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Designing data-informed support for building learning habits in the Japanese K12 context

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Abstract

While building proper learning habits has been said to enhance academic performance, it is challenging to give long-term support for building habits in educational contexts due to the lack of continuous tracing of one's habitual behaviors. With the accumulation of learning logs and the advancement of Learning Analytics (LA) techniques, this paper illustrates the data-informed support for building learning habits, which involves persuading one to change behaviors. Specifically, we tackled 2 research objectives following the Persuasive Systems Design (PSD) model. First, we defined indicators of learning habits from log data and analyzed 115,340 learning logs of 96 learners from a Japanese junior high school. As a result, the learners' types of habits could be detected even though some might not be efficient and the stages of habits fluctuated over time. We also identified differences when comparing the learning habits extracted from the log data with those reported in the questionnaire. Second, based on the understanding of the learner profiles, we designed elements of an LA dashboard to support habit-building by applying the design principles from the PSD model. Overall, the learners recognized the feasibility of integrating data-informed support into their daily learning. Therefore, we look forward to the evidence of its effectiveness on the behavior change that can be depicted by the transition between stages of different types of learning habits.

Keywords: Learning habits, Learning analytics, Learning design, Persuasive system, Behavior change

Introduction

Learning habits suggest the repeated behaviors of learners, which can be represented by the patterns of regularity in learning activities or study time (Boroujeni & Dillenbourg, 2019). In our research, we focus on the learning habits that learners tend to learn at a specific time, such as studying at certain hours of the day. Boroujeni et al. (2016) indicated that learners affirming to 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 schedule of the course. Therefore, building learning habits has become an important issue for learners, particularly for those at the K12 level since they are more constrained to a regular schedule than university students. However, it is challenging to give long-term support for building habits in educational contexts 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. 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 (Li et al., 2022). This has brought opportunities to support learners to build learning habits with real-time and continuous feedback. Therefore, we are motivated to explore how data-informed support can be provided to build learning habits.

In our previous studies (Hsu et al., 2023a; Hsu et al., 2024), we explored the methods to extract types and stages of learning habits from log data, which imply learners' temporal affinity and phases of behavior change respectively. This paper further investigates the main research question (RQ): How can data-informed support for building learning habits be designed? We set the following 2 research objectives.

- Objective 1: Defining indicators of learning habits from log data.
- Objective 2: Designing elements of an LA dashboard to support habit building.

Figure 1 depicts the structure of this research. Specifically, we refer to the Persuasive Systems Design (PSD) Model and conduct 2 studies in the Japanese K12 context. The PSD model addresses the development of Behavior Change Support Systems (BCSSs) and guides users through the process of changing behavior (Oinas-Kukkonen & Harjumaa, 2009; Steinherr, 2021). Therefore, study 1 first analyzes data to extract different types of

Main RQ	How can data-informed support for building learning habits be designed?			
Research objectives	Objective 1: Defining indicators of learning habits from log data		Objective 2: Designing elements of an LA dashboard to support habit building	
Research studies	Study 1		Study 2	
Sub RQs	SRQ 1.1	What are the efficiency profiles of the learners considering their learning habit type and stages?	SRQ 2.1	What design principles of the PSD model can be applied in data-informed support for building learning habits?
	SRQ 1.2	How do the extracted profiles of learning habits vary from the types and stages reported by the learners?	SRQ 2.2	What is the learners' perception of feedback messages related to building learning habits?

Fig. 1 Structure of this research

learning habits and their stages from 96 learners with 115,340 learning logs. We also ask the learners about their intended habits type and perceived habits stage to compare them with the extracted ones. Then, we bring the understanding of the learning context into study 2, which designs elements of the LA dashboard based on the design principles from the PSD model. Finally, we evaluate the design from the perspective of the learners who have learned for years with the dashboard where the prototype elements are planned to be implemented.

Related works

Constructs of habits

Types of habits

A habit is regarded as a repetitive behavior that responds to a certain context (Wood & Neal, 2007). In the educational context, the wide spread of ICT tools has motivated researchers to identify learning habits using the techniques of Learning Analytics (LA). Specifically, 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 example, 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.

