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Predicting Learners' State of Mind from Cross-Contextual Educational Log Data

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Abstract: This study investigated the techniques for predicting learners' state of mind from cross-contextual educational log data. The digitization of the educational environment has led to the accumulation of log data, which is expected to facilitate the identification of subtle changes in learners related to G&C characteristics. However, the utilization of log data for G&C has not been examined sufficiently, nor has the change point detection (CPD) for G&C characteristics been explored. Therefore, this study predicted learners' state of mind from cross-contextual educational log data using Bayesian Online Change Point Detection with extended processes. We applied the extended steps and resampling, which have been attempted in the medical field, on real-world educational data with many missing values. As a result, we achieved a maximum AUC of 0.697, demonstrating the potential to predict changes in learners' state of mind from educational log data. Although there are still many points to consider, such as missing value handling methods and the true positive rate for detecting students with problems, this study presents important results for capturing and predicting changes in learners' state of mind, a crucial aspect of G&C.

Keywords: Guidance and counseling, Change point detection, Learning analytics, Across context

1. Introduction

Guidance and Counseling(G&C) in school education is crucial for creating a favorable learning environment and supporting learners' holistic development (Naraswari 2024; MEXT 2022). Early detection of academic, behavioral, and social-emotional challenges, followed by timely interventions, is crucial for fostering meaningful success experiences among learners (MEXT, 2022; Ito et al., 2023; Nitz et al., 2023). Teachers, particularly homeroom teachers, are considered to play key roles in detecting these subtle changes in learners early and intervening appropriately (MEXT, 2022; Green et al., 2017). In practice, some efforts rely on homeroom teachers sharing daily observational records to identify minor behavioral changes. Nevertheless, challenges such as the burden of regular documentation and reliance on subjective assessments have been highlighted (MEXT, 2022). On the other hand, the digitization of the educational environment has led to the accumulation of log data related to learners' learning and daily lives (Ogata et al., 2023). It is expected that integrating these log data with other sources will enable teachers to better understand learners and enhance G&C strategies (MEXT, 2022). However, using cross-contextual log data for G&C has not been examined sufficiently. One reason is the difficulty of interpreting granular data without considering the subject characteristics and activity contexts.

For these challenges, Atake et al. (2024) proposed a method for extracting characteristics that collects and standardizes log data to determine if the learner is in good standing, supporting teachers' understanding of learners, even for non-subject-specific teachers. Teachers evaluated these characteristics as helpful for identifying learners' potential issues and supporting their understanding. These techniques enable the identification of learner characteristics and support teachers in understanding their learners. However, the study by Atake et al. (2024) only proposed a method for capturing learners' states at a single point in time and did not explore changes over time across contexts.

This limitation reflects a broader gap in the field of learning analytics (LA), where similar approaches, such as change point detection for risk identification, have primarily focused on predicting well-defined academic outcomes like grades or dropout. In contrast, relatively few studies have explored the detection of early warning signs or dynamic behavioral and psychological changes in real-time learning environments (Li et al., 2024). Considering the above, this study proposes a method for identifying changes in learners by combining the approach proposed by Atake et al. (2024) with the Bayesian Online Change Point Detection (BOCPD) method proposed by Adams et al. (2007) and applying it to educational log data. The objective of this study is to predict learners' state of mind, a key indicator in G&C, using educational log data. This approach contributes to proposing an innovative method for G&C, the process of identifying changes in learners' state of mind, traditionally based on observable academic behaviors or performance, by offering a data-driven perspective for capturing such changes.

2. Literature Review

2.1 Capturing learner changes in Guidance and Counseling

As part of the process of understanding the learner in G&C, recognizing learners' subtle changes is essential for early support and intervention (MEXT, 2022). According to Green et al. (2017), teachers are considered to play a key role in identifying subtle changes in learners. Then, how and what changes are expected to be identified? The specific signs are academic, behavioral, and socioemotional changes such as poor academic performance, social isolation, and sudden changes in behavior (Green et al., 2017). Green et al. (2017) emphasize the importance of integrating both observational approaches, such as teachers' intuition, and objective methods, including standardized screenings, academic data, and student self-reports. To support this process, it has adopted frameworks such as Multi-Tiered Systems of Support (MTSS), which provide tier-structured, data-driven strategies for addressing diverse learner needs (Ito et al., 2023; Nitz et al., 2023; Miller et al., 2014). In addition to these, focusing on health and changes in physical aspects is crucial (Green et al., 2017). Through the improvement of individual teachers' observation skills and sensitivity, and the development of a system of multidisciplinary cooperation and data utilization as a school organization, it is expected that a comprehensive system will be established to catch small signs of children daily without overlooking them, leading to the prevention and early resolution of problems. However, it has been noted that internal symptoms and minor signs are often overlooked because they may not be apparent in students with good academic performance (Kim et al., 2022). In addition, MTSS does not focus on real-time detection of early signs, which remains underdeveloped from data.

