Learning Habits Mining and Data-driven Support of Building Habits in Education

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Abstract: In terms of the learning logs accumulating from real-world educational activities, techniques of learning analytics help understand the characteristics of learners' behaviors. However, extracting learning habits from log data and data-driven support for building learning habits have not yet attracted much attention. Therefore, this research proposes the approach of "Learning Habits Mining", which aims to extract the types and stages of learning habits from learners' daily learning logs and support learners to build learning habits with data-driven methods. We identify two contributions of this research. First, this research reveals the learning habits of K12 learners and provides an approach to trace the process of building learning habits automatically. Second, this research proposes interventions to the data-driven support for building learning habits so that learners can build learning habits based on evidence derived from learning logs.

Keywords: Learning Habits, Daily Learning Logs, Real-World Data, Learning Analytics

1. Introduction

With the advancement of ICT, data is accumulating from real-world educational activities (Ogata et al., 2018). Take Japan for example. The Ministry of Education, Culture, Sports, Science, and Technology (MEXT) initiated the GIGA School Program (Global Innovation Gateway for All) to ensure "one computer for one student". The program allows learning in schools to be done anywhere and anytime (The Government of Japan, 2021). Students can access different learning contents using mobile technology such as tablet computers.

In terms of the accumulated learning logs, techniques of learning analytics help understand the characteristics of learners' behaviors (Li et al., 2022). For example, we analyzed the log data of various learning tools and extracted learners' self-regulated learning strategies (Hsu et al., 2022). In addition, the insights from analyzing learning logs enable data-driven learning support, which facilitates learners' decision-making based on data (Ogata et al., 2018). However, extracting learning habits from log data and data-driven support for building learning habits have not yet attracted much attention.

When it comes to learning habits, it often suggests the learning patterns that learners tend to learn at a specific time. For example, learners may have a unique habit type of preferred time to work, such as morningness-eveningness preference (Sher et al., 2022). Individual differences in types of learning habits could have an impact on learners' academic achievements (Ricker et al., 2020; Sher et al., 2022). That is, building good learning habits can help learners achieve better academic performance.

In terms of the extraction of learning habits, extracting learning habits from daily learning logs makes it possible to evaluate learning habits not simply at a specific time but automatically trace the process of building learning habits. On the other hand, data-driven support for building learning habits can help learners to build learning habits based on evidence derived from learning logs. Therefore, this research proposes the approach of "Learning Habits Mining", which aims to extract the types and stages of learning habits from learners' daily learning logs and support learners to build learning habits with data-driven methods. Based on this, we answer the following three research questions.

- RQ1: What learning habits can be extracted from learners' daily logs?
- RQ2: How do learners build learning habits?
- RQ3: What interventions can support learners to build learning habits?

2. Research Framework and Preliminary Findings

As introduced above, "Learning Habits Mining" is an approach to extract the types and stages of learning habits from learners' daily learning logs and support learners to build learning habits with data-driven methods. Figure 1 shows the three-step workflow of the approach. We have verified Step 1 and Step 2 with preliminary findings, which informed the implementation of Step 3.

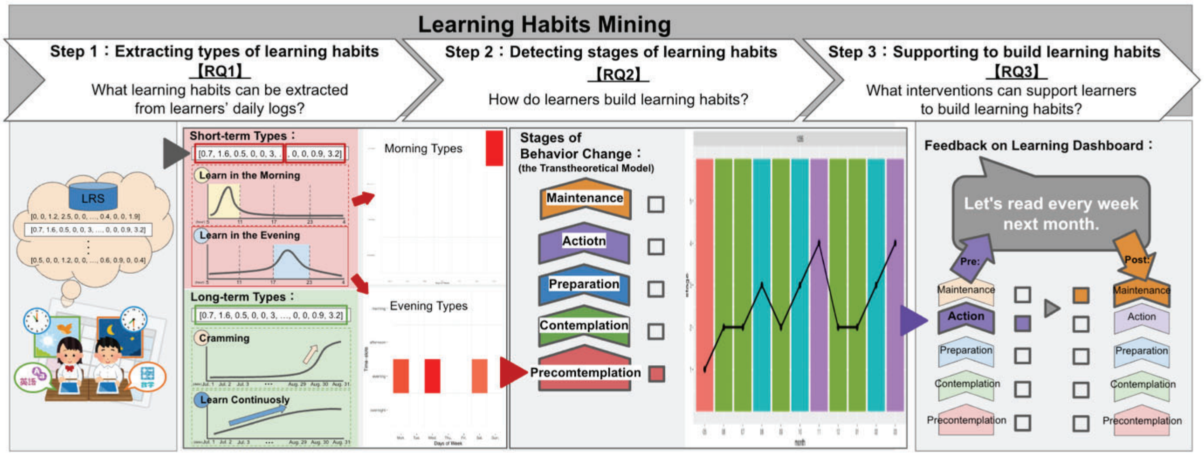

Figure 1. Workflow of Learning Habits Mining.

2.1 Step 1: Extracting types of learning habits from daily learning logs (RQ1)

In this step, we first define the types of learning habits by applying a sliding window to the time series data of learning logs (Figure 2). By the sizes of the sliding windows, we then extract different types of "short-term learning habits" and "long-term learning habits". "Short-term learning habits" indicate the active time slots when learners study within a day. "Long-term learning habits" indicate the patterns of whether learning is continued for a long time or crammed into the final stages.

For "short-term learning habits", we set the window size as one week and extracted types of learning habits, such as Morning on Weekdays, Evening on Weekdays, and Afternoon on Weekends, in terms of the weekly learning for regular math tests (Hsu, Otgonbaatar, et al., 2023). As for "long-term learning habits", we set the window size as three weeks and extracted types of learning habits, such as whether learners studied continuously or crammed to prepare for the math exam (Hsu, Horikoshi, et al., 2023).

