest silhouette score. Figure 4.5. visualizes calendar-like heat maps that depict the most active time slot in each cluster. The darkness of the color means the value of the time spent. The clusters are grouped by the maximum value in the weekly pattern as follows.

- Morning on weekdays (n=236): greatest time spent in the morning from Monday to Thursday
- Evening on weekdays (n=285): greatest Time Spent in the evening from Monday

to Thursday

- Afternoon on weekends (n=35): greatest time spent on Sunday afternoon
- Mixed (n=167): time spent on Thursday afternoon almost equals that on Sunday evening

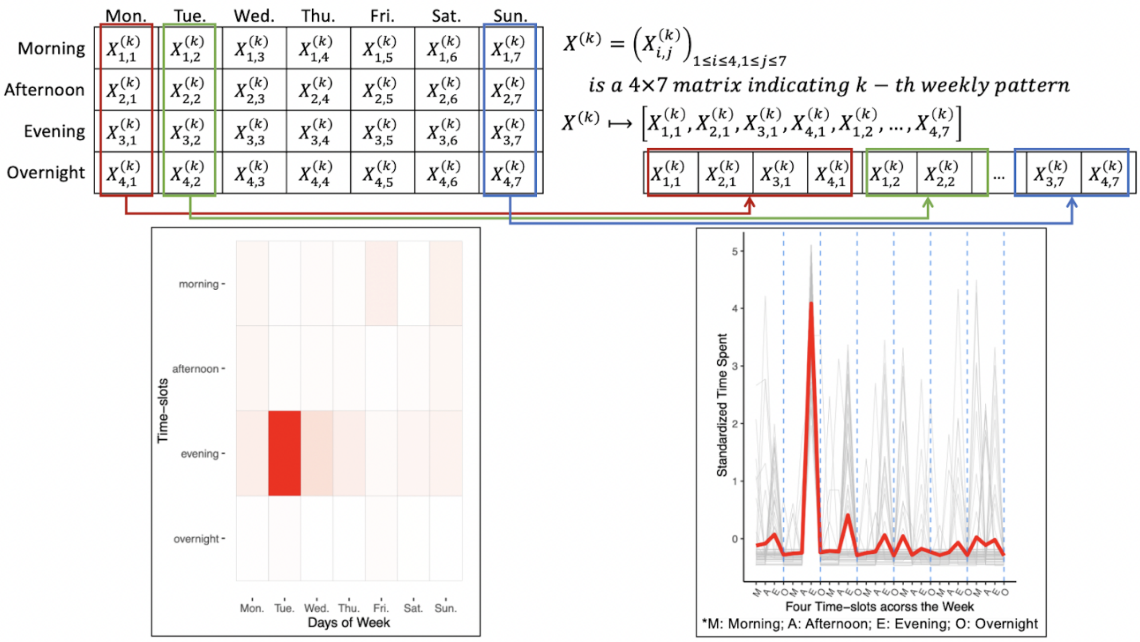


Figure 4.4: Extracting weekly patterns of practicing before tests

This study further identifies chronotypes of learning habits from the weekly patterns over the 31 tests (Figure 4.6). First, the pattern of each week is labeled with morning on weekdays, evening on weekdays, afternoon on weekends, or mixed based on the above results. Second, this study creates a sequence of the weekly patterns over the 31 tests for each learner. Third, the sequences are grouped with 3 clusters based on the hierarchical clustering tree. Fourth, the clusters are labeled by the slots of the patterns that occurred the most in the sequences. The result shows that the dataset from the learning context contained morning-type, evening-type, and inactive learners. While the learning context presented the patterns of learning in the afternoon or multiple time slots, the learners did not build them as habits since those learning patterns were not dominant in any extracted pattern sequences during the period.

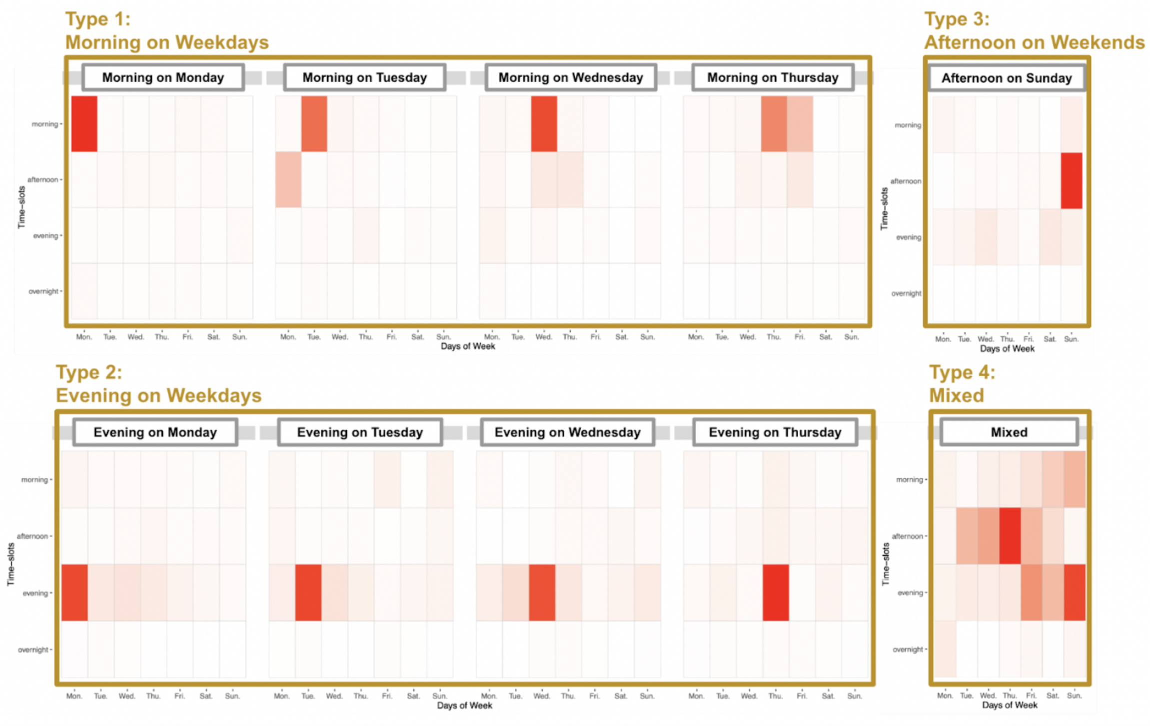


Figure 4.5: Chronotypes of learning habits from clusters

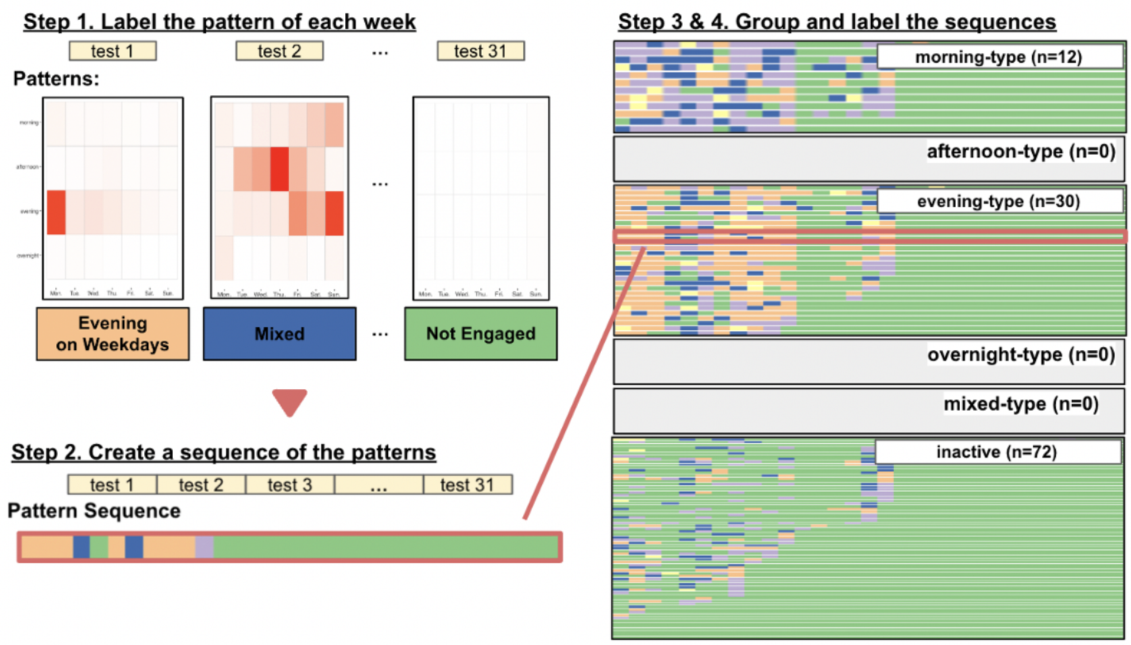


Figure 4.6: Extracting weekly patterns of practicing before tests

4.4.2 SRQ 1.4: Productivity of extracted learning habits

Habit productivity is calculated by Equation (3.1) considering Lakein (1991)'s factors of effective time management, as introduced in Section 3.3. First, learning indicators are selected to represent effectiveness, efficiency, and effortlessness in the math context.

- Effectiveness is indicated by the accuracy rate of attempts r on question i.
- Efficiency is indicated by how much time t was spent by learner j on question i, calculated in minutes.
- Effortlessness is indicated by the sensible pause counts l when learner j solved question i, which means the counts of pen pauses longer than 100 ms between two successive moves.

N indicates the total number of questions solved by learner j. The mean productivity of the dataset is 2.86 (SD=2.64; Min=0.00; Max=19.05).

Second, this study considers academic performance as the average of the test scores and tests its correlation to productivity. Productivity is shown to be correlated to performance ($r=0.247$, $p<.01$). Hence, this study verifies the use of productivity as the evaluation measure of habit outcome.

The ANOVA test is conducted in terms of the productivity of the 3 extracted habit types. The results are presented in Table 4.2. The productivity of the learners has significant differences between types of learning habits. This study further performs Tukey's post-hoc test and summarizes the results in Table 4.3. The morning and evening types of learners worked significantly better than inactive learners in terms of productivity. No significant difference could be identified between the 2 types. In other words, this study confirms that it is important to build learning habits. However, the analysis suggested that learners can choose to learn in different time sessions according to their habit types.

4.4.3 SRQ 1.5: Recommended habit types considering productivity at times of day

This study also explores the potential for recommending habit types to build considering the productivity of different time slots. First, Equation (3.1) is used to calculate the productivity of the time slots (i.e., morning, afternoon, evening, and overnight) for the

Table 4.2: ANOVA tests of productivity between habit types

	Habit types	**N**	**Mean (SD)**	**F**
Productivity	Morning	12	4.30 (5.88)	14.72***
	Evening	30	4.42 (6.88)	
	Inactive	72	1.97 (2.81)	

*** *p<.001*

Table 4.3: Tukey's post-hoc comparisons between habit types

	Habit types	**Mean difference**	**Adjusted p-value**
Productivity	Morning – Evening	– 0.120	0.987
	Morning – Inactive	2.327	$< .01^{**}$
	Evening – Inactive	2.448	$< .001^{***}$

learners. Second, this study performs the MANOVA test and compares the productivity between the types of learning habits. Figure 4.7 shows the result that the learners' productivity in each time slot has a significant difference between habit types (F=5.28, p<.001). In other words, learners with different habit types had a specific time slot to learn productively. This study uncovered that the detected habit type of learners does not always match their most productive time session. For instance, evening-type learners could learn significantly more productively in the evening. However, morning-type learners could learn significantly more productively in the afternoon. In addition, inactive learners could learn significantly more productively in the morning. Namely, it is possible to inform learners of their habit productivity as well as recommend which habit type they can consider building to increase productivity.