Additionally, 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. In contrast, Romero and Barberà (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.

Concerning the above issue, Boroujeni et al. (2016) introduced measures to capture the aforementioned 6 patterns. For example, they calculated 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 (P1) or a particular day of the week (P2). In contrast to calculating a value, our previous studies (Hsu et al., 2023a; Hsu et al., 2023b) used clustering analysis and presented the patterns by the clusters such as the learners who studied on weekday mornings (P1 and P2) or the learners who studied consistently throughout exam preparation (P6).

Stages of habits

On the other hand, habit-building is considered a process whereby a stimulus generates an impulse to change behavior (Gardner et al., 2020). Regarding behavioral changes, the transtheoretical model (TTM) suggests that people proceed through 5 linear stages (Grimley et al., 1994). In our previous work (Hsu et al., 2024), we referred to the model and operationalized the stages of building learning habits as follows. 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 based on previous studies (Gardner & Lally, 2018; Lally et al., 2010), which indicated habit-building usually takes 4 months. 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. We also proposed an approach to extracting the stages from log data. As a result, we uncovered how the learners built habits during an 11-month reading program, implemented in a Japanese junior high school.

- Precontemplation (stage 1): Learners do not read to build reading habits within the next 4 months.
- Contemplation (stage 2): Learners read to build reading habits within the next 4 months.
- Preparation (stage 3): Learners read to build reading habits within the next 30 days.
- Action (stage 4): Learners read to build reading habits within the last 4 months.
- Maintenance (stage 5): Learners read to build reading habits for more than 4 months.

Furthermore, the stages can motivate different intervention designs to support habit-building. Specifically, 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.

Based on the findings of our previous work (Hsu et al., 2024), we also designed stage-based messages that prompt the learners to transit to the next stage for building their reading habits, as listed in Table 1. We regard 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. To support learners to transit the stages and build learning habits, the relationships in Table 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. However, he or she can still return to the contemplation stage afterwards. The evidence of habit-building supported by such stage-based interventions were also confirmed in the preceding studies (He et al., 2023; Lee et al., 2017; Merz & Steinherr, 2022).

Finally, we summarize the existing approaches to detecting habits and position this research in Table 2. In the preceding educational research, it was common to extract different types of learning habits from log data, as Ricker et al. (2020) performed. However, scant attention has been paid to the extraction of the stages. On the other hand, we can also

Table 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

Adapted from Hsu et al. (2024)

Table 2 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

find studies 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. However, they mainly used different scales that rely on the self-reports of the patients (He et al., 2023). Therefore, our research can bridge the gap in the educational field related to integrating both types and stages of habits from a data perspective.

Persuasive systems design (PSD) model for designing behavior change support systems

To support learners in building learning habits–a change of behavior, we refer to the design of a Behavior Change Support System (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 Systems 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 3 summarizes the research fields, target behaviors, and data sources of the aforementioned examples. We consider the PSD model suitable for this study 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). Our work 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.

We also compare our approach with the related works to position this research in the existing designs that applied the PSD model to support behavior change. First, even though

Table 3 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	Reading regularly
Data source	Sensors	Questionnaire	Learning logs

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, our research can bridge the gap in the educational field related to support for habit-building based on the PSD model.

Research method

Learning context

In this longitudinal research, we target the learning habits of 96 learners–at the age of 15–from a Japanese junior high school. Specifically, we look at their learning activities of English reading, which have been implemented since they were in the seventh grade (13 years old on average). To support the learning activities, the school introduced an LA system, the Learning and Evidence Analytics Framework (LEAF), and the learners can read more than 500 digital picture books in English with equipped tablet computers. LEAF contains Moodle, BookRoll, and GOAL (Figure 2). Moodle is a Learning Management System (LMS) connecting BookRoll and GOAL. BookRoll is an e-book reader where the students read the books in PDF files, whose learning logs are stored in a Learning Record Store (LRS) (Ogata et al., 2015). GOAL is a self-directed learning scaffolding system, which allows the learners to plan for, monitor, and reflect on their learning (Li et al., 2021). It also provides feedback regarding the analysis of learning logs via an LA dashboard. In about 3 years (i.e., 32 months), the learners generated 115,340 learning logs from BookRoll in total.

