Chronotypes of Learning Habits in Weekly Math Learning of Junior High School

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Abstract: Learners may have a unique chronotype of learning habits that they have the preferred time of day to work. Even though learner activity extracted from trace data can provide useful and insightful information about their learning habits, there is a lack of tracing habits in daily learning at a school level from learning logs. Therefore, we propose to understand students' chronotypes of learning habits at the K12 level. We investigate the patterns one week ahead of regular tests over the year using learning analytics techniques of clustering analysis. From 92,694 daily logs of the ninth graders in weekly math learning, we find clusters of learning patterns that suggest different chronotypes of learning habits. The findings enable context-aware recommendations for a more authentic learning experience with adaptivity and personalization, which is potential for enhancing pedagogical practices in mobile, contextualized, and ubiquitous learning environments in future research.

Keywords: Learning Habits, Ubiquitous Learning, Trace Data, Learning Analytics, Adaptive Learning

1. Introduction

When it comes to the preferred time of day to work, learners may have a unique chronotype, such as morningness-eveningness preference (Sher, Hatala, & Gašević, 2022). The chronotype 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, Rotelli, & Monreale, 2022).

As an approach to deal with the above problem, learner activity extracted from trace data can provide useful and insightful information about the amount and type of activity occurring as well as the time and duration of that activity (Ricker, Koziarski, & Walters, 2020). However, the 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. Therefore, extracting the chronotypes of learning habits is important to understand students' learning behaviors at the K12 level.

In this study, we investigate the patterns one week ahead of regular tests over the year using learning analytics techniques of clustering analysis. The objective is to extract learners' chronotypes of learning habits from their daily logs. We answer the research question: What clusters of learning patterns can be extracted from the daily logs of math learning?

2. Study Context and Collected Data

In this study, we target the learning context of practicing and testing math exercises in a Japanese junior high school. Figure 1 shows the workflow of the learning activities in the study context. On a tablet computer, learners access an e-book reader, BookRoll (Ogata et al., 2015), and practice exercises of a math concept for a week and then take a test of the same concept on 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 in a Goal-Oriented Active Learning system, GOAL (Li, Majumdar, Chen, & Ogata, 2021). This workflow was implemented repeatedly on a weekly basis from April 2022 to February 2023.

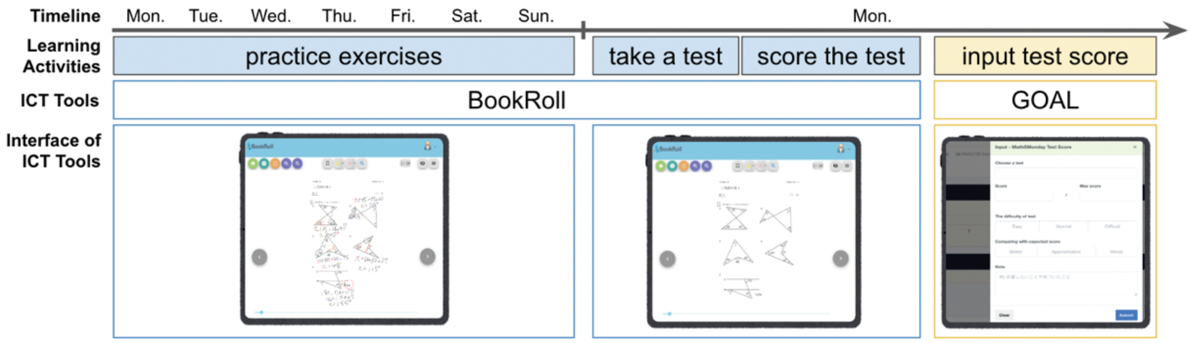

Figure 1. Workflow of Weekly Math Learning in Study Context of Junior High School.

From the study context, learning logs collected by BookRoll and GOAL accumulate in the Learning Record Store (LRS). We regard 114 ninth graders as the participants of this study. 92,694 learning logs are extracted for the analyses. In terms of the logs, we calculate the indicator of Time Spent for the analyses to answer the research question in this study. The indicator indicates the minutes a learner spends on a PDF file within an hour. To calculate it, we aggregate the operations from the same PDF file and sum up the difftime in minutes on an hourly basis. Therefore, its value ranges from 0 to 60.