4.5 Discussion

For long-term habit types, this study found consistent learners referring to answers performed significantly better than those clustered as cramming learners. However, 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.

This indicates the types of learning materials might have different effects on the re-

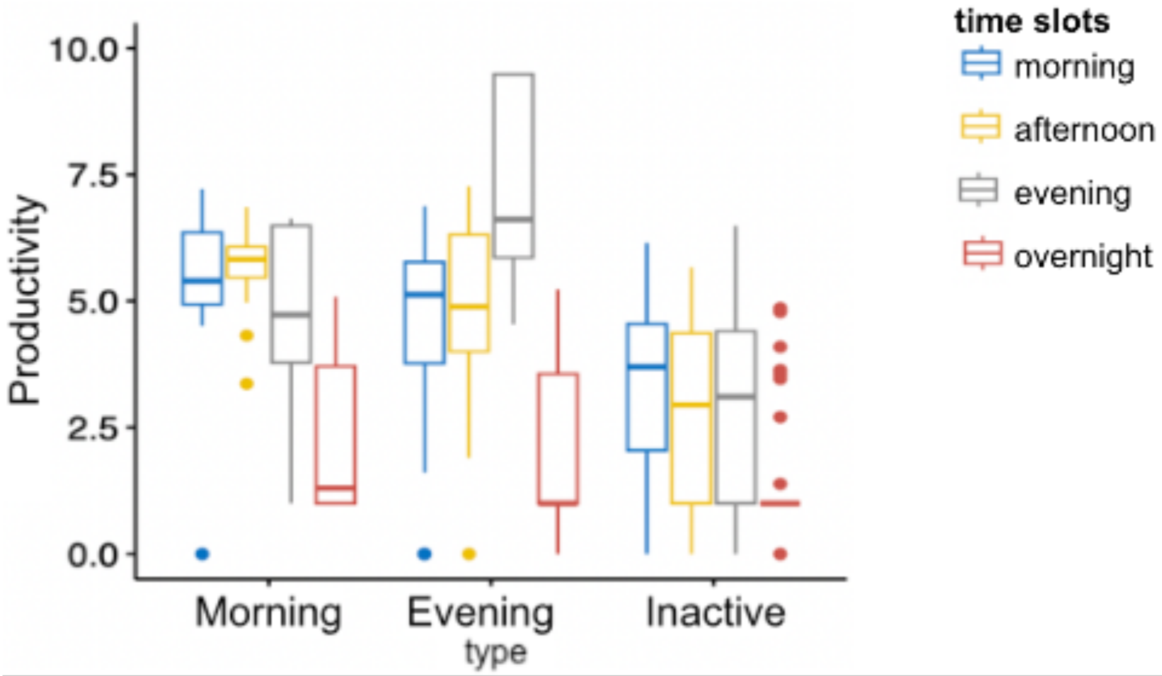


Figure 4.7: Learning productivity of different time sessions between habit types

lationship between time allocation and performance (Jenifer et al., 2022). However, the tendencies might not affect students' performance. As previous studies suggested, students can have their own learning strategies. There is no common strategy applied to all students, but a strategy suitable for a certain group of students (Parra, 2016; Schmeck, 1988; Tian et al., 2007).

Andergassen et al. (2014) provided an example of students' potential strategies for exam preparation. Students tended to understand the concepts first by reading the textbook and then doing exercises to strengthen their understanding. Verschaffel et al. (2019) also argued that doing exercises plays a main role in students' math learning. By referring to answers, students review their understanding (Higgins et al., 2019). Considering the approaching of the exam, students might increase their study time to enhance the effects of learning, which is regarded as cramming behavior by Chung and Hsiao (2020).

In this study, Figure 4.8 shows the difference in the daily reading time (DRT) patterns between active and inactive learners. In the beginning, (a) both spent time on textbooks, but (b) active learners 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 active learners spent more time than inactive learners. Also, (e) active learners studied the example answers at the same time. From such patterns, this study identified that (f) the students in active learners tend to do exercises and refer to answers throughout the period, which implies the drill-and-practice strategy for math learning.

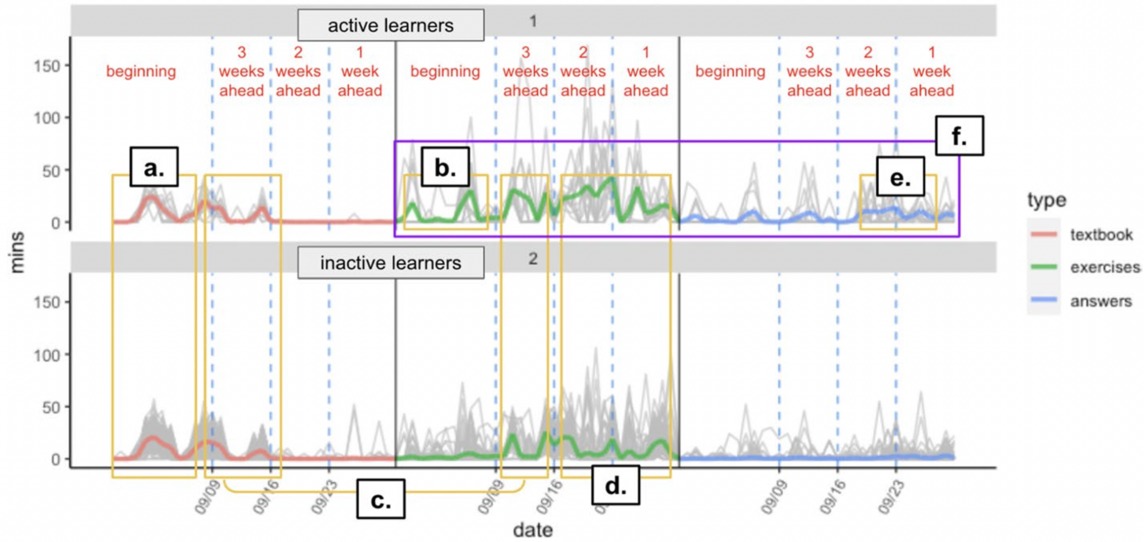


Figure 4.8: Clusters of patterns of daily reading time (DRT)

This study also compares the performance between the 2 groups clustered in terms of the overall DRT patterns in the period via independent samples t-test. The result does not show a significant difference between the performance of active learners and the others (Table 4.4).

Table 4.4: 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		

For short-term habit types, the key findings are as follows. (1) This study can identify different habit types of learners from their learning patterns over time. However, some learners did not keep learning and could not build learning habits from long-term perspectives. (2) Learners could build an appropriate habit type by learning productively at a specific time. However, some learners might be able to learn more productively if they built another type of learning habits.

This implies the problems that the learners might encounter through the lens of the time management cycle, which involves goal setting, time awareness/tracking, planning, taking action, and time shifting/adjusting (Peng & Kamil, 2018). First, inactive learners might need more motivation to take action continuously. Second, the learners who built less appropriate habit types might not be well aware of the time of day at which they could learn productively.

On the other hand, Liu et al. (2022) suggested that there exists a time-of-day effect on one's memory, interest, motivation, and achievement. Specifically, the circadian rhythms in cognitive processes affect school-related activities such as executive functions, which refer to the ability to program or regulate behavior and are essential for problem-solving. Continuously working at non-optimal times could lead to chronic circadian rhythm disruption and result in the deterioration of physical and mental health (Clarizio & Gill, 2022). Therefore, it is important to cater aspects of everyday learning to an individual's optimal time of day.

Chapter 5

Study 2: Detecting and tracing stages of learning habits

5.1 Overview

This study aims to develop a data model to extract the stages of building learning habits based on the transtheoretical model (TTM). To demonstrate the application of the proposed data model, this study uses learning logs of self-directed extensive reading as an example considering the importance to monitor whether learners build learning habits in the context. This study targets the dataset of 120 seventh-graders at the age of 13 on average from May 2020 to March 2021, for 11 months. The following sub-RQs are addressed.

- SRQ 2.1: How can a data model be developed to extract stages of learning habits from learning logs?
- SRQ 2.2: What insights can the data model provide regarding the stages of learning habits in the context of self-directed extensive reading?

5.2 Related works

When discussing habit stages, past studies have focused on building habits in the contexts such as physical activity or diet. Jimmy and Martin (2005) evaluated the patients' answers to a questionnaire and provided feedback regarding their current stage of change related to health-enhancing physical activity. In this case, the precontemplator (stage 1) was inactive, with no intention of becoming active, while the contemplator (stage 2) formed an intention to become active. Therefore, they presented people in stage 1 with varied benefits. People in stage 2 were provided leaflets with further information on how to become active. Similarly, Bahrami et al. (2022) investigated the effect of an educational intervention based on the physical activity stage of diabetic patients. Answering to the statements “I do not intend to exercise regularly in the next 6 months, I intend to exercise regularly in the next 6 months, I intend to exercise regularly in the next 30 days, I have been exercising regularly for less than 6 months, I have been exercising regularly for more than 6 months.”, the patients were respectively placed in one of the stages of change (precontemplation, contemplation, preparation, action, and maintenance). In case of the first 3 stages, the intervention strategy was presented in the form of the cognitive field, such as providing solutions to increase physical activity, how to do all kinds of physical activities, and so on.

On the other hand, in Clark et al. (2004) study, respondents were asked to classify themselves by selecting 1 of the 5 stages in terms of their fat intake. For example, those in the precontemplation stage did not consider the fat in their diet any thought at all, whereas those in the maintenance stage consciously avoided fat in their diet for longer than 6 months. The findings demonstrated that participants perceived themselves to have changed from contemplation to action in terms of reducing their fat intake at the 3-month assessment. Tsampoula et al. (2023) also investigated the nutritional behavior regarding the introduction of alternative proteins. The classification questionnaire in the stages of the transtheoretical model was completed at the beginning and end of the intervention to evaluate the movement of the participants from one stage to another. The transition of the stage, such as moving from the contemplation to action stage, was considered an indicator of successful non-modification of eating behavior by including functional foods and compliance with preventive controls. However, few studies have addressed the stages of habits in the context of learning.

This study focuses on extracting the stages of learning habits from the log data. Discussions in the medical field have elucidated the stages of habits. However, the approach to evaluate the stages have relied on self-reporting in questionnaires. On the contrary, while learning habits have gained attention in the educational field, past studies have focused on the different types—instead of stages—of learning habits. Moreover, the approach for extracting the types of learning habits has recently been enhanced using data-driven methods. Therefore, this study bridges the research gap in the approach of evaluating the stages of learning habits using learning logs.

5.3 SRQ 2.1: Data model of extracting habit stages from learning logs

To model the stages of learning habits from learning logs, this study proposes a data model based on the phases of behavior change, as conceptualized in Section 3.3. Figure 5.1 presents the 3 steps involved in deriving the stages that a learner undergoes when building learning habits.

