Jiang, B. et al. (Eds.) (2025). Proceedings of the 33rd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Trial Analysis on Behavioral Logs to Identify Risk Tactics and Infer Non-Cognitive Skills in Elementary Students

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Abstract: This study explores whether risk-oriented behaviors—such as rapid, browse-like clicking—can be identified in students' learning tactics, and whether non-cognitive skills can be inferred from learning strategies that include such behaviors. Data from 42 students aged 7 to 11 were analyzed using Cronbach's α, the Kruskal–Wallis test, and the Steel–Dwass post hoc test. Results show that students employing the risk-oriented tactic display distinct learning patterns, and that learning strategies are statistically associated with meta-cognition and social competencies. These associations offer insights into how behavioral logs may reflect non-cognitive skills in K–12 education and provide a foundation for future predictive models and targeted interventions.

Keywords: Learning tactic, Learning strategy, Non-cognitive skills, Risk behavior, K-12

1. Introduction

Recent advances in educational analytics have enabled researchers to examine students' learning tactics and strategies through behavioral log data collected from digital platforms such as Moodle and LEAF (Matcha et al., 2019; Ogata et al., 2022).

Learning tactics are specific actions for task completion (e.g., summarizing), while learning strategies are broader patterns formed by combining these tactics to achieve learning goals (Malmberg et al., 2010; Weinstein et al., 2000). While the use of diverse tactics from learning strategy is often associated with improved self-regulation and academic performance (Fan et al., 2021; Matcha et al., 2019), certain tactics—such as rapid and frequent clicking—may reflect uncertainty or shallow engagement (Huber & Bannert, 2023). However, existing studies predominantly focus on university students, leaving open questions about how elementary school students interact with digital learning tools.

Non-cognitive skills—including motivation, meta-cognition, and social competencies—are also increasingly recognized as critical to student development and academic success in K–12 education (Higgins et al., 2005; Kato, 2020). Deficiencies in these areas have been linked to disengagement, ineffective learning strategies, and difficulties in social interaction (Zynuddin et al., 2023). For instance, students with low motivation are more likely to exhibit signs of academic disengagement, experience burnout, or even drop out of school.

These non-cognitive constructs play a vital role in sustaining learning engagement, supporting emotional regulation, and fostering interpersonal communication. However, their connection to cognitive behaviors—especially in digital learning environments—remains underexplored. While prior research has leveraged behavioral log data to infer learning strategies associated with academic performance (Matcha et al., 2019), relatively few studies have investigated whether non-cognitive skills themselves can be inferred from such behavioral patterns.

Previous findings suggest that certain behaviors may reflect risk or instability. For example, (Huber & Bannert, 2023) reported that rapid page transitions may be associated with shallow engagement and low self-regulation, while (Malmberg et al., 2013) found that elementary students who used fewer tactics performed better, implying that tactic overuse may signal strategic indecision. These insights raise the question of whether behavioral log data might offer early indicators of deeper cognitive or non-cognitive issues in younger learners. To address these gaps, this study explores two research questions:

- RQ1: Can elementary students' behavioral log data during digital learning reveal specific risk-oriented tactics, such as rapid, browse-like clicking, and identify learning strategies characterized by the overuse of such tactics?
- RQ2: If such risk-oriented tactics and strategies are identified, can we infer specific non-cognitive skill constructs—such as meta-cognition or social competencies—from the learning strategies that incorporate them?

By investigating these questions, we aim to uncover actionable insights that support early detection of shallow engagement and guide the development of more responsive learning systems for K–12 students.

2. Methods

2.1 Procedure

The methodological procedure involved 42 elementary school students (aged 7-11) engaged in a summarization task appropriate for their age. First, they completed a 33-item non-cognitive skills questionnaire using a 6-point Likert scale. Then, they engaged in a digital learning activity using BookRoll from the LEAF system (Ogata et al., 2022), which recorded their interaction logs. All activities were conducted during regular classes.

