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Identifying Key Indicators of Proficiency in Junior High Math: Roles of Daily Handwriting Learning Logs

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Abstract: This study proposes indicators from daily handwritten math learning logs of junior high school students to model knowledge proficiency, and analyzes the extent of their actual correlation with proficiency using the LEAF system. Our analysis reveals that specific pen stroke behaviors, such as writing speed and task engagement time, show significant, though weak, correlations with proficiency levels. These findings suggest that handwritten logs can serve as effective indicators of student proficiency, offering valuable insights for enhancing educational outcomes.

Keywords: handwriting, log data, learning analytics, proficiency, correlation

1. Introduction

In Japan, the GIGA School initiative is advancing the adoption of one device per student in many K12 schools. This initiative is creating an environment where vast amounts of log data are accumulated from daily learning activities, driving progress in the field of Learning Analytics (LA). Since the primary goal of basic education is the acquisition of knowledge, understanding learners' knowledge proficiency is critical in the context of LA, where learners and teachers aim for efficient learning. Learning logs collected from learning portals are action-based, and research focused on estimating learners' knowledge states from these logs is growing (Takii et al., 2024).

In math learning, the frequent use of the "handwriting" function on devices has made the pen stroke analysis a key focus in math LA. The LEAF system, an LA platform to support teachers and learners with educational log data, incorporates handwriting logs tailored for math education (Ogata et al., 2018). BookRoll, an e-book reader as a key component within the LEAF system, allows teachers to upload learning materials, and students can use handwriting tools to interact with these materials (Yoshitake et al., 2020).

Previous studies have reported correlations between problem difficulty and pen stroke characteristics (Luria and Rosenblum, 2012), as well as between "cognitive load"—the psychological burden on learners—and the vertical direction speed of pen strokes (Lin et al., 2013). However, in K12 education, fundamental knowledge and comprehension are emphasized, while the relationship between pen stroke data and foundational knowledge acquisition levels has not been sufficiently examined. Therefore, we focus on the foundational levels (knowledge and comprehension) of Bloom's taxonomy, a model outlining the stages of knowledge and skill acquisition, to explore the potential connections between pen stroke features from BookRoll and proficiency at these levels (see Figure 1). We set the following two research questions:

- RQ1: How can effective indicators be extracted from handwritten notes in everyday math learning?
- RQ2: How closely are these indicators related to actual math proficiency?

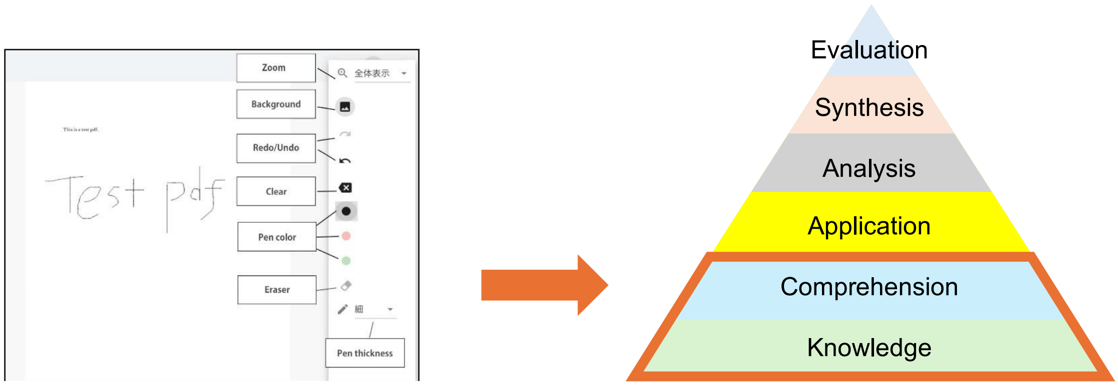


Figure 1. The interface of BookRoll's handwriting tool (Yoshitake et al., 2020) and potential connections to Bloom's Taxonomy

2. Proposal of New Indicators

Given that K12 mathematics often involves calculation tasks, we hypothesized that the extent of active handwriting use could be an effective indicator of proficiency. We also assumed that highly proficient students quickly understand tasks, start solving them immediately, and complete them without breaks. Therefore, we identified three key learning behaviors: (1) reviewing the problem before writing, (2) pen movement during problem-solving, and (3) use of the eraser function.

To address RQ1, we proposed new indicators based on aforementioned factors, which can be collected from daily math learning logs (Tables 1 and 2 explain each parameter and its definition).

