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PAPER

A Quantitative Model for Evaluating the Effectiveness of Lifelong Education for Highly Skilled Professionals Supported by Mobile Technology

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ABSTRACT

With the rapid advancement of the global economy and technology, the demand for highly skilled professionals has continued to rise. Lifelong education has emerged as a crucial pathway for developing such professionals. The widespread application of mobile technology has created new opportunities for lifelong education, enabling learning to take place anytime and anywhere. However, existing evaluation methods primarily rely on traditional tools, which lack real-time monitoring and quantitative evaluation of the learning process, making it challenging to address the complexity and dynamic nature of learning. To address these limitations, a quantitative evaluation model for the effectiveness of lifelong education for highly skilled professionals supported by mobile technology was proposed in this study. The model consists of two primary components: (a) real-time monitoring and prediction of learning engagement and (b) detection of abrupt anomalies in learning behavior. This study aims to support educational administrators and learners in decision-making, advance lifelong education, and provide robust data-driven insights for educational policy formulation.

KEYWORDS

highly skilled professionals, lifelong education, mobile technology, educational effectiveness evaluation, learning engagement monitoring, behavior anomaly detection

1 INTRODUCTION

With the rapid advancement of the global economy and continuous technological innovation, the demand for highly skilled professionals has been steadily increasing [1, 2]. To address this growing demand, lifelong education has become a crucial pathway for cultivating highly skilled professionals [3]. The widespread adoption of mobile technology has provided new opportunities for lifelong education, removing the constraints of traditional educational models [4–7] and enabling learning to take

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place anytime and anywhere. However, despite the extensive application of mobile technology in the educational domain [8, 9], an urgent challenge remains in the quantitative evaluation of learning effectiveness for highly skilled professionals in lifelong education. Therefore, the development of a quantitative evaluation model for lifelong education effectiveness, supported by mobile technology, holds significant practical importance.

Lifelong education for highly skilled professionals not only facilitates individual career development but also plays a critical role in driving national and societal economic growth. However, existing research on lifelong education effectiveness has predominantly focused on qualitative analyses and conventional evaluation frameworks [10, 11], lacking real-time monitoring and quantitative evaluation of the learning process [12]. In particular, limited attention has been given to individual differences, learning engagement, and abrupt changes in learning behavior. Thus, the implementation of precise technological methodologies for the quantitative evaluation of learning effectiveness has become a key issue in advancing lifelong education for highly skilled professionals. Such research is expected to enhance educational outcomes while providing a scientific basis for the formulation and refinement of educational policies.

Existing evaluation methods primarily rely on traditional learning evaluation tools, which are inadequate for addressing the complexity and dynamic nature of the learning process for highly skilled professionals [13–16]. The approach proposed by Zareisaroukolaei et al. [17] fails to account for individual differences and behavioral patterns among learners, while the evaluation criteria lack real-time adaptability, making it difficult to accurately reflect changes in learning effectiveness. Furthermore, Hammond and Brown [18] did not fully leverage the advantages of mobile technology, such as real-time data acquisition and intelligent prediction, thereby failing to provide a comprehensive quantitative analysis of learning outcomes. These limitations indicate that existing evaluation models are insufficient for meeting the demands of lifelong education for highly skilled professionals, highlighting the need for improved methodologies.

The research presented in this study comprises two primary components. The first focuses on real-time monitoring and prediction of learning engagement in lifelong education for highly skilled professionals. By employing data mining and intelligent analysis techniques, learning engagement was quantitatively assessed and predicted, providing decision-making support for educational administrators and learners. The second component involves the detection of abrupt anomalies in learning behavior. By dynamically tracking learning behaviors, abnormal fluctuations in the learning process can be promptly identified, enabling educators to implement effective interventions. The significance of this research lies in the application of technological methodologies to develop an innovative approach for the quantitative evaluation of lifelong education effectiveness, facilitating the advancement of highly skilled professional education and providing robust data support for educational policy formulation.

2 REAL-TIME MONITORING AND PREDICTION OF LEARNING ENGAGEMENT IN LIFELONG EDUCATION FOR HIGHLY SKILLED PROFESSIONALS

Lifelong education for highly skilled professionals typically involves the acquisition of highly specialized knowledge and advanced skills. The learning process for this group differs from that of general learners, often requiring a higher intensity of engagement and sustained effort. Therefore, real-time monitoring and prediction of learning engagement are of significant importance for accurately evaluating learning effectiveness. Learning engagement reflects the extent to which learners invest their time, effort, and emotional commitment during the learning process. This investment directly influences both the depth of learning and overall outcomes. In the context of lifelong education for highly skilled professionals, real-time monitoring of learning engagement not only enables educators to gain insights into learners' status but also facilitates the provision of personalized learning recommendations by optimizing the allocation of time and cognitive resources, thereby enhancing learning outcomes.