2.2 Change Point Detection Techniques

Although mean and variance are generally used to understand changes from educational big data, they can capture only broad changes, such as those occurring over large intervals as statistical indicators (Nakamura et al., 2024). Therefore, the Change Point Detection (CPD), which refers to the technique for identifying points in time-series data where statistical properties change, is necessary to find notable changes over time (Nakamura et al., 2024). CPD methods are generally categorized into two types: offline methods, which analyze data retrospectively, and online methods, which detect changes in real-time as data is collected (Truong et al., 2020). This study focuses exclusively on online methods for real-time monitoring.

Previous studies have examined several online methods. Eubanks-Carter et al. (2012) investigated CPD techniques to detect key moments in psychological therapy, specifically "ruptures" and "resolutions" in the therapeutic alliance, evaluating four main approaches: Control chart methods, Partitioning methods, Criterion-based methods, and Regression-based methods. Control chart methods, such as Shewhart charts, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA), detect changes sequentially with low computational cost. In educational research, they have been applied to real-time monitoring of learner performance and engagement (Prasad, 2020; Shimada et al., 2018). For instance, Prasad (2020) used control charts to track learner grades, highlighting that Shewhart charts are more sensitive to abrupt shifts, while CUSUM is better suited for detecting small, sustained changes. Shimada et al. (2018), although not explicitly referring to "Control charts," proposed an online method that updated models per minute to detect changes in click activity during lectures. Early warning systems in learning analytics often use threshold-based triggers, which conceptually resemble simplified control charts for engagement indicators. However, few studies have addressed multivariate control charts or personalized chart designs that account for individual differences. Partitioning methods divide the entire time series into multiple segments to detect multiple change points. Representative techniques include Binary Segmentation and PELT (Pruned Exact Linear Time) (Truong et al., 2020). Nakamura et al. (2024) proposed a method using PELT to automatically detect changes in learners' engagement levels during class, based on digital textbook logs. However, these methods may involve high computational costs and statistical limitations. Most applications in education have been restricted to univariate or low-dimensional data.

As a means of addressing these challenges, there is the Bayesian online change point detection method (Adams et al., 2007). While conventional methods detect change points retrospectively based on all past data, this method uses only the data observed so far to predict what will happen next while detecting change points. Additionally, while many previous Bayesian methods were offline methods, this method enables real-time prediction based on accurate Bayesian inference, allows for sequential updates, and features a modular design that provides flexibility for easy application to various types of data (e.g., Gaussian, Poisson). However, this method is designed under the assumption of continuously observed data, where the run length is updated sequentially at each time step. As such, it does not natively handle missing observations, and additional mechanisms are required to accommodate data with random missing values. Furthermore, the proposed approach primarily targets univariate or low-dimensional data and does not readily scale to high-dimensional settings, where computational and statistical challenges arise.

An example application is found in Romero-Medrano (2022), who extended a BOCPD method to detect behavioral shifts in individuals with mental disorders using multiple sensor data from smartphones and wearable devices. The objective was to predict self-injurious and aggressive behaviors, including suicide risk, up to one week in advance, and the result showed an AUC of 0.79. The system utilized high-dimensional, heterogeneous, and frequently missing data such as step counts, GPS-based mobility, time spent at home, app usage, sleep patterns, and emotion logs, collected via the digital app. To address real-world constraints—irregular sampling, missing values, and mixed data types—the method integrated BOCPD with latent variable models, local observation models, and weighted integration mechanisms, was validated as effective.

2.3 Significance of This Study and Research Questions

The digitization of educational environments has led to the daily generation and accumulation of a large volume of log data related to learners' learning activity and daily lives. This growing body of educational log data provides an unprecedented opportunity to quantitatively evaluate learners' behavior and its changes. On the other hand, there are few examples of real-time change point detection for multiple log data in a real-world educational context, and these are the few that have been studied to improve teachers' G&C (Table 1).