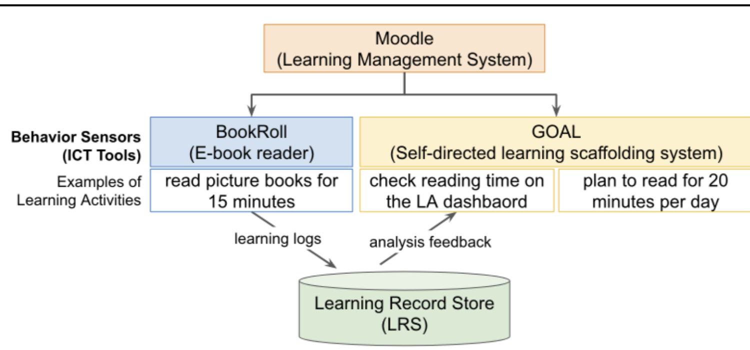

Fig. 2 Reading English picture books in the Learning and Evidence Analytics Framework (LEAF)

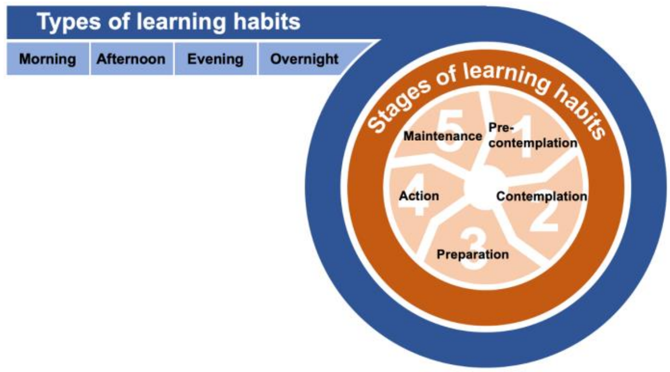

Fig. 3 The framework for detecting learning habits from log data

Framework for detecting learning habits from log data

In terms of the research objectives, we propose a framework for detecting learning habits from log data to guide the research. We operationalize learning habits in 2 constructs: types and stages of learning habits (Figure 3). First, types of learning habits refer to temporal affinity with a specific time slot, such as reading English books in the morning. Second, each type can have stages of learning habits, which means different phases of behavior change. Specifically, the stages stem from the transtheoretical model (TTM), indicating that habit-building involves a change of behavior and that people undergo different phases (i.e., precontemplation, contemplation, preparation, action, and maintenance stages) in the process (Grimley et al., 1994).

Data collection

Learning logs

The learning logs record the learners' actions in the digital English picture books by the data fields as follows. From the log data, we can derive who (*data field: user_id*) did what (*data field: operation_name*) on which page (*data field: page_no*) of what content (*data field: content_id*) with how many words (*data field: word_count*) for how long (*data field: diftime*) at what time (*data field: timestamp*). Particularly, we calculate the learning indicators listed in Table 4 for further data analysis. We also summarize their descriptive statistics during the whole period of data collection–32 months.

Questionnaire

In addition to analyzing the log data of the 96 learners, we also approach them and carry out a questionnaire for their perception of learning habits and opinions about the support design. We develop the questionnaire with the following process. First, we design the

Table 4 Learning indicators from log data and their descriptive statistics

Indicators	Definition	Fields for calculation	M	SD	Min	Max
Reading time	Total minutes a learner reads in an hour	diftime	9.51	10.38	0	60
Reading speed	The number of words a learner reads in a minute	word_count, diftime	124.70	123.71	1	1521
Reading categories	The number of books a learner reads	content_id	2.20	2.12	1	23
Reading amount	The number of pages a learner reads	page_no	32.59	47.96	1	1061

questions based on our proposed learning habits detection framework. Second, we validate the items in the questionnaire with the research team members as LA experts. Third, we verify 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 (Figure 4.a). Then, we present an example that illustrates 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 (Figure 4.b). Finally, we provide our feedback design based on each stage and ask the learners who perceive to stay in that stage whether the feedback can help them build learning habits. We further request them to elaborate on the reason from the perspective of the concepts applied from TTM (Figure 4.c). In total, we collect the responses from all the learners (i.e., rate of response: 100%).