To address the challenge of real-time monitoring and prediction of learning engagement in lifelong education for highly skilled professionals, a real-time monitoring and prediction model based on a dual sliding window approach and Gene Expression Programming (GEP) was proposed in this study. The model employs a dual sliding window mechanism to segment time-series streaming data, treating each window as an independent training sample. These data include not only key indicators such as learning duration, learning frequency, and interactive participation but also their associated timestamps. By adopting this segmentation strategy, fine-grained tracking of learning dynamics and adaptive adjustments can be achieved. Each time the sliding window is updated, the prediction model is reconstructed using the GEP algorithm, ensuring that the model continuously reflects the most recent learning status of the learner. To enhance the accuracy and stability of the prediction model, a population-based hill-climbing algorithm was incorporated to optimize the parameters of the GEP algorithm, thereby maintaining high predictive performance in dynamic learning environments. Given that learning data in lifelong education for highly skilled professionals may be affected by various external factors, a data fusion method was integrated into the model to mitigate the impact of noise. By fusing multidimensional data, the influence of noise on the prediction model was effectively reduced, improving both the stability and reliability of the prediction results.

2.1 Dual sliding window

The learning engagement of highly skilled professionals is influenced not only by individual learning habits but also by external factors such as work commitments and family responsibilities. Consequently, fluctuations in learning engagement exhibit strong dynamism and volatility. In a streaming data environment, conventional fixed-window methods are inadequate for capturing these frequent and unpredictable variations in learning behavior. The dual sliding window approach dynamically adjusts window sizes based on data volatility, thereby improving the accuracy and real-time performance of the prediction model by capturing short-term variations in learning engagement more effectively.

The dual sliding window method adapts to variations in time-series data fluctuations through the use of both fixed and variable-length windows. In lifelong education for highly skilled professionals, learning engagement exhibits distinct fluctuation patterns. When a learner's engagement remains stable, a smaller window size allows for efficient detection of learning patterns under stable conditions. However, when learning behavior is affected by external factors or emotional changes, leading to increased volatility, a larger window width enables the incorporation of more historical data, preventing the loss of long-term behavioral trends that a short-term window might overlook. Through this dynamic adjustment mechanism, the dual sliding window approach can rapidly adapt to changes, thereby enhancing the accuracy of future learning engagement predictions. A schematic representation of the dual sliding window approach is illustrated in Figure 1.

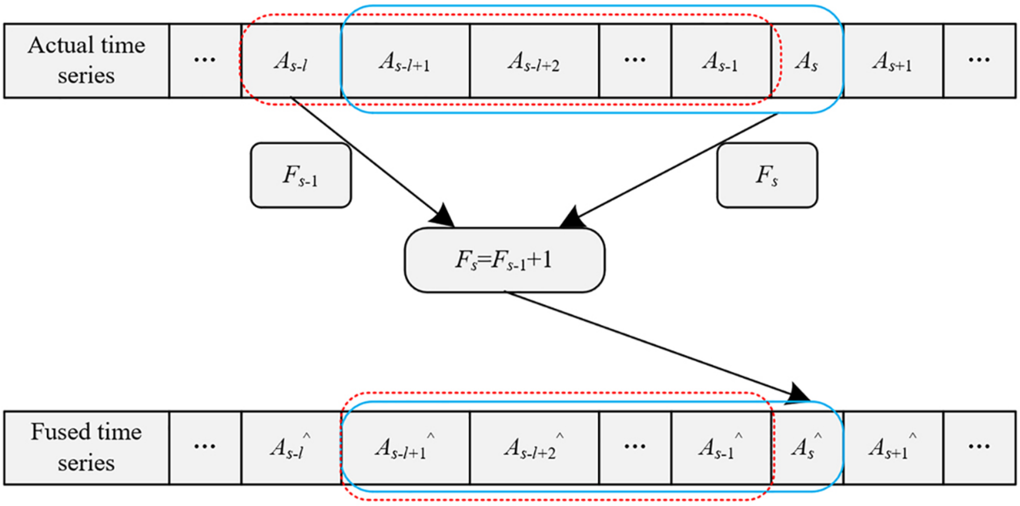


Fig. 1. Schematic representation of the dual sliding window

In the context of lifelong education for highly skilled professionals, variations in learning engagement are often influenced by recent behavioral patterns and external environmental factors. The dual sliding window approach utilizes a sliding window mechanism for sample selection, ensuring that each model training iteration is based on a small segment of historical data near the current time point. By selecting a limited range of historical data as training samples, recent variations can be captured more effectively without relying on long-term historical data. This approach not only reduces computational complexity and enhances real-time performance but also ensures that the prediction model continuously reflects the learner's most recent learning state, minimizing the impact of outdated data on prediction accuracy. When constructing the model using the GEP algorithm, training based on the most recent data better aligns with the requirements of real-time prediction.