Therefore, this study aims to verify the applicability of BOCPD on real-world educational log data and to predict learners' mental health conditions using these data. To this end, we propose using the Bayesian Online Change Point Detection (BOCPD) method and its extension developed by Romero-Medrano (2022) in the field of psychiatry and applying it to educational log data in this study. As an important G&C indicator, we utilized state of mind, a subjective self-report input by learners, and applied BOCPD techniques innovatively. This is expected to contribute to the early identification of changes in learners within the G&C

framework. To clarify the scope of this study, and based on a comprehensive review of the existing literature, the following research questions are posed:

- RQ1: How much change can be detected using BOCPD on real-world educational log data?
- RQ2: To what extent can learners' state of mind be predicted based on educational log data?

Table 1 Research Position of this study

	Nakamura et al. (2024)	Eubanks-Carter et al. (2012)	Romero-Medrano (2022)	This Study
Educational-Context	✓	×	×	✓
Multi-contextual log data	×	×	✓	✓
Real-time detection	×	✓	✓	✓
Method	PELT	EWMA, CUSUM etc.	BOCPD	BOCPD
Proposal	Detects multiple changes using PELT from educational big data	Detects alliance ruptures and resolutions in psychotherapy	Predict self-injurious and aggressive behaviors up to one week	Predicting changes in learner's state of mind from cross-contextual log data

3. Data Context and Methods

3.1 Data Collection and Context

This study used log data of daily activities in the Goal-Oriented Active Learner (GOAL) system to address RQs. This system serves as a tool to support learners' activities both within and beyond the school curriculum and collects and integrates personal health and learning data logs from multiple sources, such as a GARMIN device and the e-book reader (Li et al., 2021). From a G&C perspective, this is valuable as it enables comprehensive tracking of learners' activities. We used five contexts of log data: math activity time, English activity time, math score, stress level, and steps taken. The data gathered from 116 learners covers the period from June 2020, when the learners enrolled (the start was two months later than usual due to COVID-19), to March 2023. In addition, we use the state of mind (self-reported data input by learners) data collected through health observations on Moodle. Health observations are mandatory in Japanese public schools, and with the recent spread of ICT tools, data such as sleep duration, temperature, and state of mind (recorded as numerical values ranging from 0 to 100) have been collected. This study analyzes the five educational log data points and the state of mind data.

3.2 Data Processing

Figure 1 shows the procedure of data processing. The five log data sets and the state of mind data are from different activity contexts, so the original values have different meanings. Therefore, we first attempt to collect and standardize the data using the characteristics proposed by Atake et al. (2024). The scaled values range from 0 to 10, where 10 indicates a positive state and 0 indicates a negative state in any context.

Next, the five log datasets are resampled on a daily and weekly basis because the log data is collected at different times and recorded regardless of whether a weekday or a weekend. In addition, the state of mind is generally recorded daily during the school year, but not on weekends, holidays, or during long school breaks. For these reasons, we resampled data 1 day and 7 days to attempt to detect changes in learners. This enabled us to capture both short-term fluctuations and medium- to long-term behavior patterns. During this process, activity time-related metrics are rescaled based on the total activity time for that day, while other metrics are averaged over the day or week. The resampled data is restructured according to activity time and described in five dimensions, and we applied BOCPD to these two types of data to compare which is the most effective in predicting learners' state of mind.

Furthermore, we confirmed the available data points and obtained the results shown in Figure 2. Therefore, in this study, we finally chose the period from October 2021 to March 2022, which is six months with abundant data for the five indicators.