After excluding 7 incomplete responses, data from 35 students and 51 learning sequences were analyzed. We evaluated the questionnaire's internal reliability and computed dissimilarities between sequences using Euclidean distance. Learning tactics were identified via clustering of action sequences, and learning strategies were determined by clustering students based on tactic usage. Finally, we examined group differences in four non-cognitive constructs.

2.2 Questionnaire

The questionnaire, adapted from Kato (2020), comprised 33 items across four theoretical constructs: Motivation, Expectancy-Value Theory, Meta-cognition, and Social Competencies.

Each item was rated on a 6-point Likert scale. Motivation was assessed via 12 items aligned with self- determination theory's regulatory styles. Expectancy-value theory was measured with 8 items covering ability beliefs and task values. Meta-cognition included 6 items related to planning and self-monitoring strategies, while Social Competencies were assessed through 7 items addressing interpersonal and prosocial skills. We used Cronbach's α to assess the internal consistency of the four constructs.

2.3 Analysis

We analyzed LEAF learning logs, defining sequences as actions occurring within 5 minutes of each other, which covers about 95% of the observed time gaps (51 sequences from 35 students).

To identify learning tactics, we used the TraMineR package in R to analyze action sequences. Dissimilarities were computed using Euclidean distance based on action frequencies, and hierarchical clustering was performed using Ward's method. The optimal number of clusters was determined using the WeightedCluster package.

To identify learning strategy groups, we calculated three variables for each student: the proportion of sequences in each tactic cluster and the total number of sequences, normalized these to the [0,1] range, and again applied hierarchical clustering with Ward's method based on Euclidean distance. The results were visualized through a dendrogram, which was also used to determine the optimal number of clusters.

Finally, to examine group differences in non-cognitive skills, we used the Kruskal–Wallis test and the Steel–Dwass post hoc test, which are appropriate for small, non-normally distributed samples.

3. Result and Discussion

3.1 RQ1: Detection of Learning Tactics and Strategies

3.1.1 Detection of Learning Tactics from Students' Interaction Logs

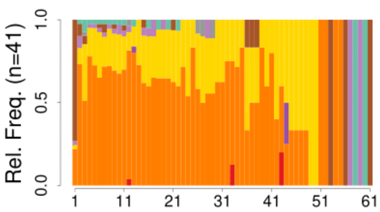
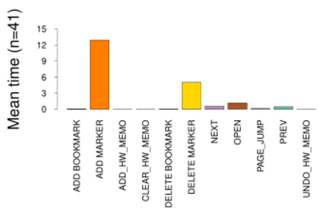
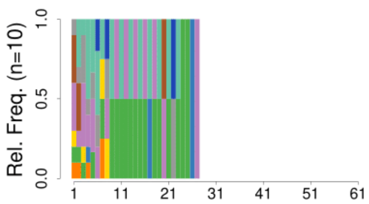
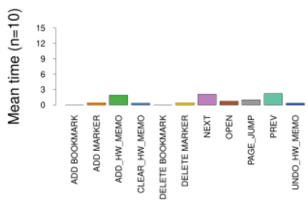
Table 1 presents the characteristics of the two detected tactics (ASW = 0.538).

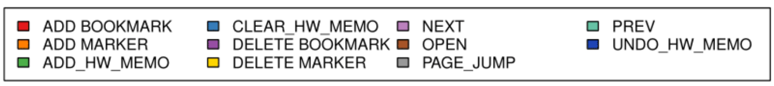
Tactic 1 – Marker oriented (N = 41, 80.39% of all sequences) featured the longest sequences (median = 16 actions), primarily composed of marker additions and deletions following initial page-opening actions.

Tactic 2 – Browse oriented (N = 10, 19.61% of all sequences) involved short sequences (median = 6.5 actions), mostly consisting of frequent rapid page transitions, and may indicate shallow engagement risk-oriented (Huber & Bannert, 2023).

While both involved browsing actions (e.g., PREV, NEXT), Tactic 1 reflected more targeted activity, whereas Tactic 2 showed diverse but less focused interaction.

