

# Handwriting Patterns Across Different Learning Tasks: A Case Study in Special Needs Education

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**Abstract:** With digital learning tools, students' handwriting interactions can be recorded as log data, enabling analysis of how learning tasks are carried out beyond final answers. However, prior studies often treat the handwriting behaviors as general tendencies, without separating them by the characteristics of the task. Given that learning tasks often come in various formats, and may prompt different response processes, handwriting behaviors may also differ across tasks. This distinction among the tasks is likely relevant in special needs settings where teachers regularly adjust tasks and pacing based on each individual student. Therefore, this case study examines how handwriting behaviors differ across two different task characteristics for an individual student with special needs by using handwriting logs captured during regular learning activities. The student completed two tasks, which consisted of a language-based selection task and a visual matching task. We compared the handwriting process indicators and examined behavioral patterns through the visualization. Overall, the language-based task showed greater interruption and revision while the student was working, whereas the visual matching task showed the opposite pattern. Scribble was also observed in both learning tasks, but at different frequencies and timings, which may carry different meanings depending on when it occurred. The findings extend prior handwriting research by revealing that the student exhibits different approaches across two different learning tasks. These differences offer indicators that may support teachers' monitoring and intervention.

**Keywords:** Handwriting patterns, learning analytics, log data, special needs education

## 1. Introduction

Digital learning technologies can now record the handwriting process, providing access to students' detailed actions during task execution. These traces can be stored as handwriting logs, enabling analysis of the writing process rather than only the final answer (Yoshitake et al., 2020). Accordingly, handwriting logs provide a practical way to observe how students carry out these processes over time, which provides insights into students' patterns during task execution. For example, prior studies using handwriting logs have suggested that revision behaviors, such as repeated erasing and corrections, can indicate moments when students experience difficulty or get stuck when solving a task problem (Atake et al., 2023; Ogata et al., 2024). While these studies offer valuable insight into the students' approach to execute the task, prior studies using handwriting logs have predominantly analyzed behavioral patterns within a single task type (Okayama et al., 2024; Tonosaki et al., 2024). Yet in real classroom settings, students encounter a variety of tasks that differ in their format and demands. Drawing on Cognitive Load Theory, Sweller (2011) argues that the characteristics of task can impose different levels of working memory load depending on element interactivity. Indeed, classroom observations have shown that students with learning difficulties respond differently depending on task demands, spending less time on-task when cognitive load is higher (Krupski, 1985). As a result, the handwriting pattern reflecting how tasks are performed may vary depending

on the type of task they are given, rather than representing a fixed characteristic of a single student. This is particularly relevant in special needs education, where teachers make ongoing instructional adjustments based on observations of students' academic performance and behavior, including adapting tasks and pacing to individual needs (McLeskey et al., 2017). However, it remains unclear whether observable handwriting behaviors systematically differs across different learning tasks in special needs contexts. Therefore, this study investigates such behavioral variation in an individual case of a student with special needs, using handwriting logs to characterize the learning task execution patterns beyond the final answer. Accordingly, we address the following research question:

RQ: How do handwriting behaviors differ between learning tasks for a student with special needs, as captured in handwriting logs?

## 2. Methods

This study used handwriting log data collected from a third-grade student in a special needs classroom at a Japanese elementary school. The data were generated while the student completed two learning tasks on a digital learning platform during regular classroom activities over a three-month period. Task A involved circling the word that matched a picture, while Task B involved connecting identical pictures with lines. In total, 32 sessions were collected (17 for Task A and 15 for Task B). The dataset comprised 975 log entries, including 694 and 281 entries, respectively. Two analyses were conducted. First, we examined the frequency of key log operations related to writing, erasing, undo, and redo, as well as time gaps between strokes to capture fluency. Second, we analyzed how the student's actions unfolded over time during task execution using replay-based visualization of the handwriting process.

## 3. Results and Discussion

As shown in the boxplots in Figure 1, sessions in Task A and Task B differ in stroke rate, task completion time, mean pause interval between strokes, and revision-related operations. Sessions in Task A generally took longer to complete and showed longer mean inter-stroke pauses than those in Task B, suggesting more prolonged interruptions during task execution. Task A sessions also exhibited more frequent revision behaviors, as reflected by the higher erase and undo rates. Whereas Task B sessions showed near-zero erase and undo rates in most sessions. Meanwhile, redo operations were infrequent in both types of tasks.

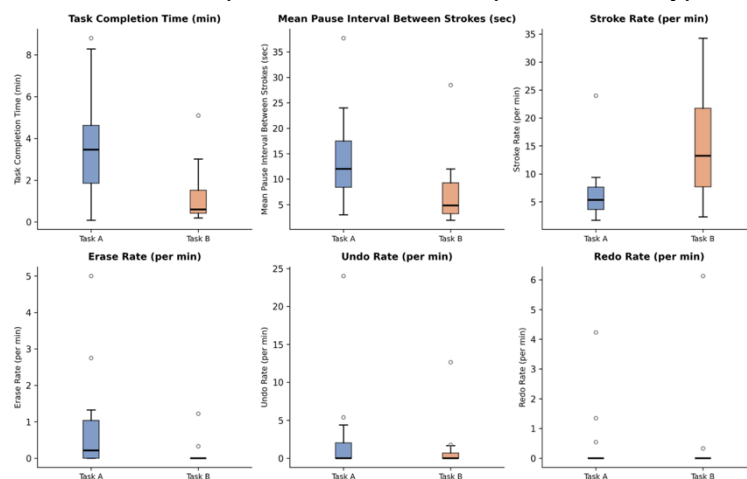


Figure 1. Boxplots of handwriting indicators for Task A and Task B across sessions

When reviewing the handwriting sessions, we observed several scribble behaviors across the sessions in both learning tasks. In Task A sessions, the student tends to produce scribble strokes more often while actively working on the tasks. Across the 17 sessions, scribbles occurred in 12 sessions, which corresponds to around 70% of the sessions. These scribbles appeared mainly in the early to middle part of the sessions, indicating that they occurred during active task execution rather than after the task was completed. Most scribble

strokes were shortly followed by erase and undo events. Through visual inspection of the handwriting session, many of these erase and undo events appeared to remove the scribble, and in some cases were also used to revise the student's answers. After scribbling, the student typically re-engaged with the task and continued to make progress throughout the sessions. Therefore, this pattern may reflect moments of uncertainty or increased cognitive demand while the student is actively working on the task. In contrast, scribble strokes were much less frequent in Task B sessions. Across the sessions in Task B, only 4 of 15 sessions contained the scribble strokes, and these occurred only after the student had completed the task.

#### 4. Conclusion

Overall, the results suggest that the student's behaviors differed between the learning tasks. The visual matching task, which can be viewed as a relatively less demanding task, was generally completed in shorter sessions with briefer inter-stroke pauses and low revision activity. On the other hand, the language-based selection task, which added linguistic processing beyond visual recognition, tended to show the opposite pattern. In addition, scribbles observed during task execution may also carry different meanings depending on both the task type and when they occur. This suggests that teachers may need to respond differently depending on the context. In practice, teachers can use these cues to judge whether the student needs immediate support or can continue with ongoing monitoring, depending on the task and when the behavior occurs. These cues also provide a basis for developing automated detection models, whose outputs can be confirmed with the teachers' validation. The main limitation of this study is that it focuses on a single student from one special needs classroom. Thus, the observed task-dependent patterns should be interpreted as case-specific and may not generalize to other students or settings. Future work should extend this analysis to larger and more diverse student samples to assess the generalizability of these patterns and validate the identified behavioral cues against teacher judgments and classroom observations.

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