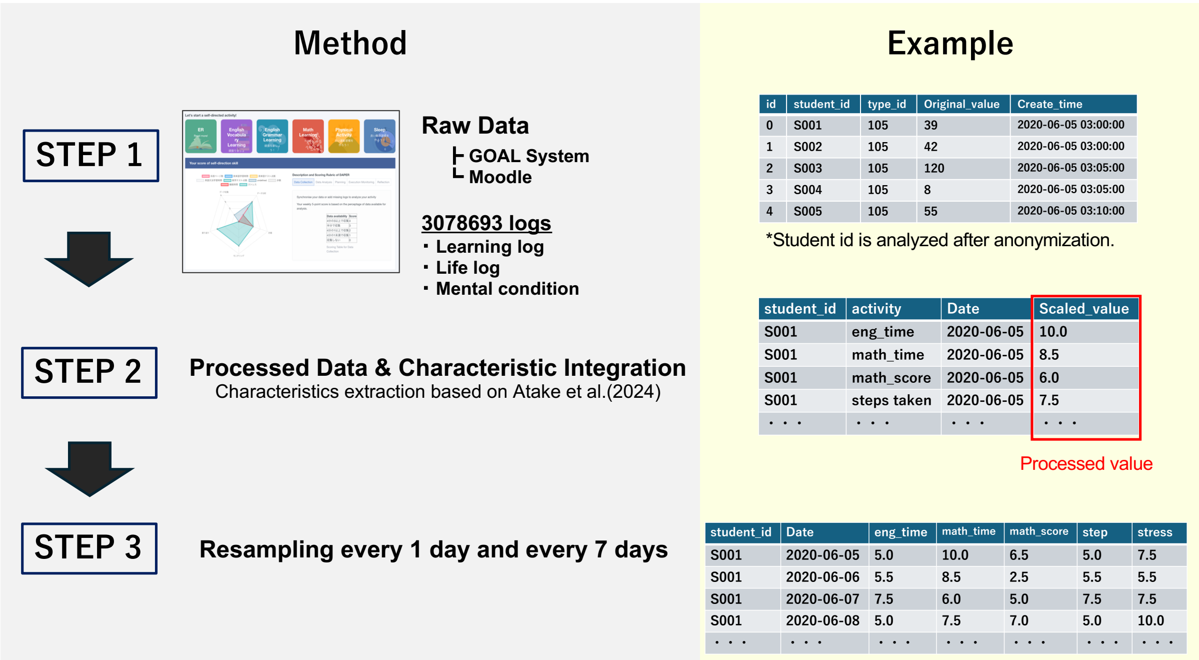

Figure 1 The Procedure of Data Processing

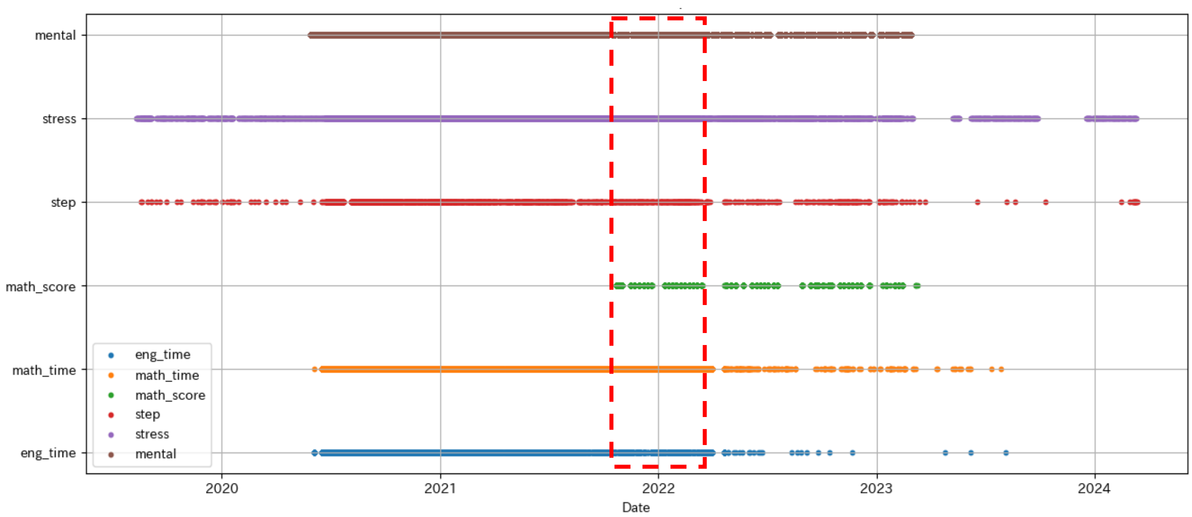

Figure 2 Available Data Periods in Each Dataset

3.3 Extension of Bayesian Online Change Point Detection

The original BOCPD method assumes continuously observed data and does not contain missing values. Therefore, we first confirmed the extent of missing values, and many missing values were identified, especially in variables such as steps and stress that were not directly linked to school activities. To address this, we compared two different strategies for handling missing values: (i) imputing missing entries with zero, treating them as if there was no activities, following the proposal by Atake et al (2024) and (ii) a proposed weighted approach in which weekly aggregated data were used while reducing the influence of weeks with high proportions of missing observations. In addition, following the proposal by Romero-Medrano (2022), some process steps were conducted. Although each variable has been rescaled to a standardized 0–10 score, the original data are derived from heterogeneous sources with different statistical types and missing patterns. Thus, despite standardization, the underlying structure remains high-dimensional and complex. To capture latent patterns of behavior, we apply a Latent Variable Model (LVM) to map each day's observation to a probabilistic mixture of classes (1).