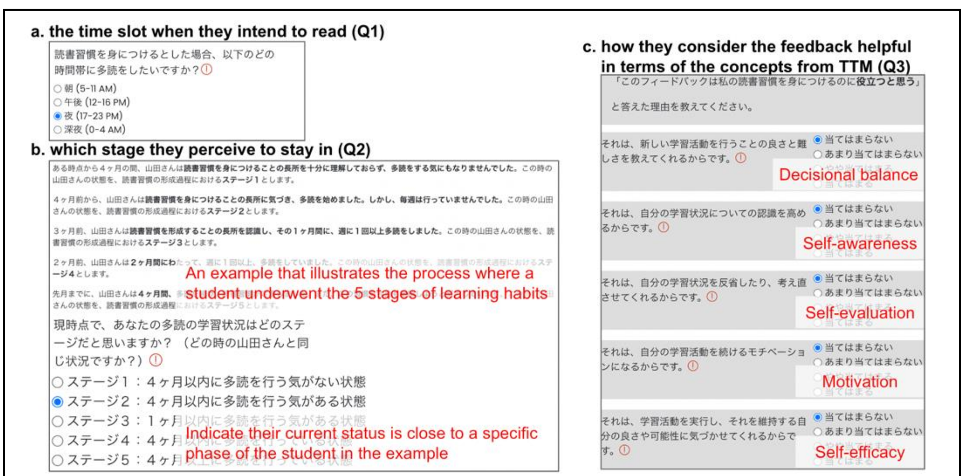

Fig. 4 Questionnaire for learners' perception of their learning habits

Study 1: Defining indicators of learning habits from log data

Overview

Study 1 aims to define indicators of learning habits from log data. First, we define 3 indicators (i.e., temporal affinity, phases of behavior change, and habit outcome) and explain how we extract them from data. Then, we analyze the collected learning logs and generate the efficiency profiles of the learners considering their types and stages of learning habits. Finally, we compare the extracted types and stages with the results reported by the learners in the questionnaire. The following 2 sub research questions (SRQs) are answered.

- SRQ1.1: What are the efficiency profiles of the learners considering their types and stages of learning habits?
- SRQ1.2: How do the extracted profiles of learning habits vary from the types and stages reported by the learners?

Definitions of indicators to operationalize the constructs

Temporal affinity: related to types of learning habits

The type of learning habits is indicated by the peak slot where a learner reads for the most time in a day. First, we divide the slots of the day into morning (05:00–11:00), afternoon (12:00–16:00), evening (17:00–23:00), and overnight (00:00–04:00). Then, we sum up the reading time in different slots and extract the peak of the day. Finally, we count the days when the peak of each slot is located and determine one's type of learning habits. For example, a learner is identified to have the morning type when he or she reads the most in the morning on most days during a period (e.g., 32 months).

Phases of behavior change: related to stages of learning habits

The stage of learning habits is indicated by the frequency of how a learner reads each month. First, we categorize the frequency into not reading at all, reading in random week(s), and reading every week. Then, we extract the frequency of each month and create a sequence of the frequency during a period (e.g., 32 months). Finally, we examine the order of the frequency in the sequence and determine one's stage of learning habits each month. For example, a learner is identified to stay in the precontemplation stage (stage 1) when not reading at all in the first month of the period. If the learner reads in the random week(s) of the second month, he or she is identified to go up to the contemplation stage (stage 2). If the learner reads every week in the third month, he or she is identified to go up to the preparation stage (stage 3). Similarly, the learner is identified to go up to the action stage (stage 4) when reading every week in the fourth month. Finally, the learner is identified to reach the maintenance stage (stage 5) when reading every week in the fifth month. In the process, the learner might fall to stage 2 when he or she cannot continue reading every week for a month. Additionally, the learner might fall to stage 1 when he or she does not read at all for more than 4 months. In these cases, the learner should continue to read every week to return to the upper stages.