Fluctuations in learning engagement often reflect a learner's psychological state, learning progress, and the intensity of external disruptions. The dual sliding window approach measures data volatility by calculating the variance within a fixed-length window and adjusts the length of the variable-length window accordingly. The variance within the fixed-length window provides an intuitive measure of fluctuations in learning engagement, allowing for dynamic window size adjustments. When increased volatility is detected, indicating abnormal fluctuations in learning behavior, a larger historical data range is required for modeling to improve the accuracy of the prediction model. Conversely, when volatility remains low, indicating a relatively stable learning state, a smaller window is sufficient for model training. Let L_s represent the length of the variable-length window at time s and F_s denote the variance of data within the fixed-length window at time s, then the length of the variable-length window can be calculated as follows:

$$L_s = \begin{cases} L_{s-1} + 1, if \quad F_s > F_{s-1} \\ L_{s-1} - 1, if \quad otherwise \end{cases} \tag{1}$$

where, L_s is constrained within predefined upper and lower limits, with L_y denoting the upper limit and L_m representing the lower limit, respectively. If $L_s > L_y$, then $L_s = L_y$; if $L_s < L_m$, then $L_s = L_m$.

2.2 Population-based hill climbing algorithm

Due to the continuous influence of external factors and variations in learners' internal states, fluctuations in learning engagement often exhibit complex nonlinear characteristics. This dynamic nature makes it challenging for traditional single-model algorithms to adapt to rapidly changing data patterns. The GEP algorithm can converge quickly and establish an initial prediction model with relatively high accuracy. However, as data are continuously updated, population homogeneity may occur within the algorithm, potentially leading to premature convergence at local optima. This limitation restricts the model's ability to fully capture the most recent learning engagement patterns of learners. To address this challenge, a population-based hill climbing algorithm was introduced in this study to maintain population diversity, ensuring that the algorithm can escape local optima when new variable-length window data are introduced and expand the search space, thereby discovering hidden new patterns and trends in learning engagement data.

The fundamental principle of the population-based hill climbing algorithm is to maintain the breadth and global reach of the search space by adjusting the population structure through an "elimination" strategy. In the monitoring and prediction of learning engagement in lifelong education for highly skilled professionals, learning engagement patterns may undergo significant changes as new data are introduced. This is particularly evident when learning progress is altered or when external work and life conditions shift, rendering previously established models obsolete. The population-based hill climbing algorithm addresses this issue by reordering and filtering the population based on fitness whenever new data are introduced. Low-fitness individuals are eliminated, while the remaining individuals undergo reinitialization. This adaptive mechanism effectively prevents the model from stagnating at local optima while ensuring rapid responsiveness to data fluctuations, thereby enhancing the model's ability to capture evolving trends in learning engagement.

2.3 Data fusion

Learning engagement data are influenced by multiple factors, including personal emotions, external work pressure, and family conditions. These factors introduce noise, resulting in deviations between observed data and actual trends. The presence of noise may lead to underfitting or overfitting when modeling with the GEP algorithm, thereby affecting the accuracy and stability of the prediction model. To enhance the accuracy of learning engagement predictions, a data fusion method was proposed in this study. By integrating noisy observed values with historical predictions for correction, the impact of noise on the model can be reduced, improving both the reliability and precision of predictions.