$$p(x_t|\theta_t) = \sum_{k=1}^{k} p(x_t|z_t = k) \cdot p(z_t = k|\theta_t) \qquad (1)$$

This equation shows that the observed data x_t is generated from a latent class z_t, where each class has a different probability and a different distribution.

Next, the ambiguity of the multi-class distribution is treated in multinomial Sampling, and the same method is applied in this study. Since the output of latent variable models is probability-based, it is often a flat distribution. Therefore, multinomial Sampling is effective to address the challenge. One sample is selected according to the probability distribution and treated as a pseudo-definite "observation class. This is said to increase the accuracy of the change point detection model used in the next step (2).

$$z_t^s \sim Categorical\big(p(z_t|x_t)\big) \text{ for } s = 1, \ldots, S \qquad (2)$$

This produces S samples for each time t, which reflect the likely latent states.

Based on the above steps, the analysis can be performed by BOCPD, which estimates the probability that a change has occurred at each time point. If the latent class series suddenly changes, it is detected as the beginning of a new behavior pattern. The joint distribution of run-length and data sequence is given by(3)

$$p(r_t|z_{1;t}) = \sum_{r_{t-1}} p(r_t|r_{t-1}) \cdot \Psi_t^{(r)} \cdot p(r_{t-1}, z_{1:t-1}) \qquad (3)$$

$\Psi t(r)$ shows the predictive likelihood of the current latent class given the past, and rt is the time since the last change point. Based on the above processing, to answer RQ1, we will verify the applicability of BOCPD by examining the consistency rate between the log data applied with BOCPD and the state of mind. Then, to answer RQ2, we will investigate whether it is possible to predict state of mind using logistic regression based on the change points detected by BOCPD.

4. Result and Discussion

4.1 RQ1. Exploring the Applicability of BOCPD Through Change Point Overlap Rates

To answer RQ1, we used BOCPD to extract behavioral change points based on educational and life logs and examined the extent to which they matched learners' self-reported "state of mind," which was treated as a pseudo ground truth. In this study, we analyzed 116 learners, and it was difficult to retrospectively obtain teacher-provided labels for behavioral change. Therefore, even subtle changes in the self-reported mental states were regarded as valid labels, and the overlap between these labels and the behavioral change points extracted from five log indicators was evaluated.

To capture overlaps, we compared cases where detected change points coincided perfectly with the date of the state of mind change (±0 days), as well as cases allowing for temporal tolerance (±1 day in the 1-day resampled data and ±7 days in the 7-day resampled data). For each setting, we computed precision, recall, and F1 scores between the detected change points and the state of mind change points. Table 2 summarizes the results.

Table 2 Result of Analysis

Resampling Unit	Method	Target Range	Precision	Recall	F1 Score
1 day	Zero-fill	±0 day	0.096	0.513	0.162
		±1 day	0.367	0.994	0.536
	Weighted	±0 day	0.109	0.224	0.147
		±1 day	0.197	0.411	0.266
7 days	Zero-fill	±0 day	0.094	0.179	0.123
		±7days	0.243	0.465	0.319
	Weighted	±0 day	0.109	0.115	0.112
		±7days	0.230	0.245	0.238

Under a strict matching criterion of ±0 days in the 1-day data, precision was relatively low at 0.096, while recall reached 0.513. This yielded an F1 score of 0.162, indicating that although BOCPD was able to detect a substantial portion of actual psychological shifts (moderate recall), many of the detected points were false positives, with low precision.

However, when a time tolerance of ±1 day was introduced, precision significantly improved to 0.367 and recall increased to 0.994, resulting in a notably higher F1 score of 0.536. This suggests that BOCPD is more effective when slight temporal offsets between behavioral and psychological changes are permitted. In practice, such flexibility is valuable because behavioral cues may not align perfectly with the moment learners report psychological distress.