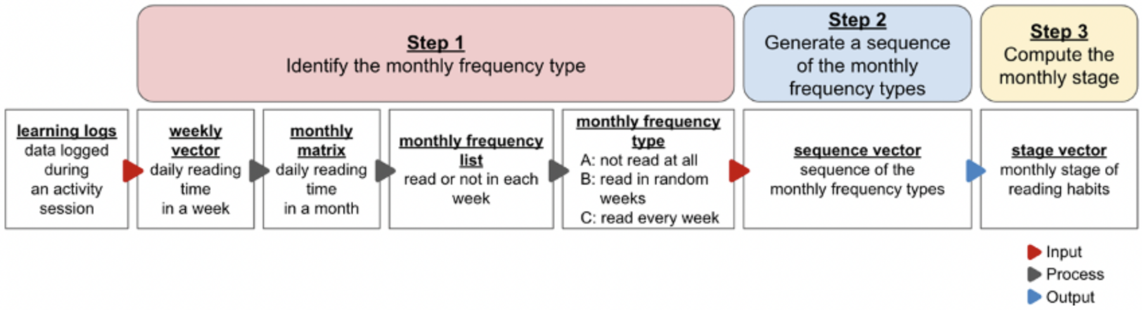


Figure 5.1: Workflow of extracting stages of learning habits from learning logs

Step 1: Identify the monthly frequency type

First, this study sums the learner's everyday reading time and aggregates the sum values into a weekly vector with 7 elements to present the reading time from Monday to Sunday. Second, this study creates a monthly matrix by binding every four weekly vectors. Third, based on the monthly matrix, this study creates a list presenting the frequency with which students read each month. Fourth, this study converts the frequency list into a categorical value representing the monthly frequency type (see Figure 5.2, i.e., A = not read at all, B = read in random weeks, and C = read every week).

Step 2: Generate a sequence of the monthly frequency types

This study creates a sequence of monthly frequency types and aggregates their values of monthly frequency types into a sequence vector. The sequence vector stores the monthly frequency types chronologically. For example, x^s is a sequence vector for learner s, comprising the elements of x^s_i. x indicates the categorical value of the monthly frequency type, and i indicates the i_{th} month. The sequence vector such as [B, B, C] suggests that Frequency B occurs in the first and second months, followed by Frequency C (see

Figure 5.3).

Step 3: Compute the monthly stage

This study computes the stages of the learning habits and generates a stage-computing algorithm with a calculation rule based on the measurements described in Section 3.3. By inputting a sequence vector into the algorithm, this study outputs a stage vector. The stage vector lists the stages a learner has undergone in the process of building learning habits. The stage in the vector is represented by an integer ranging from 1 to 5 (i.e., from precontemplation to maintenance stage). For example, y^s is the stage vector for learner s as follows. It contains the elements of y_i^s. y indicates the integer representing the stage, and i indicates the i_{th} month. The stage vector such as [2, 2, 3] suggests that the learner was in contemplation stage for 2 months and proceeded to preparation stage in the last month (see Figure 5.4).

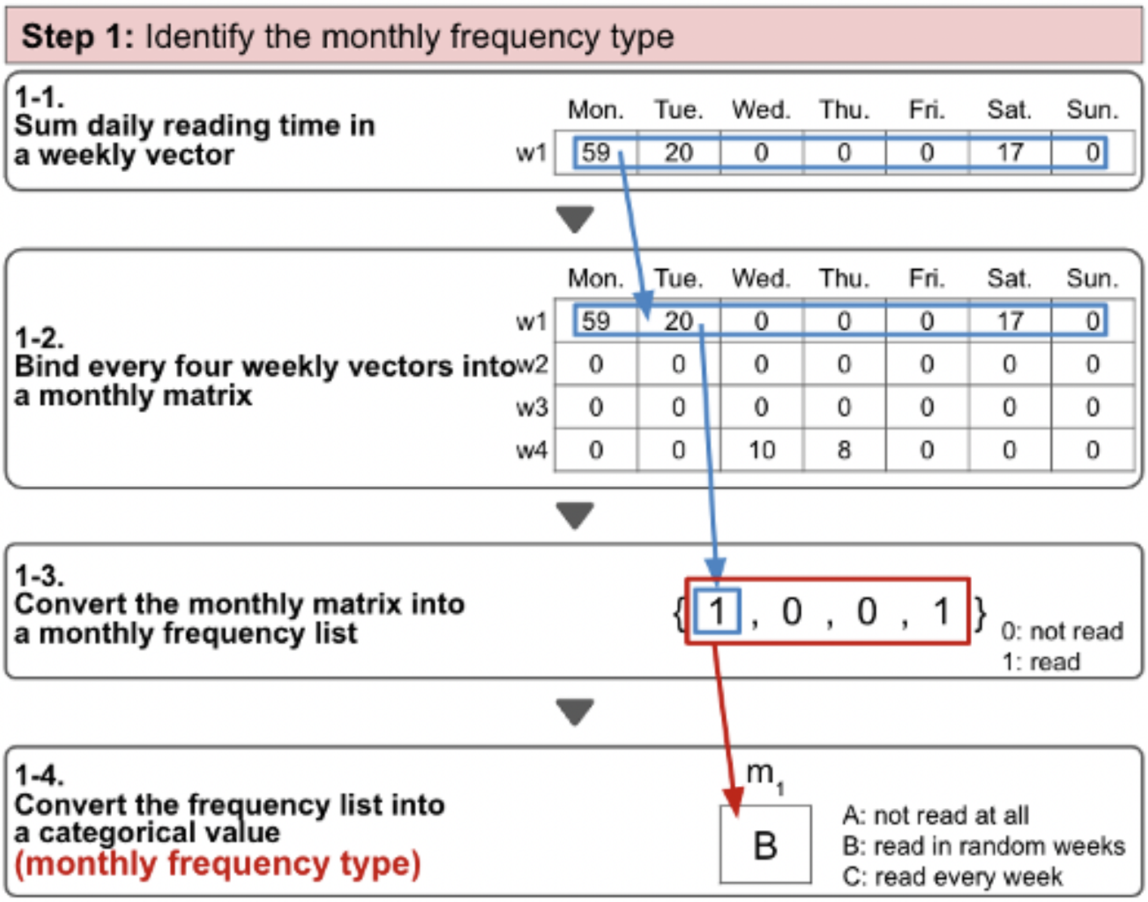


Figure 5.2: Identifying the monthly frequency type

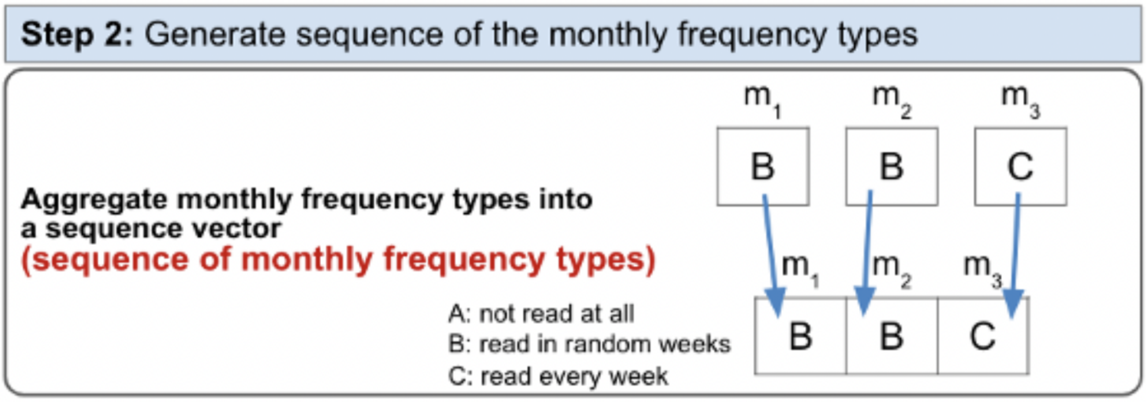


Figure 5.3: Generating a sequence of monthly frequency types

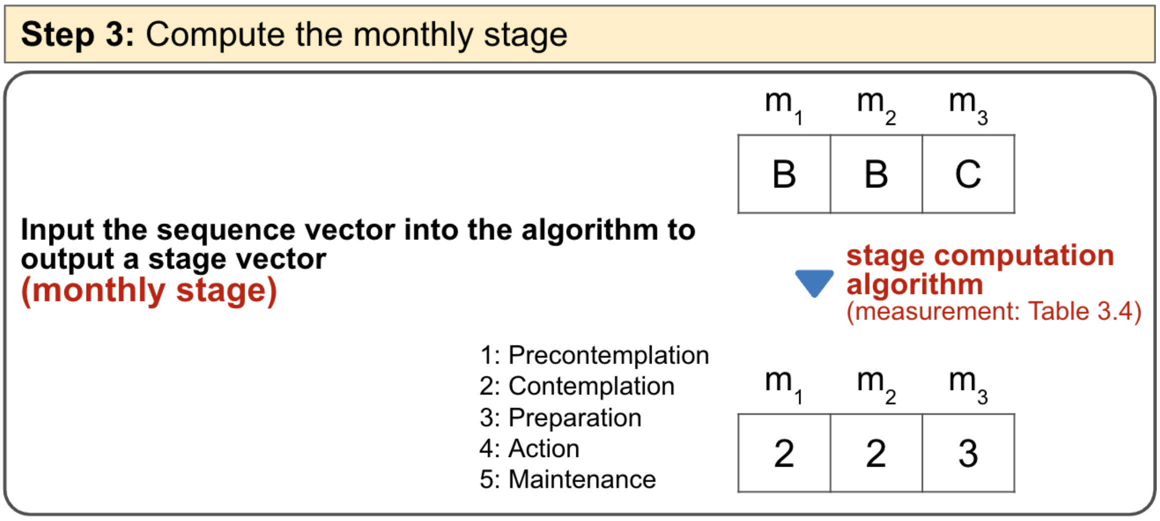


Figure 5.4: Computing the monthly stage

5.4 SRQ 2.2: Process of building English reading habits

5.4.1 Stages of self-directed extensive reading habits

Figure 5.5 focuses on data from a random student, to show how this study extracts stages of self-directed extensive reading habits from log data and provides examples of visualizations that specify the student's reading behaviors in months. For example, the visualizations based on the monthly matrices suggest that the student read in random weeks (i.e., weeks 1 and week 4) in the first month (a). By quantifying these behaviors and processing them using the algorithm, this study derives the output of a vector. The vector enables the visualization of the stages that the student underwent across these months (b). The following pattern provides further explanation for identifying the process of how students build learning habits based on their reading behaviors. The student read in random weeks in the first month, indicating he or she was considering building learning habits (i.e., staying in contemplation stage). The line in the visualization indicates that the student started from contemplation stage, proceeded through preparation and action stage, and entered maintenance stage, despite returning to contemplation stage.

Collectively, this study determines the proportion of the maximum stage that students achieved. During this period, as their maximum stage, 19 students reached the contemplation stage at most (15.8%), 39 students reached the preparation stage at most (32.5%), 34 students reached the action stage at most (28.3%), and 28 students reached the maintenance stage at most (23.3%). Thereafter, students are distinguished into those who achieved the maintenance stage (Figure 5.7) and those who did not (Figure 5.6). This study focuses on the stages after the maintenance stage, as presented in Figure 5.7, to describe students' behaviors after they built their learning habits.

Figure 5.6 presents the behaviors of those who did not reach the maintenance stage, which suggests that they had not yet built reading habits. Students (e.g., student S086) who reached the contemplation stage as their maximum, remained stuck there for months. This behavior can also be identified in the students (e.g., student S089) who reached the preparation stage as their maximum. Further, some other students (e.g., student S051) who moved back and forth between stages during this period. This study identifies the above 2 behaviors in the students (e.g., student S043, S113, and S007) who reached the action stage as their maximum. Additionally, this study distinguishes the students (e.g., student S113) who moved back and forth between the preparation and earlier stages, despite once entering the action stage, from those (e.g., student S007) who moved back and forth between the action and earlier stages.