Table 1. *The meaning of each parameter*

Parameter	Description	Parameter	Description
s	student	r	resource
m	the number of strokes for that resource	k	stroke number
V_L	the speed of a stroke (length direction)	V_X	the speed of a stroke (horizontal direction)
V_Y	the speed of a stroke (vertical direction)	$t_p(s,r,k)$	the time that learner s generated the kth pen stroke for resource r
$t_e(s,r,k)$	the time that learner s generated the kth eraser stroke for resource r	$t_{open}(s,r)$	time when learner s opened resource r in BookRoll
$t_{close}(s,r)$	time when learner s left the last stroke for resource r		

Table 2. *The Definition of Indicators and its description*

Indicator Definition	Description
$AVL\ (s,r) = \frac{1}{m}\sum_{k=1}^{m} V_L(s,r,k)$	Average speed along the length of the entire stroke

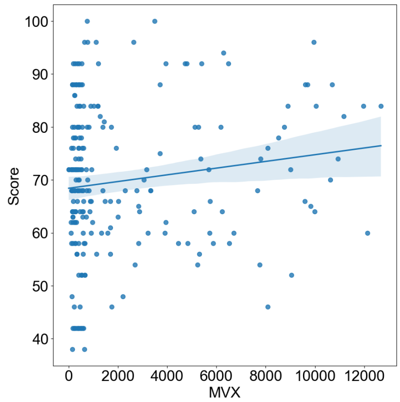
$MVL(s,r) = \max(V_L(s,r,k))$	Max speed along the length of the entire stroke
$AVX(s,r) = \frac{1}{m}\sum_{k=1}^{m} V_X(s,r,k)$	Average speed of the entire stroke (horizontal direction)
$MVX(s,r) = \max\,(V_X(s,r,k))$	Max speed of the entire stroke (horizontal direction)
$AVY(s,r) = \frac{1}{m}\sum_{k=1}^{m} V_Y(s,r,k)$	Average speed of the entire stroke (vertical direction)
$MVY(s,r) = \max\,(V_Y(s,r,k))$	Max speed of the entire stroke (vertical direction)
$RUT(s,r) = \frac{t_p(s,r,1) - t_{open}(s,r)}{t_{close}(s,r) - t_{open}(s,r)}$	The ratio of time that student spend thinking before writing
$RWT(s,r) = \frac{\sum_{k=1}^{m} t_p(s,r,k)}{t_{close}(s,r) - t_{open}(s,r)}$	The ratio of time that student moves the pen while solving the problem
$RET(s,r) = \frac{\sum_{k=1}^{m} t_e(s,r,k)}{t_{close}(s,r) - t_{open}(s,r)}$	The ratio of time that student uses the eraser while solving the problem

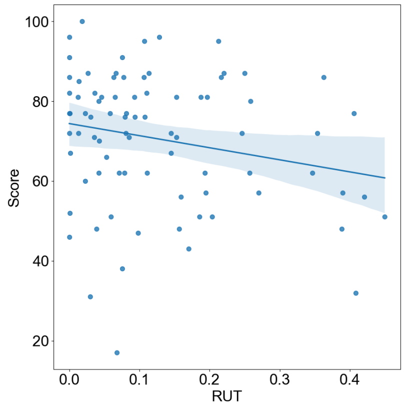
3. Preliminary Correlation Analysis

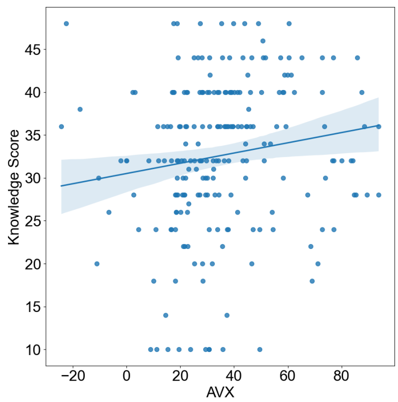
As for RQ2, we collected daily math learning logs from 120 first-year junior high school students in Japan, using BookRoll within the LEAF system for daily mathematics learning, where each page contains a math problem. We extracted logs from the problem pages that met the following criteria: (1) the page has sufficient (100+) pen stroke data, (2) problems from the same unit as the unit test, given at the end of each unit, and (3) logs are recorded before the unit test. We calculated indicator values for each learner and performed a correlation analysis between indicator values and the total unit test scores, which we considered as overall actual proficiency (Analysis A).

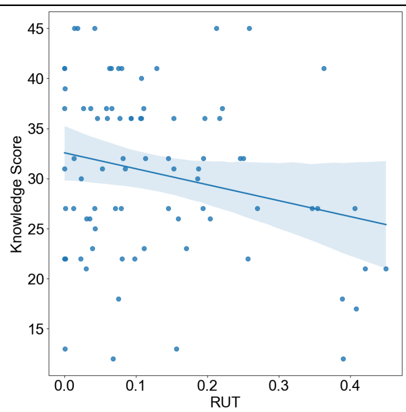
The unit tests classified problems into "knowledge" and "thinking" categories. We conducted correlation analyses between the indicator values and these scores, assuming they correspond to the "knowledge" (Analysis B) and "comprehension" (Analysis C) levels in Bloom's taxonomy. Considering the cognitive difference, we selected "equations and inequalities" as the representative algebra unit and "spatial figures" as the representative geometry unit. Table 3 presents the results of significant correlations.