Similarly, in the 7-day-level data, precision and recall under a ±0-day window were 0.094 and 0.179, respectively, yielding a low F1 score of 0.123. However, with a broader ±7-day range, precision improved to 0.243 and recall increased to 0.465, resulting in a higher F1 score of 0.319. Although lower than the performance observed in the 1-day data, this still implies that BOCPD can offer meaningful signals, especially in contexts where broader behavioral trends across weeks may reflect shifts in learners' mental states.

Comparing the two missing-data handling strategies, the Zero-fill method generally yielded higher recall but tended to inflate false positives, while the Weighted method, which downweighed weeks with higher missingness, achieved slightly higher precision at the cost of recall. For example, in the 1-day ±0-day setting, Zero-fill achieved a recall of 0.513 but very low precision = 0.096, whereas Weighted reduced the recall to 0.224 but improved the precision to 0.109. One likely explanation for these results is that real-world educational log data contained many missing or sparse entries, especially for steps and stress, which are not directly tied to school curriculum activities. In the Zero-fill setting, these missing values were treated as zeros, potentially exaggerating activity fluctuations and inflating false positives. It is undeniable that this missing value, which was processed to 0, may have ultimately affected the accuracy. By contrast, the Weighted method mitigated this influence but reduced overall detection sensitivity.

These results indicate that even with multiple educational log data with many missing values, BOCPD can be applied by extending it with the latent variable model proposed by Romero-Medrano (2022) and multinomial sampling. Especially, these findings demonstrate that BOCPD has potential as a practical tool for detecting early signs of psychological change in learners, particularly when used with appropriate temporal tolerances that account for real-world variability in the timing of behavioral and emotional transitions.

4.2 RQ2. Predicting Learners' State of Mind using BOCPD

To address RQ2, we predicted the changes in state of mind using the BOCPD scores and run lengths extracted from logs by BOCPD as characteristics. For prediction, the logistic regression model was constructed, and we divided the data set into a training set and a test set (9:1). The prediction model was trained and evaluated using data resampled on a daily and weekly basis, like RQ1. Prediction accuracy was evaluated using Accuracy and Area Under the Curve (AUC) (Table 3). In addition to reporting Accuracy and AUC values, we visualized the prediction performance using Receiver Operating Characteristic (ROC) curves (Figure 3). The ROC curve enables a more detailed examination of the trade-off between true positive and false positive rates across different thresholds, complementing the scalar AUC score.

Table 3 Result of prediction of state of mind using BOCPD

Resampling Unit	Method	Accuracy	AUC
1 day	Zero-fill	0.858	0.637
	Weighted	0.856	0.591
7 days	Zero-fill	0.867	0.697
	Weighted	0.832	0.611

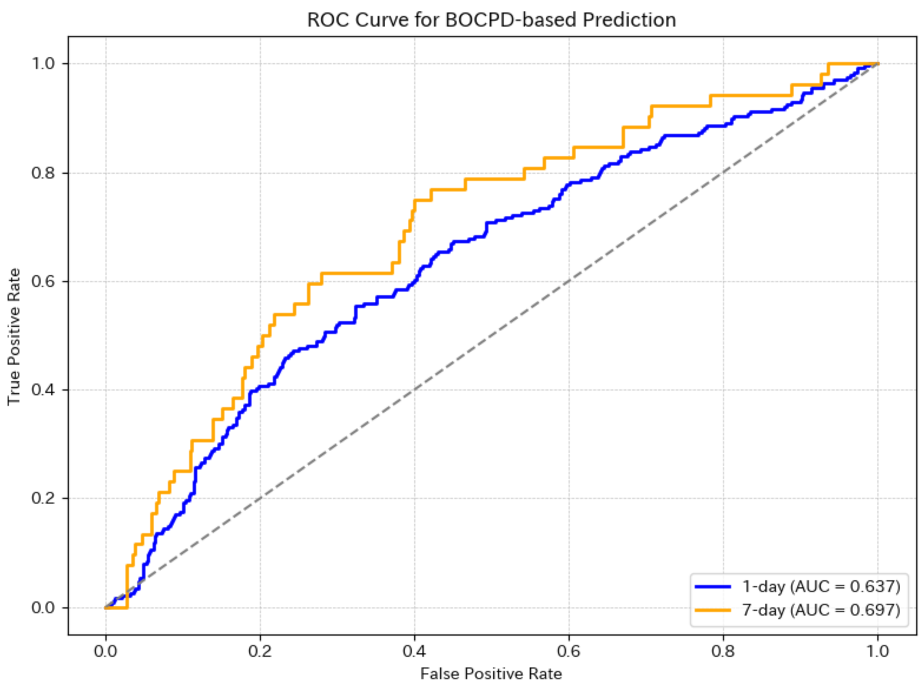

Figure 3 ROC curve for BOCPD-based prediction (Zero-fill method).

