Majumdar, R. et al. (Eds.) (2025). Proceedings of the 1st International Conference on Learning Evidence and Analytics. Asia-Pacific Society for Computers in Education

Exploring Learning Behaviour of Students with Special Needs through Handwriting Logs

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Abstract: Students' handwriting log data can now be collected through digital devices. Several studies have utilized this data to understand the condition of learners, but few have specifically examined the writing behavior of students with special needs while working on task-based activities. This study aims to identify characteristics of the writing behavior of students with special needs through the analysis of handwriting log data. Four main features were analysed: the number of strokes, the number of erases, the number of pauses, and the duration of writing. The agglomerative hierarchical clustering algorithm was used to group students based on the similarities in their behavior. One group showed higher average values across all features, while the other showed lower values. These findings suggest that students with special needs have diverse learning patterns, which can be mapped through handwriting data and possibly used to support more adaptive learning design.

Keywords: Handwriting, learning analytics, log data, special needs students, clustering

1. Introduction

Handwriting is a coordinated activity that combines perceptual, muscular, kinesthetic, and cognitive processes (Milani et al., 2018). In an education context, analyzing students' handwriting offers valuable information about how they approach learning tasks, not just through outcomes but also through their writing process. In Japan, the Global and Innovation Gateway for All (GIGA) program provides one device for one student, enabling the collection of detailed learning logs, including handwriting data. Prior studies have shown that handwriting features, such as stroke count, erase frequency, pause behavior, and total duration, can reflect a learner's situation, provide insight into their writing behavior during problem-solving, and their proficiency level (Atake et al., 2024; TONOSAKI et al., 2024). However, those previous studies have focused on students in regular classes or general education settings. Limited attention has been given to analyzing how students with special needs engage in the writing process during classroom tasks. Students with special needs may face various difficulties when writing, such as problems with handwriting, spelling, building sentences, writing smoothly, or making corrections, which may arise from challenges in hand movements or struggle with focus or thinking processes (Donne & Hansen, 2023). Because of these differences, the way they go through writing tasks might not be the same as that of other regular students. Therefore, it is important for teachers in special needs education to understand their writing engagement patterns to identify underlying difficulties and respond with personalized support. This study aims to identify patterns that describe how students perform writing tasks by clustering the handwriting logs. Accordingly, the research question of this study is as follows:
RQ : What characteristics of writing behaviors can be identified from the handwriting logs of special needs students?

2. Methods

This study involved 27 students from 1st to 6th grade in a special needs class in a Japanese Elementary School. Over one month, students completed Japanese and Math writing tasks using BookRoll, a digital reader that allows handwriting input via stylus (Ogata et al., 2018). Their pen strokes were automatically recorded as log data for analysis, resulting in 61 handwriting activities. To analyze the possible types of students' writing behavior, we used an agglomerative hierarchical clustering, as it is suitable for small data sizes (Abdalla, 2021). The clusters were formed based on four handwriting features: strokes, erases, pauses, and writing duration. The number of pauses is selected as it is often associated with cognitive difficulties such as planning or revising (Olive et al., 2009). On the other hand, erases can be seen as moments of struggle because the writer tries to adjust their writing and make sense of their own words (Tenório et al., 2017). In addition, knowing the number of strokes allows teachers to detect students who may be experiencing difficulties (Coradinho et al., 2023). Writing duration is also included because it can be influenced by individuals' skill level and task complexity, providing meaningful information for further analysis (Goldhammer et al., 2014).

3. Results and discussion

We used Silhouette method to identify the optimal number of clusters, resulting in $k = 2$ with the highest average silhouette score of 0.54. Based on the number of clusters and average values shown in Table 1, two distinct handwriting behaviour patterns of special needs students were identified. Cluster 1 included 14 handwriting activities, and Cluster 2 comprised 47 handwriting activities, as visualized in dendrogram shown in Figure 1.

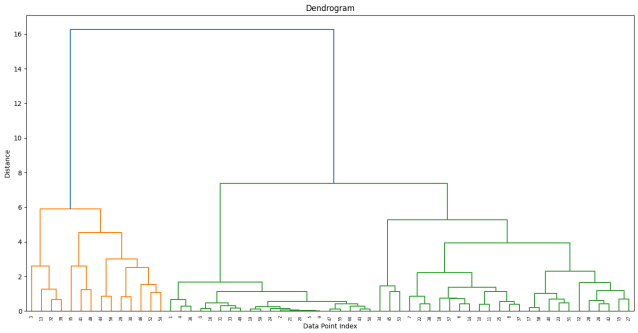
- Cluster 1 : This group shows higher average values for the number of strokes, number of erases, pause count, and writing duration. Students in this cluster demonstrate long writing sessions with frequent pauses, strokes, and erasures. This may indicate that they are working carefully because they spend time thinking, making detailed adjustments, and revising on purpose. Alternatively, these behaviours may also suggest that they are unsure and have difficulty putting their thoughts into writing, possibly because the task was cognitively challenging.
- Cluster 2 : This group displays significantly lower average values across all features, indicating shorter writing sessions with fewer strokes, pauses, and erasures. While this may reflect fluent writing behavior as they found the task did not require much effort, it is also possible that these students were less engaged, rushed through the task, or struggled to sustain attention over time.

While a previous study in a general classroom described frequent pauses or erasures as separate learning patterns (Atake et al., 2024), our clustering results show that these behaviours can co-occur within the same learners. Separately, the identified clusters in this study revealed a positive relationship between the number of strokes and total answering time, consistent with findings identified by TONOSAKI et al. (2024). Building on prior studies that highlighted the potential of understanding handwriting behaviour to support more contextualized and adaptive intervention, this study provides a slightly different implication by offering more personalized suggestions. By understanding the characteristics of each group, teachers may identify the students' specific needs and adjust the support accordingly. For Cluster 1, teachers are suggested to determine which part of the task is challenging to give the right help to students. On the other hand, to provide support for Cluster 2, adjusting the level of task challenge may help increase student engagement, while reducing the task length could help accommodate students' attention span.

Table 1. *Average values of handwriting features for each cluster*

	num_strokes	num_erases	pause_count	duration
Cluster 1	368.2	39.7	45.3	1294.6
Cluster 2	100.0	7.3	11.4	337.4

Figure 1. Dendrogram for hierarchical clustering



4. Conclusion

This exploratory study used a small set of handwriting logs to generate initial insights into special needs students' handwriting patterns based on data available at the time of analysis. Although students' grades varied, developmental differences were not analyzed due to the limited sample size. Two distinct patterns have been identified by clustering the logs based on selected features. For more comprehensive results, further studies should include other potential handwriting features and increase the data size. In addition, this study is based solely on analyzing handwriting logs, limiting the ability to directly infer students' cognitive states or difficulties. Future works should support these interpretations using multiple data sources to confirm the findings, such as observation, teacher interviews, or student self-reports.

Acknowledgements

This work was partly supported by Council for Science, Technology and Innovation (CSTI), 3rd SIP JPJ012347 and JSPS KAKENHI Grant Number 23H00505. Indonesia Endowment for Education (LPDP) Grant Number SKPB-1585/LPDP/LPDP.3/2025 also supported this work.

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