Habit outcome: related to the efficiency of learning

Learning efficiency is indicated by 3 learning indicators: Reading speed, Reading categories, and Reading amount. First, we calculate the value of the indicators in each time slot of the day. Then, we average the value during a period (e.g., 32 months) to get the learning efficiency of each time slot. Finally, we compare the learning efficiency between the time slots and determine whether one has high or low efficiency in each slot. For example, a learner is identified to have high learning efficiency in the morning when at least 2 of the learning indicators have a higher value than those in the other time slots. The learning efficiency suggests the habit outcome and indicates which type of learning habits should be built.

Results

SRQ1.1: What are the efficiency profiles of the learners considering their types and stages of learning habits?

We consider the above indicators of learning habits and generate the efficiency profiles of the learners using their log data (Table 5). First, we summarize the learners who have different types of learning habits. Then, in terms of each type, we extract 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. Finally, we examine the learning efficiency and identify the learners who have high efficiency in the time slot corresponding to each type of learning habits.

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). Finally, high learning efficiency is shown by more than half of the learners with the afternoon (63%, n=12), evening (56%, n=9), and overnight (100%, n=1) types of learning habits. However, 44% (n=24) of the learners with the morning type present high learning efficiency in the corresponding time slot.

Table 5 The efficiency profiles of the learners considering their types and stages of learning habits

Types of learning habits	Total learners	Learners in each stage			Learners with high efficiency
		Stage	Max	Current	
Morning	54	precontemplation (stage 1)	0	54	24 (44%)
		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	12 (63%)
		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	9 (56%)
		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	1 (100%)
		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, we also identify 6 learners (6%) whose logs show more than 2 peaks in their reading time. We consider these learners to have mixed types of learning habits. This suggests they might tend to read both in the morning and evening, for example. However, we further examine their learning efficiency and find that 2 of them can have high efficiency in the afternoon. On the other hand, 4 of them have high efficiency in the evening. Therefore, from the learning efficiency, we can tell which of the two habit types is recommended to be built.

SRQ1.2: How do the extracted profiles of learning habits vary from the types and stages reported by the learners?

In terms of the extracted types of learning habits from log data, we further compare them with the types that the learners intend to build. First, we summarize the learners who reported building different types of learning habits from the questionnaire. Then, we compare whether the intended type reported by a learner is consistent with the extracted type from his or her learning logs. Finally, we count and present the ratio of the learners whose intended types match their types of learning habits extracted from the data. For example, a learner is categorized into the cohort with consistency since the learner reported to build the morning type and we also identify he or she has that type of learning habits from the log data.

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 the extracted stages of learning habits from log data, we also compare them with the stages where the learners perceive to stay. First, we summarize the learners who reported staying in different stages of learning habits from the questionnaire. Then, we look at the current stages extracted from a learner's log data and examine whether they are consistent with his or her perceived stage. Finally, we count and present the ratio of the learners whose perceived stages match their current stages of learning habits. For example, a learner is categorized into the cohort with consistency by current stage since the learner reported staying in the contemplation stage (stage 2) and we also identify he or she stayed in that stage of learning habits from the log data.

The questionnaire shows 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. As for the action (stage 4) and maintenance (stage 5) stages, 1 learner (1%) perceives to stay in each of them. Furthermore, we make a comparison between the perceived and extracted stages for the learners reported to stay in the precontemplation stage (stage 1). The results indicate that 98% (n=63) of them show consistency when compared to the extracted current stage. However, based on the current stage, we cannot find consistency for the cohort of the contemplation (stage 2), preparation (stage 3), action (stage 4), and maintenance (stage 5) stages.

Discussion

We generated the efficiency profiles of 96 learners based on the indicators of temporal affinity, phases of behavior change, and habit outcomes–related to the constructs of habit and the efficiency of learning. The results show that the learners' types of habits could be detected even though some might not be efficient and the stages of habits also fluctuated over time. Furthermore, we identified differences when comparing the learning habits extracted from the log data with those reported in the questionnaire.