Figure 5.7 presents the behaviors of those who achieved the maintenance stage, which suggests that they had built reading habits. In particular, we focused on their behaviors after they entered the maintenance stage (i.e., how they maintained their reading habits). Some students (e.g., student S035) stayed in the maintenance stage, while others (e.g., student S088, S016, and S044) returned to the earlier stages. Among the students in the latter case, some (e.g., student S088) returned and remained stuck in the contemplation stage. Some students (e.g., student S016) returned and tried to (but could not) re-enter

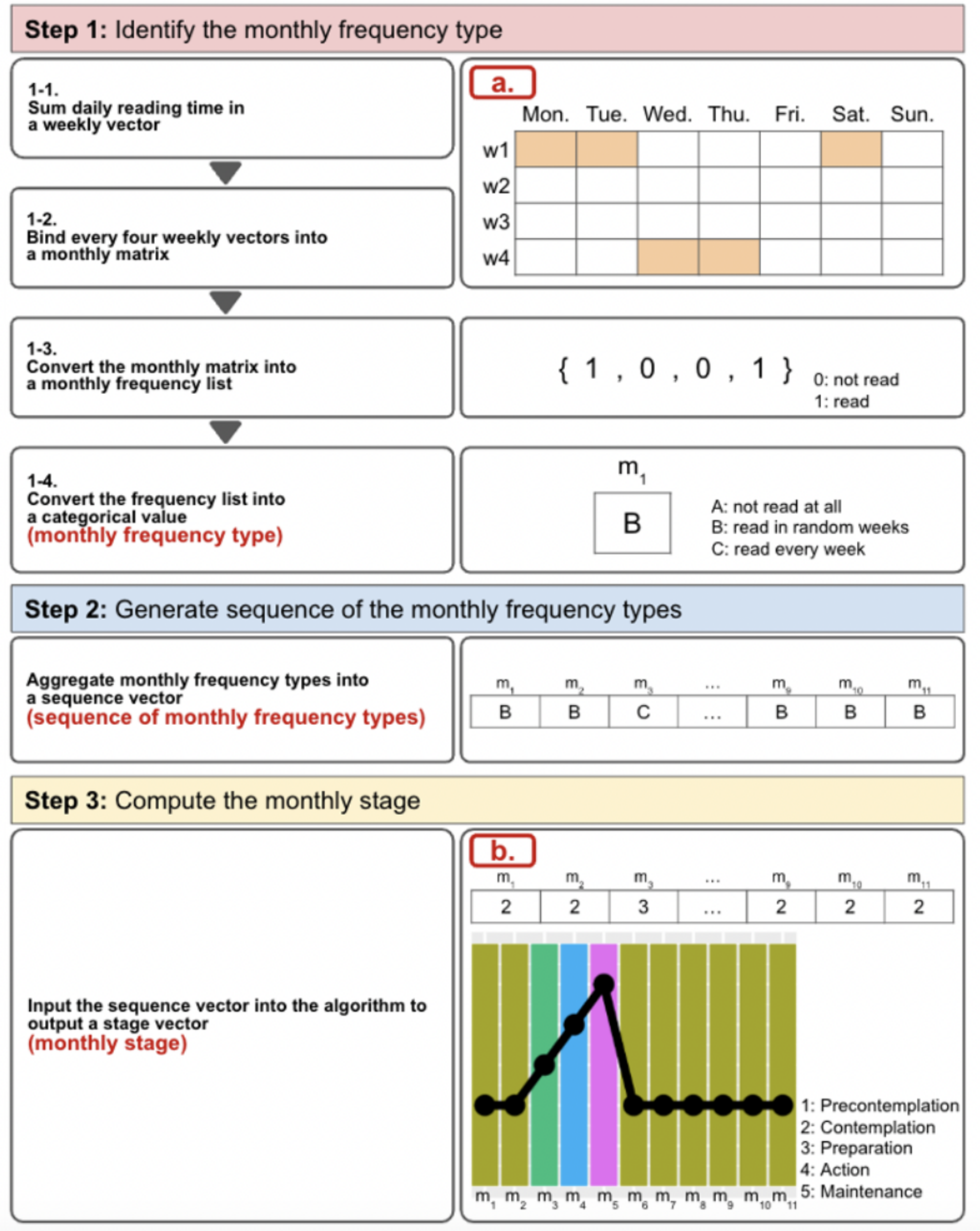


Figure 5.5: Extracting stages of self-directed extensive reading habits

the maintenance stage by moving back and forth between the stages. Others (e.g., student S044) returned and re-entered the maintenance stage after moving between the stages.

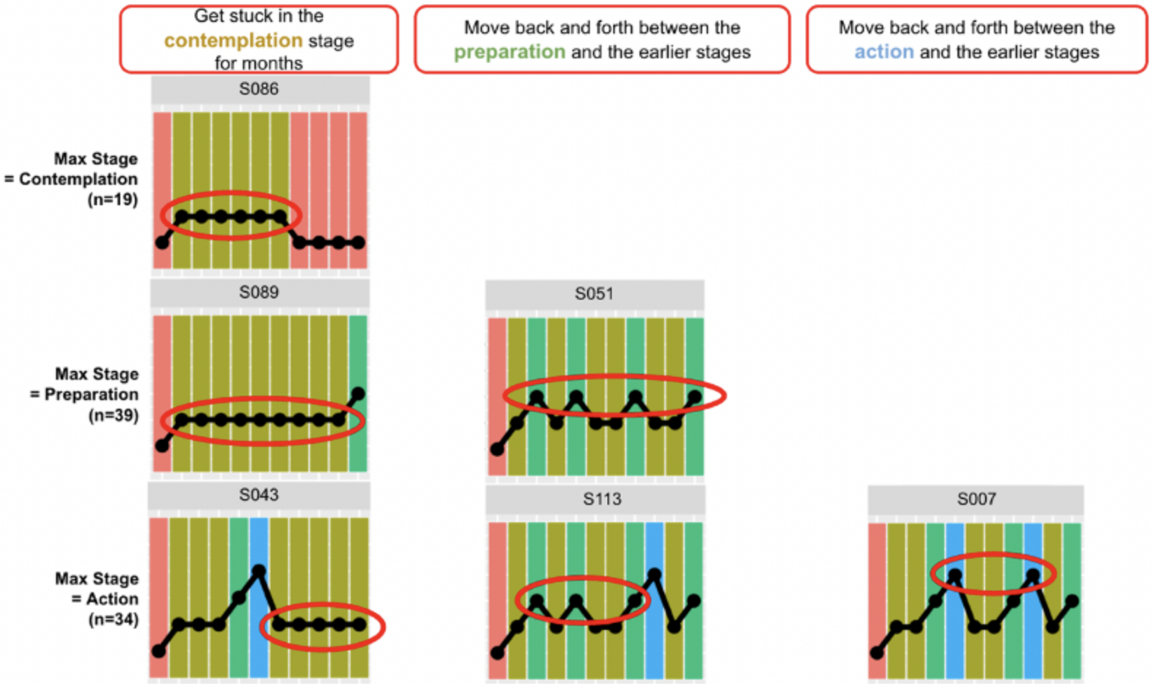


Figure 5.6: Behaviors of students who did not achieve the maintenance stage (not built reading habits yet)

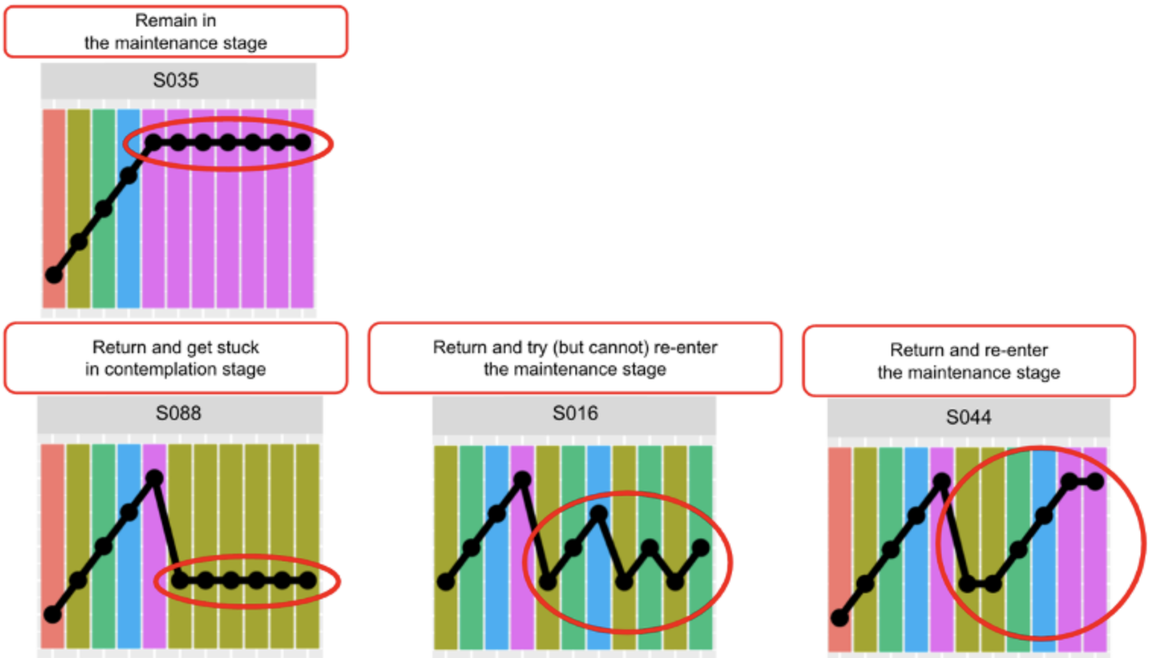


Figure 5.7: Behaviors of students who achieved the maintenance stage (built reading habits)

5.4.2 Stage-based interventions to support learning habit-building

The stages can motivate different intervention designs to support habit-building. Specifically, the transtheoretical model (TTM) guided the designers to apply different concepts in the feedback message for the people in each stage (Grimley et al., 1994). The following lists the concepts and their definition.

- Motivation: People's intention to execute and maintain behaviors.
- Self-evaluation: People's evaluation and reflection of their behaviors.
- Self-efficacy: People's belief in their capacity to execute and maintain behaviors.
- Decisional balance: People's assessment of the positive and negative consequences of selecting a new behavior.
- Self-awareness: People's awareness of the status of their behaviors.

This study also designs stage-based messages that prompt the learners to transit to the next stage for building their reading habits, as listed in Table 5.1. This study regards the stages as levels that learners can go up and down over time. For instance, a learner can start from the contemplation stage, proceed through the preparation and action stage, and enter maintenance stage. However, he or she can still return to the contemplation stage afterwards. To support learners to transit the stages and build learning habits, the relationships in Table 5.1 present the transition between each 2 stages can be prompted by a specific feedback message that applies the supporting concepts from the transtheoretical model (Grimley et al., 1994). For instance, the message–reading can help improve your English ability–tackles learners' motivation and decisional balance between pros and cons of habit-building, aiming to facilitate learners transfer from the precontemplation to contemplation stage. The evidence of habit-building supported by such stage-based interventions were also confirmed in the preceding studies (G. He et al., 2023; Lee et al., 2017; Merz & Steinherr, 2022).