Table 1. State distribution within sequences and action frequency for the two learning tactics

Tactics	State Distribution	Frequency of Action
1		
2		



3.1.2 Detection of Learning Strategies Through Students' Use of Tactics

Table 2 summarizes key statistics for the clustering input variables across the three identified learning strategy groups, including the frequency of each learning tactic used and the total number of tactics employed by each student.

Strategy Group 1: Rapid-clicking Strategy (N = 10, 28.57%) uniquely adopted Browse-oriented tactics, operationalized as frequent transitions between distinct actions, and was the only group using both tactics.

Strategy Group 2: Marker Focused Strategy: This was the largest cluster (N=17, 48.57%). Students primarily used the marker tactic and did not engage in browsing, showing the fewest total tactics.

Strategy Group 3: Intensive Marker Strategy: This was the smallest group (N = 8, 22.86%). Students showed the highest use of the marker tactic, with no browsing behavior.

Table 2. Summary statistics for each strategy group (median, 1st and 3rd quartile)

Tactics	Strategy 1	Strategy 2	Strategy 3
1	1.0 (1.0-1.0)	1.0 (1.0-1.0)	2.0 (2.0-2.0)
2	1.0 (1.0-1.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
Total	2.0 (2.0-2.0)	1.0 (1.0-1.0)	2.0 (2.0-2.0)

3.2 RQ2: Associations between Learning Strategies and Non-cognitive Constructs

3.2.1 Reliability of the Questionnaire

The internal reliability of the non-cognitive skills questionnaire was evaluated using Cronbach's α.

The Motivation (MOT) scale, with α of 0.7388, met the acceptable threshold, indicating reliable responses across its 12 items. Both the Expectancy-Value Theory (EVT) (α = 0.8590) and Meta-cognition (MC) (α = 0.8582) scales showed high internal consistency, suggesting that the items within each construct measured cohesive aspects of students' learning beliefs and cognitive self-regulation, respectively. Notably, the Social Competencies (SC) scale yielded the highest reliability (α = 0.8677), indicating that participants responded consistently to items related to interpersonal and emotional skills. These results support the appropriateness of using these scales for further analyses.

3.2.2 Group Differences in Non-cognitive Skills Across Learning Strategies

To examine differences in non-cognitive skill constructs across learning strategy groups, we used the combined statistical summary and significance tests, as shown in Table 3.

Figure 1 shows significant differences in learning strategies and non-cognitive constructs. For Meta-cognition, the Marker Focused Strategy showed higher scores than the Rapid- clicking Strategy, suggesting that students in the Marker Focused group tend to have a clearer understanding of their learning methods, while the Rapid-clicking Strategy group's use of both marker and browse tactics may reflect uncertainty or an exploratory stage in their strategy development. The browse tactic, often associated with surface-level learning, could indicate a less stable approach to learning.

For Social competencies, the Intensive Marker Strategy group scored higher than the Rapid-clicking Strategy group, indicating a possible association between the Intensive Marker group's consistent and goal-oriented learning behaviors and stronger social competencies. The Rapid-clicking Strategy group, characterized by lower social interaction and a less focused approach, may need support to improve social engagement and self-regulation.

Overall, the effect sizes for Meta-cognition ($\eta^2 = 0.284$) and Social Competencies ($\eta^2 = 0.218$) are large, indicating that differences between strategy groups are practically meaningful and reinforce the relevance of the statistical findings.

Table 3. Non-cognitive scores across three strategy groups with nonparametric tests

Skills	Strategy Groups Median (Q1-Q3)			Kruskal-Wallis Test		Steel-Dwass Test
	Strategy 1	Strategy 2	Strategy 3	p-value	η^2	
MOT	3.4 (3.1-3.6)	3.8 (3.6-4.2)	3.6 (3.4-4.7)	0.1440	0.059	–
EVT	4.4 (3.8-5.3)	5.4 (5.1-5.8)	5.1 (4.6-5.8)	0.0677	0.106	–
MC	3.2 (3.0-3.6)	4.7 (4.3-5.0)	4.7 (3.6-5.3)	0.0039^{**}	0.284	S1<S2: $p = 0.0012^{**}$
SC	4.4 (3.6-5.4)	5.3 (4.6-5.7)	5.7 (5.6-5.8)	0.0113^{*}	0.218	S1<S3: $p = 0.0116^{*}$
Score	9.5 (8.2-18.0)	13.0 (9.0-20.0)	11.0 (7.5-17.0)	–	–	–