The results showed that the prediction model using change points extracted from learning and lifestyle logs as features using BOCPD achieved an accuracy of 0.858 and an AUC of 0.637 for daily data with Zero-fill, and an accuracy of 0.867 and an AUC of 0.697 for weekly data with Zero-fill. The Weighted method showed slightly lower AUC values (0.591 for daily and 0.611 for weekly), indicating that the Zero-fill method provided more stable predictive performance in this setting.

These results suggest that change point information obtained using BOCPD may have a certain validity for predicting learners' mental states. From the perspective of AUC, the prediction performance was higher for 7-day data than for 1-day data, suggesting that weekly changes in behavior and lifestyle rhythms may be more closely related to psychological states than daily fluctuations.

On the other hand, the AUC was only around 0.7 at its highest. While this result indicates that learners' state of mind can be predicted with a certain degree of accuracy from log data, it cannot be said that the predictions are highly accurate. This reaffirms that behavioral logs alone cannot fully explain psychological changes, as psychological state changes are complexly influenced by factors other than behavior (such as family environment, interpersonal relationships, sleep, and personality traits).

Nevertheless, the fact that this method can extract certain signs of internal changes in learners that are difficult for teachers to observe daily from log data suggests that it has potential for early support and preventive intervention in educational settings. In the future, combining this method with other predictive models or integrating multiple data sources (multimodal analysis) is expected to enable more accurate predictions and practical support.

In summary, applying BOCPD to educational log data has shown that it is possible to predict learners' mental health conditions to some extent. However, challenges remain in achieving higher accuracy.

5. Conclusion and Future Work

In this study, we investigated the applicability and potential of predicting learners' state of mind by applying BOCPD to cross-contextual educational log data. The results demonstrated that BOCPD should be applied to educational log data by adding extensions such as latent variable models, and that it is possible to predict learners' mental health conditions. This method has the potential to contribute to early support and preventive interventions in Guidance and Counseling settings, as it can extract signs of internal changes in learners that are difficult for teachers to observe daily from log data. The novelty of the study lies in applying BOCPD methods to real-world data with random missing values, commonly seen in the medical field, and in demonstrating their applicability to educational logs by revealing a certain level of predictability from their change points.

There are two points of discussion for future work. The first concerns the AUC accuracy, and the results may have been affected by missing data. According to Romero-Medrano (2022), the structure of missing data is complex, and non-random missing (MNAR) caused by user behavior and device operation is more likely to affect model accuracy than random missing (MCAR). In this study, there was a significant amount of missing data, particularly in steps taken and stress, and several processing steps were applied to address this. As a result, while the consistency rate of change points was higher with daily resampling, the prediction accuracy of the state of mind was higher with weekly resampling, leading to inconsistent results. Educational log data collected in the real world is prone to missing data for a variety of reasons. Therefore, a more robust justification for the imputation strategy is required. For example, future work should explore and compare alternative missing-data handling methods, including more sophisticated imputation techniques or approaches that explicitly model missingness rather than relying on simple imputation. A sensitivity analysis demonstrating the impact of different imputation strategies on the results would also significantly strengthen the findings.

The second point concerns the applicability of this approach in educational settings. To date, even data-driven frameworks such as MTSS have not been able to predict learners' states of mind from learning log data. The findings of this study could be used, for example, to alert teachers through an early warning system integrated into a dashboard, or as an additional resource for assessing school climate. Predicting changes in mental health conditions is an important process that allows teachers to consider the background and development of learners, and it also provides an important opportunity for communication with learners in G&C. Appropriate intervention can help learners overcome mental health crises, which in turn fosters restorative emotional experiences. In this regard, BOCPD is particularly promising compared to existing CPD methods. Further consideration is needed regarding the amount and context of data that can be applied, but BOCPD holds promise for interventions in G&C.

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