5.5 Discussion

In brief, the students who did not reach the maintenance stage could be stuck in the contemplation stage or move between stages. The stages wherein the students moved

Table 5.1: Feedback messages that prompt the transition to the next stage

Transition between stages	**Feedback messages**	**Applied concepts from TTM**
Precontemplation to contemplation stage (stage 1 → 2)	Reading can help improve your English ability.	Motivation, decisional balance
Contemplation to preparation stage (stage 2 → 3)	Let's increase the reading time!	Self-evaluation, self-awareness
Preparation to action stage (stage 3 → 4)	Let's find a good way to keep reading!	Self-evaluation, self-awareness
Action to maintenance stage (stage 4 → 5)	Let's keep reading!	Self-evaluation, self-awareness
Remain in maintenance stage (stage 5 → 5)	Let's be confident in maintaining reading habits!	Self-efficacy

between differed from their maximum achieved stages. By contrast, students who achieved the maintenance stage remained in the stage or relapsed to the earlier stages. Among those who relapsed, some could re-enter the maintenance stage, while others could become stuck in the contemplation stage or move between stages. That is, the behaviors of getting stuck in the contemplation stage and moving between stages could be identified both before and after the students entered the maintenance stage, which might indicate different statuses for the students.

The transtheoretical model informs the possible interpretations for the behavior of becoming stuck in the contemplation stage. Those who were stuck and could not achieve the maintenance stage were thinking about building learning habits but might not have had enough motivation. The transtheoretical model suggests that people in the contemplation stage may still feel ambivalent toward changing their behavior (Grimley et al., 1994). However, those who achieved the maintenance stage but relapsed and became stuck thereafter built learning habits but could not maintain them. This might be because they recognized the pros of changing their behavior and took action even though the emphasis on the pros might still be equal to the cons (Grimley et al., 1994).

Lally et al. (2010) indicated that people repeat a behavior until they automatically respond to a context with the habits that they built. Therefore, the students who moved back and forth before entering the maintenance stage might repeat the behavior to build learning habits and require more time to achieve the automaticity. Additionally, this study distinguished the behavior of moving between the preparation and earlier stages from that of moving between the action and earlier stages. Gardner et al. (2020) indicated that the frequency of the behavior and the intention to perform the behavior determines the strength of habits. This difference might indicate the different strengths in students' learning habits accordingly. On the other hand, Lally et al. (2010) indicated that people act to maintain their habits. This explains why the students tried re-entering the maintenance stage after relapse. The behavior of moving between stages identified at this time might represent the students' efforts to maintain their learning habits.

Chapter 6

Study 3: Prototyping and evaluating data-informed support for learning habits

6.1 Overview

This study aims to design LA dashboard elements to guide learners through the process of building learning habits–a change of behavior. This study investigates a dataset of 96 learners, at the average age of 15, extracted from the 32-month English extensive reading program. The insights into the context are brought to proposing the system-generated persuasion mechanism–HAbit-Building Informed by Trace data (HABIT)–based on the Persuasive System Design (PSD) model. To explore the potential of the proposed data-informed support, this study further surveys learners' perceptions of their learning habits and performs a comparative analysis of discrepancies between self-report and log data. The following sub-RQs are answered.

- SRQ 3.1: How can data-informed support for building learning habits be designed?
- SRQ 3.2: Do learners identify their learning status as the log data detects?

6.2 Related works

Past studies indicated significant associations between types of learning habits and academic achievements of learners (Itzek-Greulich et al., 2016; Randler & Frech, 2006). Ariel and Dunlosky (2013) found that students who were most active in the morning significantly outperformed students who were most active in the afternoon and evening. On the other hand, Romero and Barbera (2011) reported a close relationship between evening time slots and better academic performance in collaborative activities, whereas both morning and evening were closely related to academic performance for individual activities. While the results might differ on learning activities, types of learning habits can imply how well learners can perform. Therefore, it has become important to investigate how the types can be extracted from learning logs.

This study can also find works related to habits in the medical field. Similarly, the researchers extracted types of habits from the data of physical sensors that record people's daily activities (Duchêne et al., 2007). Furthermore, they evaluated stages of habits when consulting and supporting the patients to build appropriate habits, such as a routine of doing exercise. They mainly used different scales that rely on the self-reports of the patients (G. He et al., 2023). While it was common to extract different types of learning habits from log data in the preceding educational research, scant attention has been paid to the extraction of the stages.

In addition, the regular scheduling of learning activities to build learning habits involves whether learners can manage their time effectively. Nowadays, societies pay more attention and care to proper time management through proper time distribution skills to ensure that their objectives are achieved (Al-Janabi et al., 2018). Lakein (1991) proposed that effective time management includes the 3 factors such as effectiveness, efficiency, and effortlessness. In terms of the evaluation, while Liu et al. (2022) considered all the factors, they relied on the self-report of learners from the questionnaire, which could be regarded as subjective. On the other hand, Ricker et al. (2020) and Sher et al. (2022) evaluated types of learning habits using test scores, which could be considered an objective indicator. However, they focused on the single factor of effectiveness in terms of time management.

Therefore, this study can bridge the gap in the educational field related to integrating both types and stages of habits from a data perspective. Furthermore, this study presents a novel evaluation of learning habits by using learning logs as an objective measurement of the 3 factors of time management. Table 6.1 summarizes the existing approaches to detecting habits and compares this study with other research works.

Table 6.1: Approaches of detecting habits in medical and educational fields

	Medical research	**Preceding educational research**	**This educational research**
Types of habits	from logs (Duchêne et al., 2007)	from logs (Ricker et al., 2020)	from logs
Stages of habits	by questionnaire (He et al., 2023)	little focus	from logs
Productivity of habits	little focus	by questionnaire (Liu et al., 2022)	from logs

6.3 SRQ3.1: Development of HAbit-Building Informed by Trace data (HABIT)

To design data-informed support for learning habit-building, this study first analyzes target dataset to extract different types of learning habits and their stages. Then, the understanding of the learning context is brought into selecting design principles from the PSD model to designs elements of the LA dashboard.

6.3.1 Understand the context: Profiles of learning habits

This study considers types and stages of learning habits and generates learners' habit profiles using their log data (Table 6.2). First, this study summarizes the learners who have different types of learning habits. Then, in terms of each type, this study extracts the max (i.e., the highest stage during the period) and current (i.e., the stage in the last month) stages where the learners stay and present their distribution.

The results show that 56% (n=54) of the learners have the morning type of learning habits, followed by the afternoon (20%, n=19), evening (17%, n=16), and overnight (1%, n=1) types. Furthermore, considering the max stage of learning habits, the learners with the morning type could reach upper stages such as the action (stage 4) and maintenance (stage 5) stages, while the learners with other types mostly reached the contemplation stage (stage 2). Considering the current stage of learning habits, 1 learner with the afternoon type is detected to stay in the contemplation stage (stage 2). In contrast, other learners stay in the precontemplation stage (stage 1).

Table 6.2: The habit profiles of the learners considering their types and stages of learning habits

Types of learning habits	**Total learners**	**Learners in each stage**		
		Stage	**Max**	**Current**
Morning	54	precontemplation (stage 1)	0	54
		contemplation (stage 2)	51	0
		preparation (stage 3)	1	0
		action (stage 4)	1	0
		maintenance (stage 5)	1	0
Afternoon	19	precontemplation (stage 1)	0	18
		contemplation (stage 2)	19	1
		preparation (stage 3)	0	0
		action (stage 4)	0	0
		maintenance (stage 5)	0	0
Evening	16	precontemplation (stage 1)	0	15
		contemplation (stage 2)	14	1
		preparation (stage 3)	0	0
		action (stage 4)	2	0
		maintenance (stage 5)	0	0
Overnight	1	precontemplation (stage 1)	0	1
		contemplation (stage 2)	1	0
		preparation (stage 3)	0	0
		action (stage 4)	0	0
		maintenance (stage 5)	0	0

In addition to the expected types (i.e., morning, afternoon, evening, and overnight) of learning habits, this study also identifies 6 learners (6%) whose logs show more than 2 peaks in their reading time. These learners are considered to have mixed types of learning habits. This suggests they might tend to read both in the morning and evening, for example. Which of the two habit types is recommended to be built can be told from further examination of their learning productivity.

6.3.2 Select PSD principles: Components of HABIT

Understanding learners' habits in the above context, this study further designs LA dashboard elements by selecting and applying design principles of PSD model, widely adopted to develop Behavior Change Support Systems (BCSSs). As a result, a system-generated persuasion mechanism, HAbit-Building Informed by Trace data (HABIT), is proposed to guide learners through the process of building learning habits–a change of behavior (Figure 6.1). Specifically, HABIT consists of 3 components: detection module, diagnosis module, and recommendation engine. The following elaborates on the components and their embedded PSD principles.

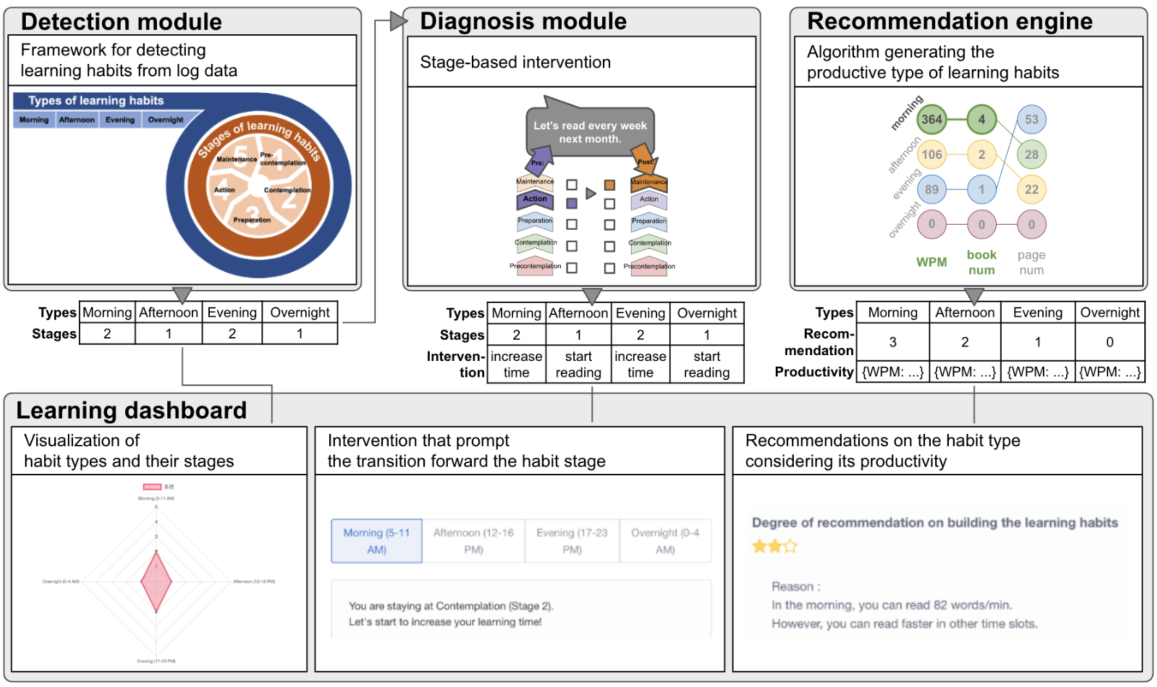


Figure 6.1: HAbit-Building Informed by Trace data (HABIT)

Detection module for learners' self-monitoring

The detection module extracts types and stages of learning habits from learners' daily learning logs. This is motivated by the extracted habit profiles, informing the learners who once reached the upper stage (e.g., action stage, stage 4) as the highest but finally relapse to the lower stage (e.g., precontemplation stage, stage 1). Hence, the design principle of self-monitoring is applied and instructs that track of one's performance or status can help achieve goals (Oinas-Kukkonen & Harjumaa, 2009). Specifically, this study designs a visualization of the monthly status of types and stages of learning habits. It shows a specific type of learning habits and its current stage (Figure 6.2). This aims to remind the learners of their learning status and whether the stages fluctuate between months.