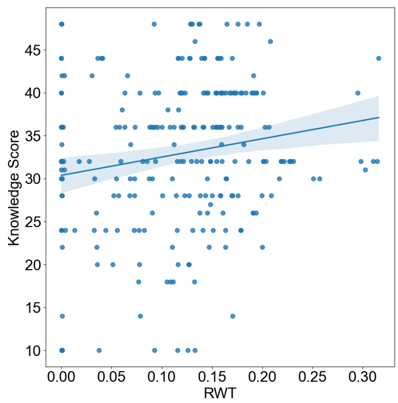
Table 3. Significant correlation between each indicator value and proficiency

<table>
<tr><th></th><th>Algebra</th><th>Geometry</th></tr>
<tr><td>Analysis A
(overall)</td><td>

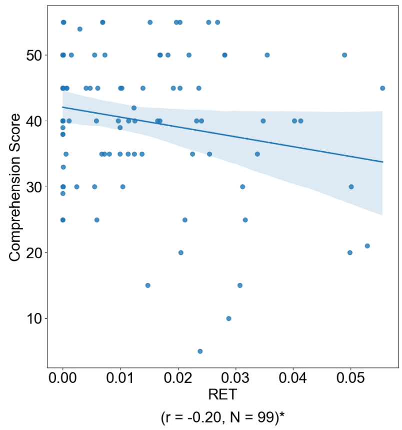
(r = 0.14, N = 228)*</td><td>

(r = -0.21, N = 82)</td></tr>
<tr><td rowspan="2">Analysis B
(knowledge)</td><td>

(r = 0.15, N = 217)*</td><td>

(r = -0.23, N = 82)*</td></tr>
<tr><td>

(r = 0.18, N = 258)**</td><td></td></tr>
</table>

Analysis C (comprehension)		

** p<.05, ** p<.01*

In the typical Algebra unit, Analysis A revealed a very weak positive correlation between MVX values and total unit test scores, while Analysis B also showed a similar correlation between AVX values and knowledge problem scores. These findings suggest that students who write faster in the horizontal direction during tasks have higher knowledge proficiency. Analysis B also found a very weak positive correlation between RWT values and knowledge problem scores, indicating that students who spend more time writing tend to have higher knowledge level proficiency. The calculation-heavy nature of the Algebra unit may have contributed to the effectiveness of these indicators.

In the typical Geometry unit, Analysis A and B identified a weak negative correlation between RUT values and test scores. This suggests that students who start solving tasks immediately after viewing the problem tend to have higher proficiency, especially at the knowledge level. Analysis C showed a weak negative correlation between RET values and thinking problem scores, suggesting that students who use the eraser less have higher comprehension proficiency. The difficulty in anticipating solutions in the geometry unit may have contributed to the effectiveness of these indicators.

These results imply that pen movement speed is linked to proficiency in certain units, partially supporting the hypothesis that highly proficient students quickly grasp tasks, start solving them immediately, and complete them without breaks.

4. Conclusion & Future Work

This study proposed indicators derived from daily handwriting math learning logs and analyzed their correlations with proficiency, finding significant correlations in certain areas. Further investigation is needed to confirm whether these indicators accurately reflect the learning behaviors we have considered. As future work, we plan to predict learners' proficiency for each unit using Principal Component Analysis (PCA) and logistic regression. We aim to construct a proficiency model that can be applied across different units and quantitatively estimate learners' knowledge states. Figure 2 presents our research plan and the positioning of this study, which will offer deeper insights into learning progress.

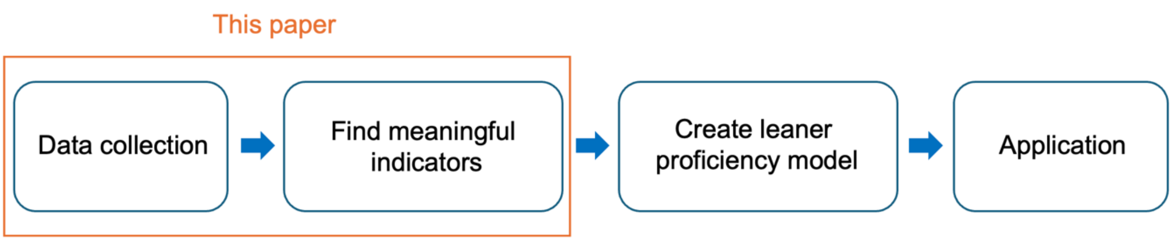


Figure 2. Positioning of this study in our whole research scope

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