The findings might result from the dynamic actions of the learners considering different strategies. As Boroujeni et al. (2016) hypothesized, the strategies can include regular or adaptive scheduling of the learning activities based on the daily work or study schedule. Hence, the learners might change their study approach during the course depending on whether they find their previous approach ineffective or inefficient. In addition, the log data presented that learners could achieve higher stages during the period despite staying lower stage at the end. This can be attributed to the novelty effect that learners might be more engaged when first using the system (Marek & Wu, 2021). As they became familiar with the system, their motivation could erode, and fewer data accumulated. Therefore, learners were detected to stay in the lower stage finally.

In terms of the above findings, we suggest further studies should perform a temporal analysis to explore the evolution of learning approaches over time. For example, Boroujeni and Dillenbourg (2019) provided methods that can be applied during the course to detect changes in behavioral patterns while the course is running. On the other hand, our previous study (Hsu et al., 2023b) investigated learning one week ahead of regular math tests over the year using clustering analysis to extract clusters of learning patterns that suggest different types of learning habits. Therefore, it is potential to extend our work with existing methods to clarify learners' decisions between the types of learning habits.

Study 2: Designing elements of an LA dashboard to support habit building

Overview

Study 2 is aimed at designing elements of an LA dashboard to support habit building. First, we select the design principles from the PSD model based on the results of study 1. Then, we apply the principles and design the prototype elements of the LA dashboard. Finally, we evaluate the prototype by the learners' opinions about the design, which were reported in the questionnaire. The following 2 sub research questions (SRQs) are answered.

- SRQ2.1: What design principles of the PSD model can be applied in data-informed support for building learning habits?
- SRQ2.2: What is the learners' perception of feedback messages related to building learning habits?

Principle selection and application to elements of LA dashboard (SRQ2.1)

Element 1: diagnostic feedback generated from the efficiency profiles (selected design principle: suggestion)

Study 1 outputs the efficiency profiles of the learners considering their types and stages of learning habits. It implies that the learners might tend to read in a time slot without high learning efficiency. We consider the design principle of suggestion from the PSD model can serve these learners since it instructs that fitting suggestions can increase the persuasive powers of changing behavior (Oinas-Kukkonen & Harjumaa, 2009). Hence, guided by the principle, we design diagnostic feedback of the LA dashboard. Specifically, it is generated from the efficiency profiles and informs the learners of the extracted types of learning habits and their current stages (Figure 5.a). Furthermore, we include the stage-based messages that embed the concepts from TTM as introduced in Table 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 5.b). The feedback also contains the diagnosis of the learning efficiency in the corresponding time slot (Figure 5.c).

Element 2: visualization of the monthly status about types and stages of learning habits (selected design principle: self-monitoring)

The efficiency profiles from study 1 also inform us of the learners who once reached the upper stage (e.g., action stage, stage 4) as the highest but currently relapse to the lower stage (e.g., precontemplation stage, stage 1). Furthermore, we identify the difference when

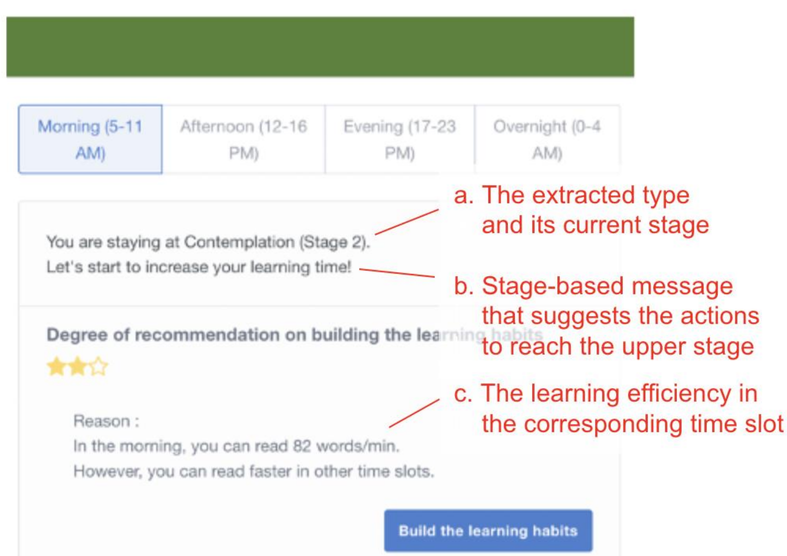

Fig. 5 Diagnostic feedback of the LA dashboard (design principle: suggestion)