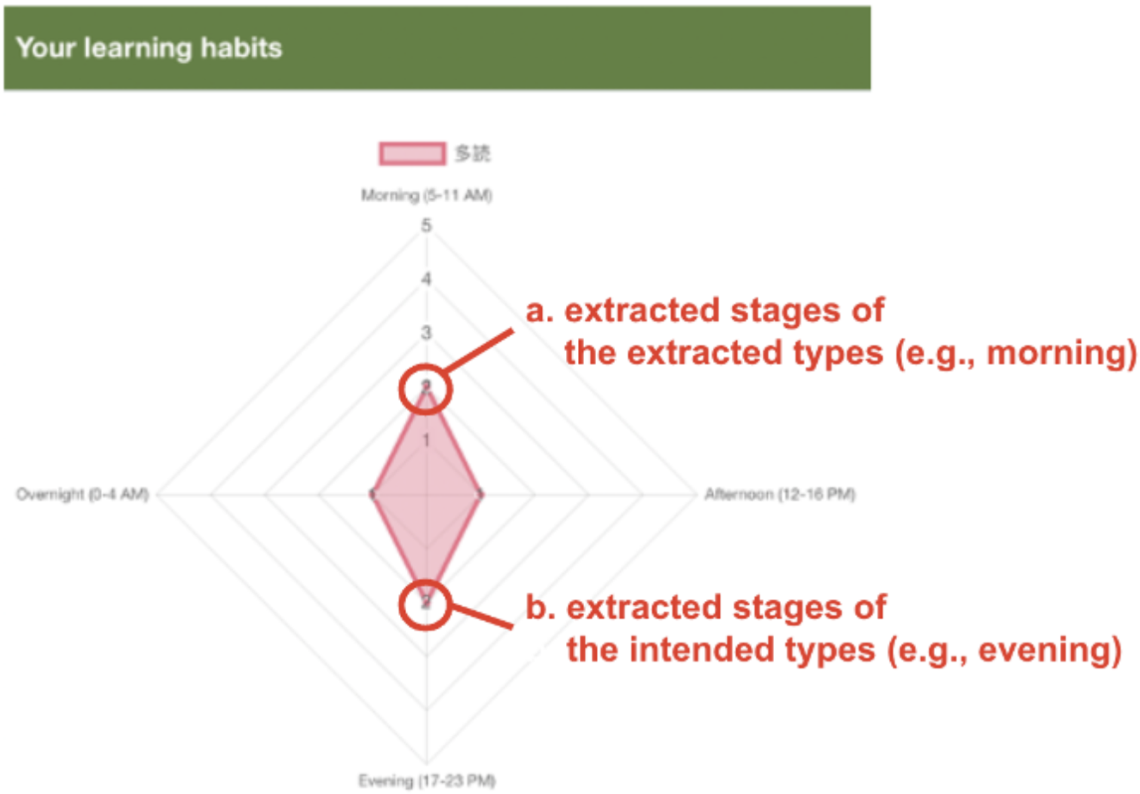


Figure 6.2: Visualization of the LA dashboard (design principle: self-monitoring)

Diagnosis module and recommendation engine for system suggestion

The diagnosis module prescribes different interventions to prompt the transition between stages, aiming to facilitate habit-building processes. On the other hand, the recommendation engine generates the computed recommendations on which habit type to build based on learners' productivity in different time slots from their learning logs. The components are implied by the understanding that the learners might tend to learn in a time slot without high learning productivity. This study considers the design principle of suggestion can serve these learners since it instructs that fitting suggestions can increase the persuasive powers of changing behavior (Oinas-Kukkonen & Harjumaa, 2009). Hence, the feedback on the LA dashboard is designed as follows.

First, stage-based messages are generated from the diagnosis module and embedded with the concepts from the transtheoretical model, as introduced in Table 5.1. The messages suggest the learners carry out different actions based on their extracted stages of learning habits to reach the upper stages and change their behaviors (Figure 6.3).

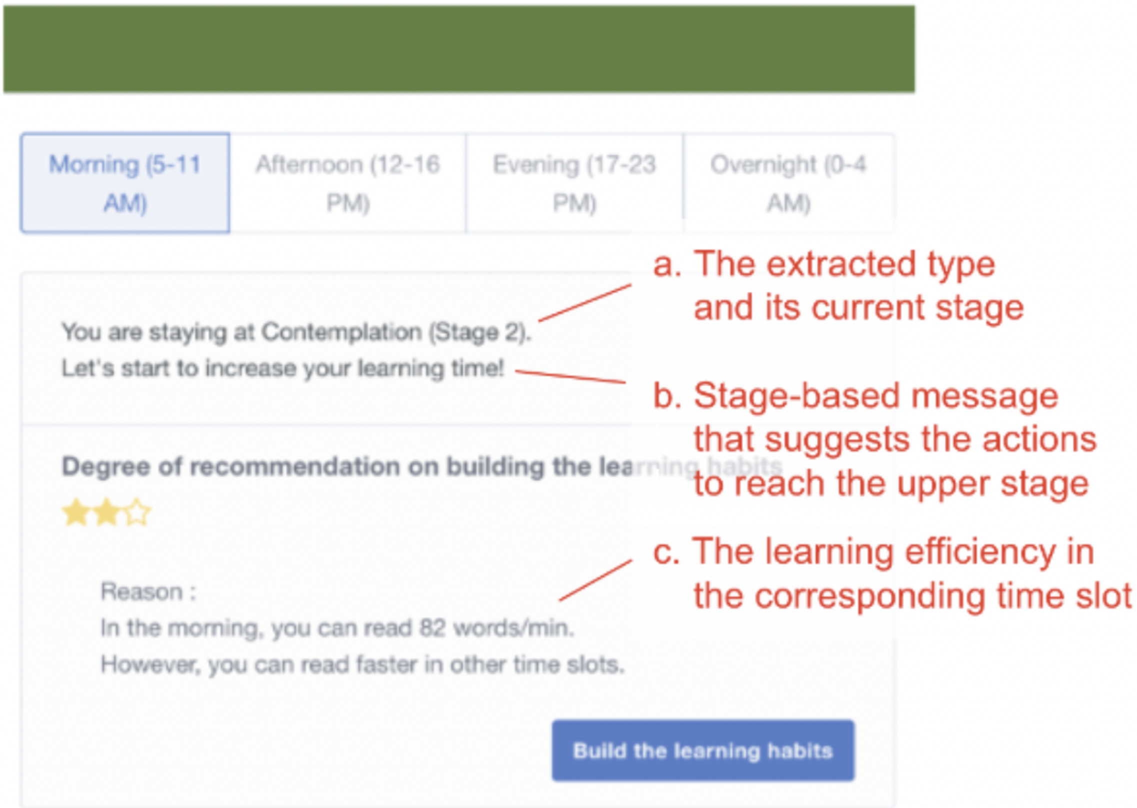


Figure 6.3: Diagnostic feedback of the LA dashboard (design principle: suggestion)

Second, the feedback also contains the suggestion on which habit type to build based on learners' productivity in different time slots, computed by the recommendation engine. This study designs Algorithm 1 for the GOAL system to generate the feedback based on their BookRoll reading logs stored in the LRS. The algorithm considers 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 learners first read in their free time and introduces 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, Figure 6.4 illustrates how the recommendation works by presenting the following example of a learner's status from the dataset of the study 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
$df \leftarrow filter(LRS, uuid = q.uuid)$
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
    $P \leftarrow sort(df, productivity)$
    $P' \leftarrow P.head$
    $F \leftarrow$ "In/at" $+ P'.slot +$ "you can read the most productively."
end if
$indicator \leftarrow []$
for i in P, P' **do**
    $indicator.append(i)$ if $max(P.i) = P'.i$
end for
$reason \leftarrow$ "Specifically, the indicator (" $+$ $indicator$ $+$ ")outperform 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. Hence, the system further outputs the indicators (i.e., number of books, number of pages, and words per minute) that also 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(s) (number of pages: 23) outperform other times of day."

Figure 6.4: Workflow of how system generates and learners receive recommendations

6.4 SRQ3.2: Comparative analysis for learners' perceptions of habit-building

This study also approaches the learners and carries out a questionnaire for their perception of learning habits and opinions about the support design (Figure 6.5). The questionnaire is developed with the following process. First, this study designs the questions based on the proposed learning habits detection framework. Second, this study validates the items in the questionnaire with the research team members as LA experts. Third, this study verifies with the schoolteacher that the items can be understood by junior high school students.

Specifically, the learners indicate the time slot when they intend to read, which suggests different types of learning habits (a). Then, an example is presented to illustrate the process where a student underwent the 5 stages of learning habits and request the learners to report which stage they perceive to stay in by indicating their current status is close to a specific phase of the student in the example (b). Finally, the questionnaire provides the feedback design based on each stage and asks the learners who perceive to stay in that stage whether the feedback can help them build learning habits. This study further requests them to elaborate on the reason from the perspective of the concepts applied from the transtheoretical model (TTM) (c). In total, this study collects the responses from all the 96 learners (i.e., rate of response: 100%).

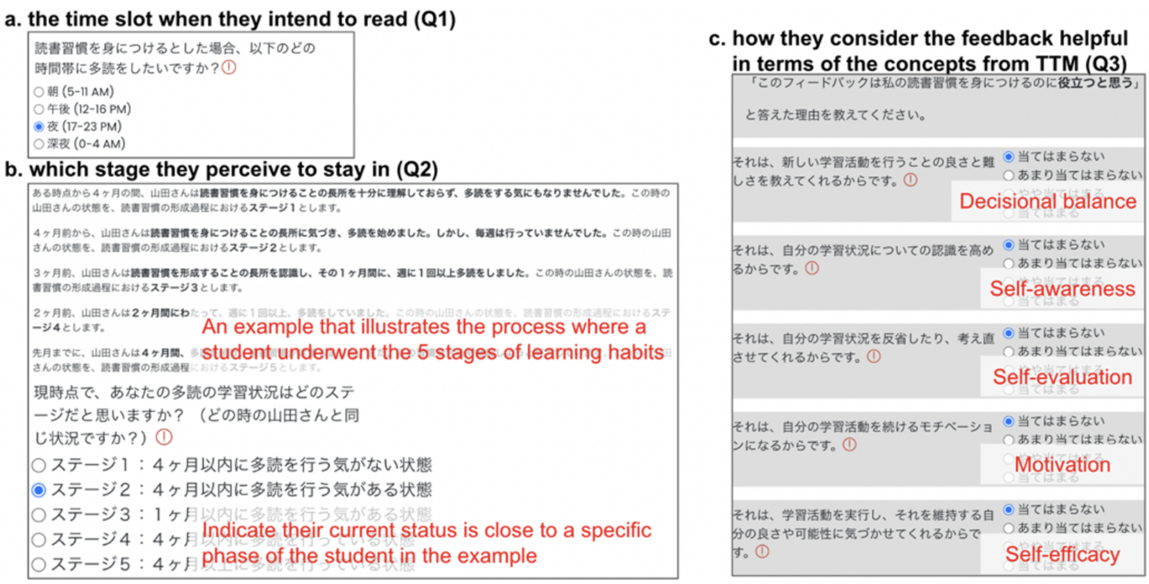


Figure 6.5: Questionnaire for learners' perception of their learning habits

6.4.1 Types and stages reported by the learners

Regarding types of learning habits, the questionnaire shows that 40% (n=38) of the learners intend to build the morning type, followed by the evening (33%, n=32), afternoon (26%, n=25), and overnight (1%, n=1) types. Furthermore, the results indicate that a high ratio–71% and 100% respectively–of learners intend to build consistent learning habits in terms of the morning and overnight types extracted from log data. In contrast, 34% and 36% of the learners intend to build consistent learning habits in terms of the evening and afternoon types extracted from log data.