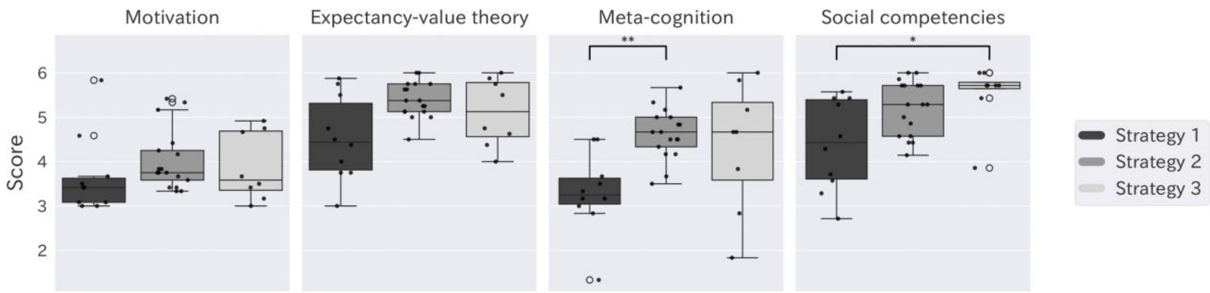


Figure 1. Distribution of strategy groups with respect to the non-cognitive four constructs

4. Conclusion, Limitation and Implication

4.1 Conclusion

This study explored two research questions related to elementary students' cognitive behaviors and non-cognitive skills. We observed that students had developed preferences for certain learning tactics and strategies. Notably, in learning tactics, we identified the marker-based highlighting tactic and the browse-oriented tactic. The rapid and frequent actions in the browse-oriented tactic align with shallow engagement patterns described by (Huber & Bannert, 2023), with frequent page transitions reflecting a less stable or goal-directed approach. In learning strategies, the Rapid-clicking Strategy involved more tactics, aligning with (Malmberg et al., 2013), who suggested excessive or unfocused tactic use may reflect uncertainty rather than effective learning.

Importantly, this study revealed certain non-cognitive skill constructs, such as meta-cognition and social competencies, are related to learning strategies including risk-oriented tactics. The Rapid-clicking Strategy group showed lower scores in both meta-cognition and social competencies compared to other groups, indicating a notable relationship between learning behaviors and non-cognitive skills.

Overall, these associations provide insights into how behavioral logs reflect non-cognitive skills in K–12 education and lay a foundation for future predictive models and interventions supporting students' learning and non-cognitive development.

4.2 Implication and Limitation

This study identifies risk-oriented tactics like rapid, browse-like clicking and highlights learning strategies that use multiple tactics, sometimes to a high degree. These findings can help educators detect shallow engagement and inform adaptive learning system developers. However, some interpretations—such as the link between browse-like behavior and lower meta- cognition—remain speculative and require cautious interpretation and further validation.

Due to the small sample size and case-study design, the generalizability of results is limited. The specific context and participants may not represent broader populations or different educational settings. As a result, this study does not yet produce actionable prediction models or interventions but lays important and incremental groundwork by identifying relevant behavioral patterns associated with non-cognitive skills.

Additionally, this study relies on Kato's questionnaire (Kato, 2020), which covers some non-cognitive skills but not the full range. Future research should use larger samples, add academic data, include qualitative methods (e.g., interviews), and explore more non-cognition skill constructs across frameworks (e.g., Big Five, CASEL) to validate results.

Acknowledgements

This study was funded by MEXT/JSPS KAKENHI Grant Number JP23H00505.

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