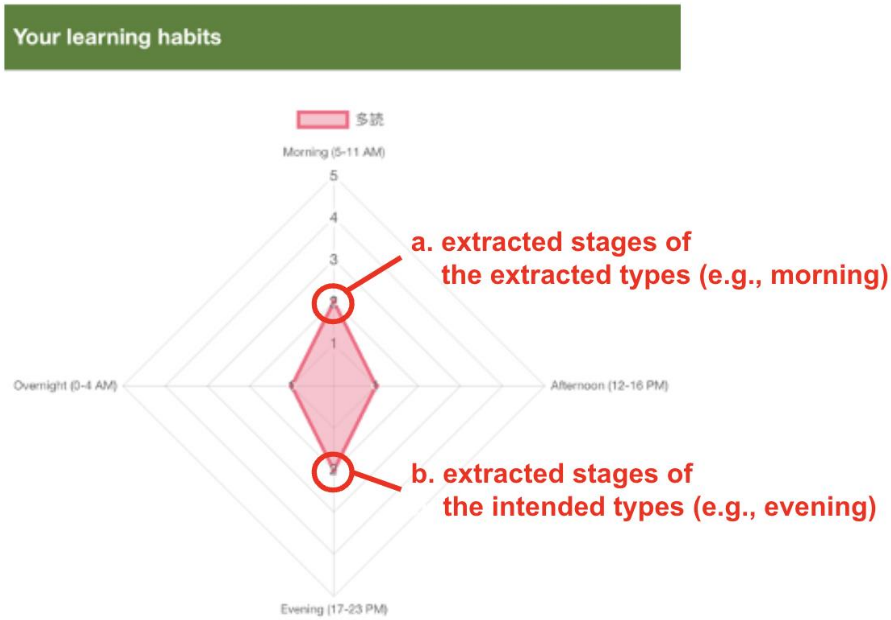

Fig. 6 Visualization of the LA dashboard (design principle: self-monitoring)

comparing the learning habits extracted from the log data with those reported in the questionnaire. These motivate us to apply the design principle of self-monitoring, which instructs that track of one's performance or status can help achieve goals (Oinas-Kukkonen & Harjumaa, 2009). Specifically, we design a visualization of the monthly status of types and stages of learning habits. First, it shows a specific type of learning habits and its current stage (Figure 6.a). We expect this to remind the learners of their learning status and whether the stages fluctuate between months. Second, it also presents the other parallel types of learning habits and their stages. This allows the learners to compare their perception of learning habits with the extraction from their learning logs (Figure 6.b). For example, by targeting their intended type, the learners can check whether their perceived stage differs from the extracted one in the visualization.

Perception of the learners regarding the feedback messages (SRQ2.2)

We collect how the learners evaluate the diagnostic feedback from the questionnaire. First, we identify the learners who consider the stage-based messages helpful in building learning habits. Second, based on each stage, we summarize how the message helps in terms of the concepts applied from TTM. We present the distribution of the learners who agree or disagree with each concept as the factor of helpfulness. Third, we look at the distribution of the concepts embedded in the message design of each stage and investigate to what extent the learners agree with the concepts. Finally, we report which concepts embedded in the message of each stage are considered helpful by the learners as we expect.

Table 6 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%

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 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.

Discussion

We selected the design principles of suggestion and self-monitoring from the PSD model and designed the dashboard elements that allow learners to monitor and receive diagnostic feedback concerning their learning habits. This fills the gap between analyzing the persuasion context and selecting appropriate design principles for a specific implementation, as Merz and Steinherr (2022) indicated. While the learners found the design helpful, the concepts of motivation and self-awareness did not function in the feedback as we expected.

The findings might result from our 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.