As for stages of learning habits, 67% (n=64) of the learners perceive staying in the precontemplation stage (stage 1), followed by the contemplation (stage 2) (22%, n=21) and preparation (stage 3) (9%, n=9) stages. For the action (stage 4) and maintenance (stage 5) stages, 1 learner (1%) perceives to stay in each of them. Furthermore, this study makes a comparison between the perceived and extracted stages for the learners reported to stay in the precontemplation (stage 1). The results indicate that 98% (n=63) of them show consistency when compared to the extracted current stage. However, in terms of the current stage, this study cannot find consistency for the cohort of the contemplation (stage 2), preparation (stage 3), action (stage 4), and maintenance (stage 5) stages.

6.4.2 Perception of the learners regarding the feedback messages

The questionnaire shows that 58% (n=56) of the learners find the diagnostic feedback helpful in building learning habits. Among these learners, 55% (n=31), 29% (n=16), 14% (n=8), and 2% (n=1) of the learners evaluate the messages from the precontemplation (stage 1) to action (stage 4) stage respectively. Table 6.3 presents to what extent the learners who perceive to stay in the 4 stages consider the TTM concepts embedded in the message can help them build learning habits. The results show a high percentage of agreement–more than 75% of the learners—on the concepts expected to contribute to the helpfulness of the message of the contemplate (stage 2) and preparation (stage 3) stages. On the other hand, more than 75% of the learner agree that the concepts of decisional balance and self-evaluation help in the messages of the precontemplation (stage 1) and action (stage 4) stages as well. However, a low percentage of the learners–less than 50%–agree with the concepts of motivation and self-awareness for the messages of the 2 stages respectively.

6.4.3 Difference among detected and perceived productive learning time slot

In the questionnaire, the learners indicated their intended time slot for building reading habits. This study compares the response with the productive time detected from their learning logs, as summarized in Table 6.4. 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,

Table 6.3: Helpfulness of the stage-based message from the perceptions of the learners

	Learners who evaluate the message	**Applied concepts from TTM**	**Ratio of agreement on helpfulness**
Precontemplation to contemplation stage (stage 1 → 2)	31	Motivation	48%
		Decisional balance	77%
Contemplation to preparation stage (stage 2 → 3)	16	Self-evaluation	75%
		Self-awareness	94%
Preparation to action stage (stage 3 → 4)	8	Self-evaluation	88%
		Self-awareness	75%
Action to maintenance stage (stage 4 → 5)	1	Self-evaluation	100%
		Self-awareness	0%

as shown from their logs. Namely, the results suggest that learners might lack awareness of their learning productivity at different times of the day.

Table 6.4: Comparison between the detected and perceived productive learning time

	Detection				**Total perception**
	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 detection	29	33	33	1	96
Consistency with detection	24%	15%	70%	0%	36%

6.4.4 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, this study examines whether learners identify their learning status at a time of day as the log data detects, as Figure 6.6 illustrates.

First, the learners are divided 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, this study investigates the unaware learning status of their focused learning activities. For instance, Learner A 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 B 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, this study aggregates 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. In other words, the learning logs of most learners uncovered the unaware learning status of their focused activities. For the learners who reported a productive learning time consistent with the detection from log data, the recommendations can inform them of the activity where they performed beyond their awareness. For the learners who indicated a different slot, the recommendations can suggest when they could work productively regarding their focused activities. Hence, the results present the potential of the recommendations to increase learners' awareness of their learning habits.

6.5 Discussion

Compared to learners' perceptions of habit-building, their logs informed this study of the misalignment between self-report and trace data. Such discrepancies can be attributed to learners' difficulties with self-regulation. As Andrade (2014) suspected, learners did not intuitively know how to regulate their learning effectively. The findings of this study also suggest that learners might lack awareness of their learning productivity and status at

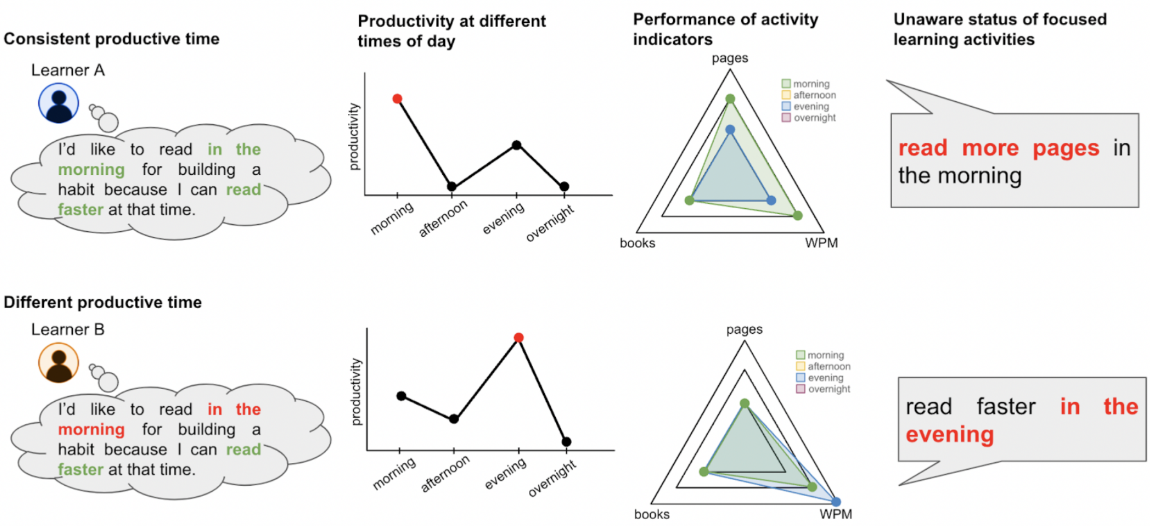


Figure 6.6: Example cases of unaware learning status detected from log data

different times of the day. On the other hand, Choi et al. (2023) argued another possible reason for the misalignment is that learners tend to describe themselves as who they *would like* to be rather than who they *will* be. Hence, their response to the questionnaire could not align with their actual learning behaviors detected from log data. Nguyen et al. (2024) considered these important to the support of adaptive learning systems. Similarly, this study presents the potential of the recommendations for assisting learners in building productive learning habits.

While the learners found the feedback design helpful, the concepts of motivation and self-awareness did not function in the feedback as expected. The findings might result from the use of a one-size-fits-all approach, which provides the same feedback to all the learners. However, as Ferron and Massa (2013) indicated, it is important to recognize that behavior change is a dynamic process that takes place over time. For instance, (pre)contemplation stages sometimes take years (Pintar & Erjavec, 2021). Similarly, Fogg Behavior Model also highlight the importance of considering learners' motivation in the persuasion design. Fogg (2009) argued that people perform a behavior based on 3 factors: motivation, ability, and triggers. If the motivation is not provided sufficiently, the target behavior will not occur even if people are able and triggered to do so. Therefore, the perceived helpfulness of the message could vary among the learners characterized by different motivational levels even if they stay in the same stage.

Chapter 7

General Discussion and Conclusion

7.1 Research summary

This research proposes to extract learning habits from daily learning logs and design data-informed support for habit-building in K12 education. Specifically, this research tackles the problems that learners might encounter regarding time management, as a strategy for learning habit-building. Figure 7.1 summarizes the sample size and period in each study. The proposed approach is adaptive to different time window, from 3 weeks to year-long, and can serve learners at different ages in various contexts such as math and English. The main research questions are answered as follows.

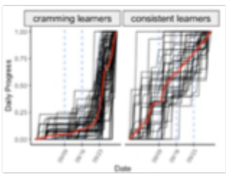
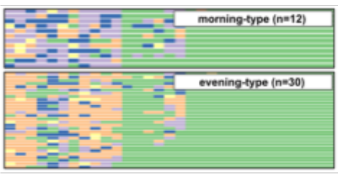
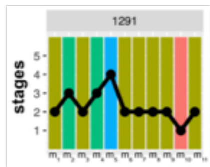
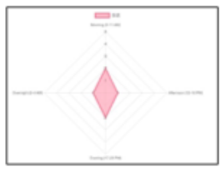
Study 1		Study 2	Study 3
			
math (exam preparation)	math (weekly test exercises)	English (extensive reading)	English (extensive reading)
3 weeks (Sep. 2020)	11 months (Apr. 2022 – Feb. 2023)	11 months (May 2020 – Mar. 2021)	2 and a half years (Apr. 2021 – Nov. 2023)
120 learners (7^{th} grade)	114 learners (9^{th} grade)	120 learners (7^{th} grade)	96 learners (from 7^{th} to 9^{th} grade)

Figure 7.1: Summary of the sample size and period in each study

7.1.1 RQ1: What types of learning habits can be extracted from learning logs?

Study 1 extracted long-term and short-term types of learning habits by applying different sizes of sliding window to the time series data of learning logs.

Regarding long-term learning habits, the window size was set as three weeks before a regular math exam. Different study time allocation patterns were extracted, such as learning continuously or cramming to prepare for the exam. Then, learners' performance was compared. The results presented that 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. In other words, types of long-term learning habits study time allocations had different effects on academic achievements.

As for short-term learning habits, the window size was set as one week ahead of weekly math tests. The learning patterns over a year were investigated and clustered into different chronotypes of learning habits, such as morning, evening and inactive types. To go beyond examining chronotypes' effects on academic performance, learning productivity was discovered to be correlated to the average test scores and thus verified as an alternative evaluation measure of learning habits. The results presented that learners could build an appropriate habit type by learning productively at a specific time of day. However, some learners might be able to learn more productively if they built another type of learning habits. Namely, Study 1 identified the potential for recommending productive learning habit types from log data.

7.1.2 RQ2: How can stages of learning habits be extracted from learning logs?

Study 2 detected stages of learning habits based on the transtheoretical model, which indicates people change their behaviors through five linear stages: precontemplation (stage 1), contemplation (stage 2), preparation (stage 3), action (stage 4), and maintenance (stage 5). Using different types of data incorporated in a workflow, the habit stages were modeled with monthly learning frequency and their sequences during a period.

To demonstrate the application of the proposed data model, Study 2 used learning logs of self-directed extensive reading and revealed the process of habit-building in the 11-month learning activity. In brief, the learners who did not reach the maintenance stage could be stuck in the contemplation stage or move between stages. The stages wherein the students moved between differed from their maximum achieved stages. By contrast, students who achieved the maintenance stage remained in the stage or relapsed to the earlier stages. Among those who relapsed, some could re-enter the maintenance stage, while others could become stuck in the contemplation stage or move between stages. That is, the behaviors of getting stuck in the contemplation stage and moving between stages could be identified both before and after the students entered the maintenance stage, which might indicate different statuses for the students.

Hence, the data model could provide insights regarding stages of learning habits in the educational contexts that shed light on monitoring habit-building processes.