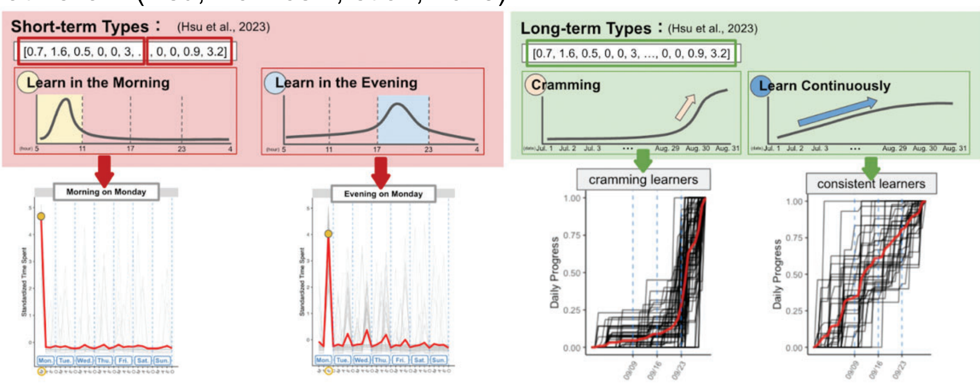

Figure 2. Examples of Short-term and Long-term Types of Learning Habits.

2.2 Step 2: Detecting stages of learning habits in the process of behavior change (RQ2)

In this step, we detect the stages of learning habits based on the Transtheoretical Model, which indicates people change their behaviors through five stages: Precontemplation (stage 1), Contemplation (stage 2), Preparation (stage 3), Action (stage 4), and Maintenance (stage 5). We refer to the Transtheoretical Model and operationalize the stages of learning habits as follows:

- Precontemplation (stage 1): Learners do not take action to build learning habits within the next four months.
- Contemplation (stage 2): Learners take action to build learning habits within the next four months.
- Preparation (stage 3): Learners take action to build learning habits within the next thirty days.
- Action (stage 4): Learners take action to build learning habits within the last four months.
- Maintenance (stage 5): Learners take action to build learning habits for more than four months.

Based on the definition, we proposed a data model to extract stages of learning habits. To show the application of the data model, we used learning logs of self-directed extensive reading. Figure 3 reveals an example of the stages a learner (e.g., 1295) underwent during the eleven-month learning activity.

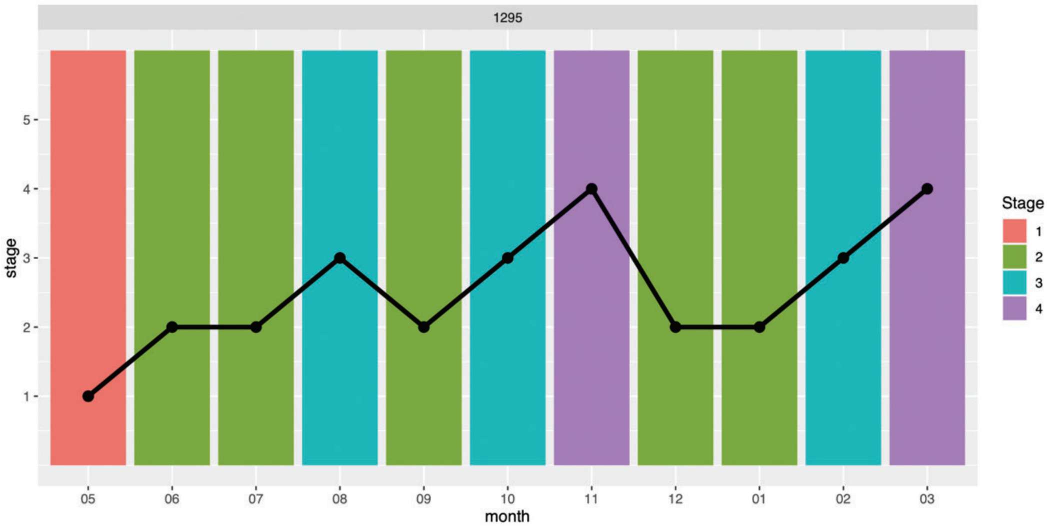

Figure 3. Stages of Self-directed Extensive Reading Habits.

2.3 Step 3: Recommending an intervention to build learning habits (RQ3)

In this step, we recommend feedback supporting learners to build learning habits based on the extracted types and stages of learning habits. Specifically, the pros and cons of different types of learning habits are evaluated and stage-based intervention is provided to support learners to achieve the maintenance stage, which means the formation of habits.

Regarding the pros and cons of different types of learning habits, we found learners who studied continuously had better performance than those who crammed to prepare for the math exam (Hsu, Horikoshi, et al., 2023). On the other hand, we can also provide a stage-based intervention for the learner shown in Figure 3, such as: “Let’s find a good way to keep reading!” The objective is to prompt him or her transit from Action (stage 4) to Maintenance (stage 5).

3. Contribution

We identify two contributions of this research from the preceding studies. First, this research reveals the learning habits of K12 learners and provides an approach to trace the process of building learning habits automatically. Second, this research proposes interventions to the data-driven 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 stages of learning habits 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 at the K12 level.

As for the second contribution, past studies looked at stages of habits to figure out appropriate support for building different types of habits, such as 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 learners achieve better academic performance. Therefore, data-driven support for building learning habits can help learners to make decisions on changing their behaviors based on evidence derived from the analysis of their learning logs.

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