3. Analysis and Results

To answer the research question, we find clusters from weekly patterns of practicing before a test. The weekly pattern is indicated by the time spent within the week before a test day. First, we extract the Time Spent with a sum greater than zero since we do not consider the week in which a learner does not spend time practicing an effective pattern before the test. Second, we divide the hours within a day into four timeslots: morning (05:00-11:00), afternoon (12:00-16:00), evening (17:00-23:00), and overnight (00:00-04:00). We sum up the Time Spent in each timeslot. Third, we make a 4×7 matrix with the standardized values of the time spent ($X_{i,j}^{(k)}$) by the learner in the four timeslots from Monday to Sunday of the week before the test day. X is the z-score of the Time Spent. i indicates the timeslot, while j indicates the day of the week. k indicates the matrix of the k$^{\text{th}}$ week. Finally, we convert the matrix into a vector with twenty-eight elements.

Regarding the clustering analysis, we input the 723 vectors that imply the weekly patterns. We adopt the Average Silhouette Method to find the optimal number of clusters and identify ten with the greatest silhouette score. Figure 2 shows the ten clusters emerging from the K-means Cluster Analysis. The red line visualizes the center weekly pattern indicated by the vector of the standardized values of the Time Spent in the four timeslots across the week.

In this study, the chronotype is indicated by the maximum value in the weekly pattern. Based on the labels of the ten clusters and their description, we group the clusters of patterns into four chronotypes:

- 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

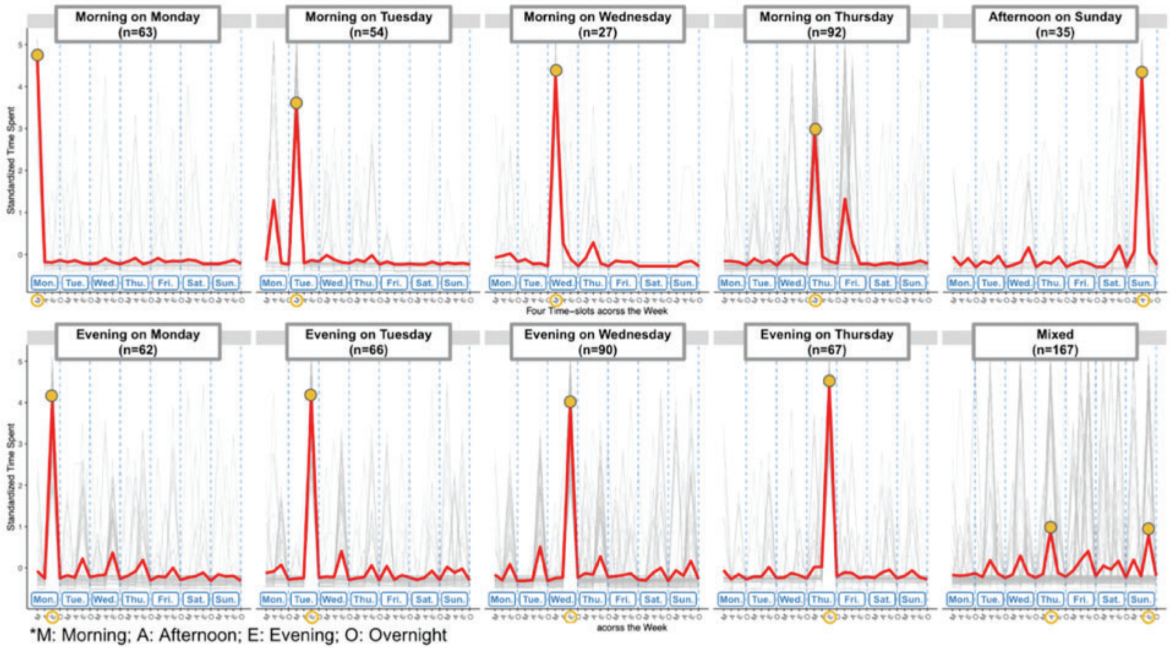

Figure 2. Clusters from Weekly Patterns of Practicing before Tests.

4. Discussion and Conclusion

Based on the findings, we can give practical suggestions such as the timing to send the notification messages considering the chronotypes of the learning habits. The knowledge of the temporal context of the learning habits can provide valuable insight into the "contextual profiling" mechanism since it will capitalize on the learner's schedule for engaging in different learning-related activities.

Collectively, we find this study makes contributions by extracting the chronotypes of the learning habits via the clustering method and dealing with innovative ideas about contextual profiling. The former is novel in identifying the chronotypes from a perspective of educational data mining, while the latter enables context-aware recommendations for a more authentic learning experience with adaptivity and personalization. Therefore, this study is potential for enhancing pedagogical practices in mobile, contextualized, and ubiquitous learning environments in future research.

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