Based on the above findings, we suggest different intervention strategies should be implemented in each stage to sustain a consistent behavioral change toward building learning habits, as considered in other domains. 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.

General discussion

Pedagogical implications

This research confirms the feasibility of implementing data-informed support for habit-building in the real educational context. While learning habits can be easily assessed by questionnaires with speedy answers, the process of building habits is dynamic. Hence, we recommend extracting types and stages of learning habits from daily learning logs and providing the visualization and suggestions of the LA dashboard for real-time and continuous feedback. On the other hand, our findings also imply the expansion of the dashboard functionalities for long-term support of habitual learning in K12.

First, we consider adding a mechanism flexible to learners' decisions between the types of learning habits. For example, from the diagnostic feedback, a learner understood he or she has the morning type of learning habits that stay in the contemplation stage (stage 2). Considering the learning efficiency detected in different time slots, the system suggests that reading in the evening is the most efficient. However, the learner still decided to build the morning type since he or she has more time in the morning and the efficiency in the slot is acceptable. Therefore, the learner followed the stage-based message and increased the reading time to achieve the preparation stage (stage 3) of the learning habits. The above mechanism can keep the learners motivated as their learning unfolds in the process of habit-building, as how Feely et al. (2023) collaborated with their users.

Second, we consider embedding an action pointer directed to the self-directed learning cycle in the GOAL system related to setting goals, making plans, analyzing and monitoring activities, and reflecting on learning (Majumdar et al., 2024). For example, by clicking a button to indicate the intended type, the learner can enter the planning panel of the GOAL system and set a goal of reading for 20 minutes every morning. Then, the learner can monitor his or her learning activities in the LA dashboard. Finally, the reflecting panel also allows the learner to record the reflection of the reading. Hence, the learners can develop a routine and build learning habits through participating in the cycle.

Limitations and future work

We identify a couple of limitations concerning our research method. First, while we collected 115,340 learning logs from the daily reading of the learners, it is notable that learning can happen everywhere and is not limited to a specific system. Second, in the questionnaire, we presented a use case that illustrates how a student can be supported by the prototype elements of the LA dashboard and asked the learners about their perceptions. However, the response might differ when the learners experience the service and encounter unexpected problems related to user workflow.

Regarding the limitations, we value the multiple data sources and friendly user experience. Currently, the data flow for the dashboard elements illustrated in this paper is being prepared based on the existing architecture of the GOAL system. Thus, once the dashboard is updated, the learners can immediately have access. In future work, we will allow the learners to increase the sources of their learning data. Furthermore, we will also carry out a heuristic evaluation to identify design problems in terms of user interface and workflow. 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. Therefore, it is important to consider the communication and cooperation between human and computer in future work.

Contribution

This paper provides a practical design of data-informed support for building learning habits, specifically in the Japanese K12 context. First, we defined indicators of learning habits from log data. In contrast to other research, we considered the constructs of both types and stages and captured the dynamic process of building habits by analyzing learning logs. As a result, we generated efficiency profiles of 96 learners that informed the personalized support. Second, we designed elements of an LA dashboard to support habit-building. Specifically, we demonstrated a novel application of the PSD model in education and provided the learners with adaptive feedback considering the types and stages of learning habits in their efficiency profiles. Therefore, our research contributes to adaptive learning and personalization through analytics, which can also be implemented in the real world.

In terms of the support for building learning habits, we look forward to the evidence of its effectiveness at the meso level when it is initially implemented in the junior high school. Given the operationalization of types and stages, we can uncover the educational evidence of behavior change such as the transition between stages of different types of learning habits. Therefore, our research is potential for evidence-based education in the current technology-enhanced teaching-learning era.

Abbreviations

BCSS: Behavior Change Support System; LA: Learning Analytics; LEAF: Learning and Evidence Analytics Framework; LMS: Learning Management System; LRS: Learning Record Store; PSD: Persuasive Systems Design; SRL: Self-Regulated Learning; TTM: Transtheoretical Model.

Authors' contributions

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

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Availability of data and materials

Not applicable.

Declarations

Competing interests

The authors declare that they have no competing interests.

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