7.1.3 RQ3: What intervention can be provided to build learning habits in digital learning environments?

Study 3 brought the above understanding into designing LA dashboard elements based on the Persuasive System Design (PSD) model, which provides the design principles to develop Behavior Change Support Systems (BCSSs). Specifically, Study 3 proposed HAbit-Building Informed by Trace data (HABIT), a 3-component persuasion mechanism to guide learners through the process of building learning habits–a change of behavior.

First, the detection module applies the design principle of self-monitoring and visualizes the stages of different habit types. This reminds learners of their learning status and whether the stages fluctuate between months. In addition, learners can compare their perceptions of learning habits with the extraction from their learning logs. For instance, by targeting their intended type, the learners can check whether their perceived stage differs from the extracted one in the visualization.

On the other hand, the diagnosis module and the recommendation engine apply the design principle of suggestion to increase the persuasive powers of changing behavior. The diagnosis module provides stage-based messages and suggests learners carry out different actions based on their extracted stages of learning habits to reach the upper stages. The recommendation engine generates the computed recommendations on which habit type to build based on learners' productivity in different time slots. By presenting their optimal learning status, further self-regulated learning (SRL) support can be provided in digital learning environments. For instance, the recommendations have the potential to assist learners in planning and scheduling their studies with timely and constructive feedback.

To explore the potential of data-informed support based on the proposed mechanism, this research surveys learners' perceptions of their learning habits and performs a comparative analysis of discrepancies between self-report and log data. The results showed that learners recognize the feasibility of integrating data-informed support into their daily learning. In addition, the log data could uncover the unaware learning status of their focused activities. Hence, the potential of the recommendations was confirmed to increase learners' awareness of their learning habits.

7.2 Contributions

From the preceding studies, 2 research contributions are identified. First, this research reveals the learning habits of K12 learners and provides an approach to trace the habit-building process automatically. Second, this research proposes interventions to the data-informed support for building learning habits.

Regarding the first contribution, past studies on learning habits are often in a self-paced learning context like a MOOC (Maslennikova et al., 2022; Ricker et al., 2020). There is a lack of understanding of tracing habits in daily learning at a school level from learning logs. In addition, the habit stages can be easily assessed by questionnaires with speedy answers. However, the results tend to be arbitrary and subjectively dependent on individual assumptions (Maslennikova et al., 2022). Therefore, extracting the types and stages of learning habits is essential to understand students' learning behaviors in K12 education.

As for the second contribution, past studies figured out appropriate support for habit-building in physical activities (Jimmy & Martin, 2005) or diet (Clark et al., 2004). However, there is little focus on the support for building learning habits even though it can help achieve better academic performance and cultivate SRL skills to be lifelong learners. The proposed data-informed support contributes to adaptive learning and personalization through analytics, which can also be implemented in the real world. Learners are facilitated to make decisions on changing their behaviors based on evidence derived from the analysis of their learning logs. Hence, this research has potential for evidence-based education in the current technology-enhanced teaching-learning era.

7.3 Implications

7.3.1 Technical implications

This research provides an innovative method to identify learning habits using learning logs. This enables it to read data from a daily perspective, giving a closer and more nuanced idea of habit-building for the behavioral change function. Further, the data used in this research gives a range of abstraction possibilities, which is not within the scope of the self-reported data that is conventionally used in earlier studies (Clark et al., 2004; Jimmy & Martin, 2005). Thus, it provides a methodological invention, at a time when learning behaviors and digital learning are intersecting. In addition, this research defines indicators of learning habits. Kuromiya et al. (2020) highlighted that indicators from log data have the potential for automatic statistical modeling to determine whether an intervention exerts a positive learning effect. The accumulated results of an intervention would generate evidence of its effectiveness and contribute to refining the learning evidence from the real world (Figure 7.2).

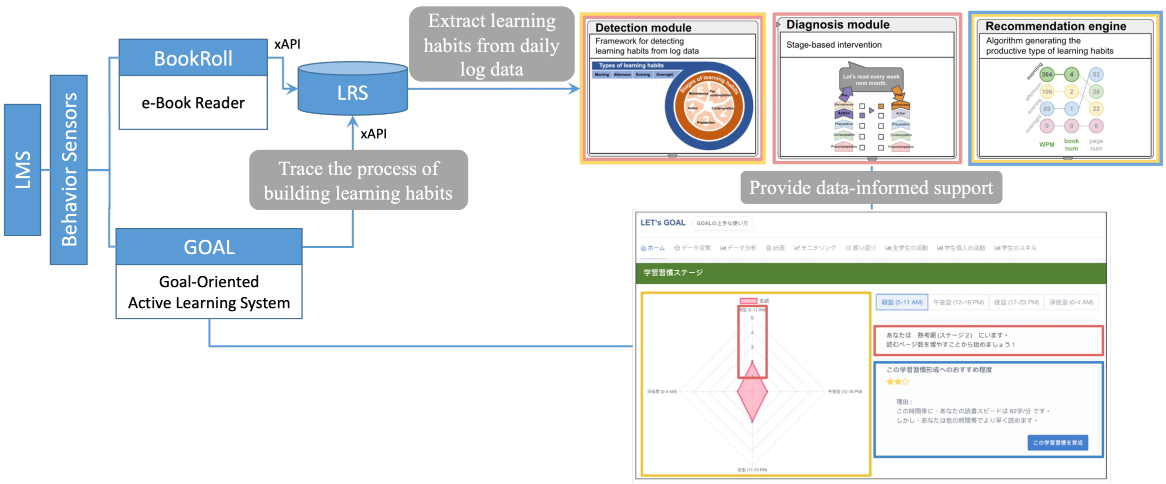


Figure 7.2: Refining evidence of learning habit-building

On the other hand, this research proposes a novel support of habit-building by recommending a productive learning time based on learners' log data. 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. In other words, the recommendations can be serendipitous and useful for learners' decisionmaking. As Feely et al. (2023) argued, recommender systems are suggested to be flexible to learners' decisions and continuously interact with their goals. Such a mechanism can keep the learners motivated as their learning unfolds in the process of habit-building.

7.3.2 Pedagogical implications

The pedagogical implication of this research would help to strengthen the teaching and learning process through a better time management strategy in terms of building learning habits. Many students face difficulties in their time management and cannot perform well in academic tasks. Peng and Kamil (2018) applied the time management cycle to make the students more organized and guide them to have better time management levels. It requires essential skills such as planning, regulation, prioritization, and control to accomplish the desired goals.

The self-directed learning (SDL) cycle in the GOAL system has the potential for implementing the support (Figure 7.3). This research identifies the constraints of the current habit types among learners and describes the recommended options for them to learn productively. Hence, the learners can have a clear goal and plan based on the feedback regarding the productivity of their learning habits. They can also monitor their use of time on learning activities in the LA dashboard. Finally, the system evaluates the effects of the completed round of self-directed learning and prompts the reflection of the learners. Through participating in multiple rounds of the cycle, they can develop a routine and build productive type of learning habits accordingly.

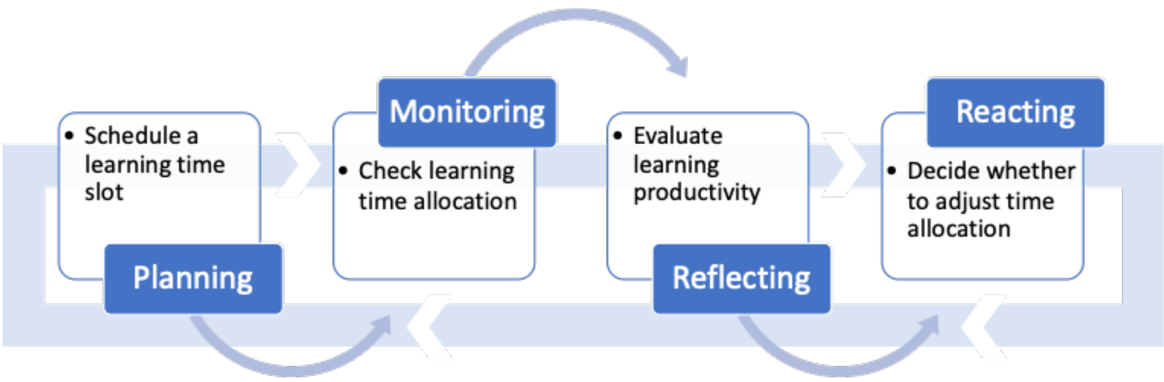


Figure 7.3: Building learning habits within SRL/SDL cycles

The above shed light on the implication of SRL support within adaptive learning systems. Regarding the SRL support within technology-enhanced learning environments, Andrade (2014) also argued that learners should practice controlling their learning processes, such as reflecting on the gaps between their learning goals and achieved outcomes. Regarding the misalignment between learners' perceptions and actual behaviors, Choi et al. (2023) suggested an implication for instructors to identify learners' potential needs for support for self-regulated learning. For instance, instructors can observe profiles in self-report data and encourage learners in different forms of engagement.

Given the operationalization of types and stages, this research can uncover the educational evidence of behavior change such as the transition between stages of different types of learning habits. They imply that personalized interventions can be provided to those who hesitate to enter the maintenance stage, and to those who relapse after building learning habits.

Specifically, this research suggests different intervention strategies should be implemented in each stage to sustain a consistent behavioral change toward building learning habits. For example, the early stages can focus on understanding, learning, and motivation, and the later stages can concentrate on resisting temptations, performing the desired behavior, and maintaining it (Ferron & Massa, 2013). On the other hand, it can also be worth considering how to shorten the early stages by applying more principles from the PSD model since people initially spend more time and have more difficulties compared to the later stages (Pintar & Erjavec, 2021). Hence, a more elaborate selection of design principles can be more effective in encouraging habit-building than the one-size-fits-all approach.

7.4 Limitations and future work

Despite the research significance, a couple of limitations can be tackled in future work. First, while this research collected log data from daily learning, it is notable that learning can happen everywhere and is not limited to a specific system. Hence, this research values the multiple data sources and friendly user experience. Currently, the data flow for the illustrated dashboard elements is being prepared based on the existing architecture of the GOAL system. Once the dashboard is updated, learners can immediately have access. In future work, learners will be allowed to increase the sources of their learning data. Furthermore, the collaboration with parents can be considered since they are also involved in learners' study, and it might be easier for them to monitor the time at home.

Second, this research compared learners' perceptions of habit-building with their learning logs and identified the potential helpfulness of the recommendations. However, this research also looks forward to learners' feedback and reaction upon the implementation. For instance, K12 learners are more constrained by a fixed school schedule. Some of them might prefer reading after their studies in the evening. This can affect their attitudes towards the recommendations. Hence, a more sophisticated evaluation is required to ensure learners' positive experiences. As indicated by Gardner et al. (2020), the change in complex human behavior patterns is not quite straightforward and might be a deeply psychological phenomenon. It is important to consider the communication and cooperation between human and computer in future work.

Third, while this research expands to explore the English and math courses in junior high school, each study targets a single context and has a potential limitation of the generalizability. 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. Learning habits can also vary with age, circumstances, and environment (Ricker et al., 2020; Sher et al., 2022). Hence, future research can work on multiple contexts across different subjects and consider the environmental differences between individuals. This research proposes a data-driven approach to extract learning habits, which can be applied to machine learning techniques in the system such as automatic, optimal scheduling or detecting proper timings during the user's timely activity to send the notification messages, as proposed by Okoshi et al. (2019) and Oh et al. (2015). This enables adaptive support for learners with different characteristics to facilitate lifelong and self-directed learning in the AI era.

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