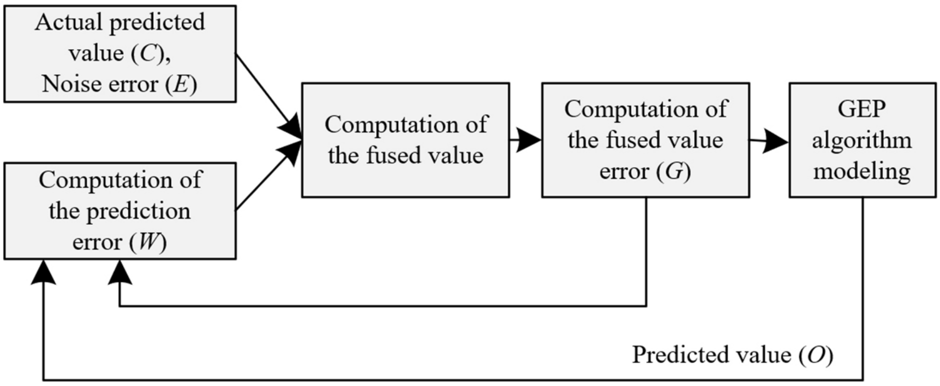


Fig. 2. Schematic representation of the data fusion principle

The fundamental principle of the data fusion method is to utilize the discrepancy between the predicted values generated by the historical-data-based prediction model and the newly received noisy observed values. Specifically, for each new data point, the system computes the predicted value at the current time based on the prediction model established using the GEP algorithm within the variable-length window of the previous time step. The discrepancy between the predicted value and the actual observed value is then analyzed for error distribution correction. This method applies weighted fusion to these data points, generating a new fused value that lies between the actual observation and the prediction. Appropriate weights are assigned based on the magnitude of each error, ensuring that the final fused value approximates the true value more accurately, thereby reducing the influence of noise. Figure 2 illustrates the schematic representation of the data fusion principle.

The data fusion method adjusts weights based on the error distribution of the prediction model and the observed values. When a new data point C is introduced, the prediction model generates a predicted value for the current time step, while the actual observed value, being affected by noise, may deviate from the true value. To correct this deviation, the data fusion method dynamically adjusts the weights of the predicted and observed values by comparing the magnitude of prediction error and observation error. If the prediction error is relatively small, the predicted value is assigned a higher weight, making the fused value closer to the prediction. Conversely, if the prediction error is large, more reliance is placed on the actual observed value. This dynamic weighting mechanism allows for the estimation of the true learning engagement level based on real-time error measurements, ensuring that the algorithm remains accurate despite the presence of complex and noisy learning data. Mathematically, let g represent the mean squared error (MSE) of the learning engagement prediction model constructed using data from the variable-length window of the previous time step, and let W denote the root mean squared error (RMSE) of the prediction error. By substituting the current timestamp into the prediction model, the predicted learning engagement value P for the current time step can be computed. The computation formula for W is given as:

$$W = \sqrt{g^2 + G^2} \tag{2}$$

When handling noise, the data fusion method specifically accounts for the potential sources of noise, which may arise from sensor measurement errors or other external factors. The error of actual observed values is typically assumed to follow a known distribution model. By modeling these known error distributions, the fusion method can effectively estimate the true value at a given time. Specifically, in this research scenario, a predicted value is generated by the prediction model, which is constructed based on historical data, and the fitted MSE of the predicted value is computed. By integrating the error distribution of the actual observed value at the current time step, the fusion mechanism produces a corrected fused value, effectively suppressing the influence of noise. Through this approach, the model minimizes the impact of noise on learning engagement predictions, thereby improving both stability and accuracy. The weight gain J is computed as follows:

$$J = W^2/(W^2 + E^2) \tag{3}$$

The fused value at the current time step is given by:

$$\hat{a} = (C - O)J + O \tag{4}$$

The RMSE (G) of the fused value is calculated as:

$$G = \sqrt{(W^2(1 - J))} \tag{5}$$

The data fusion mechanism enables the model to dynamically adapt to the time-varying characteristics of learning engagement for highly skilled professionals. During the lifelong learning process, learning engagement is influenced by multiple unpredictable factors, such as emotional fluctuations, work-related stress, and family responsibilities, all of which exhibit high randomness and unpredictability. As new data are continuously introduced, the volatility of learning engagement may also change, making it difficult for traditional models to adapt quickly. By integrating historical predicted values with newly received observed data, the data fusion method effectively balances the model's reliance on past and new data, ensuring that accurate predictions can still be generated in response to evolving conditions.

3 ABRUPT CHANGE AND ANOMALY DETECTION IN LEARNING BEHAVIOR FOR HIGHLY SKILLED PROFESSIONALS

The learning behavior of highly skilled professionals exhibits significant dynamism and complexity, particularly in the context of mobile technology, where learning behavior data can be collected and analyzed in real time. However, abrupt changes and anomalies in learning behavior may directly impact the quantitative evaluation of educational effectiveness. For instance, a sudden decline in learning interest, a significant reduction in learning time, or a drastic change in learning methods may serve as indicators of underlying issues, such as mismatched learning content or increased personal life stress. These anomalies not only affect the accuracy of learning effectiveness evaluations but may also delay timely interventions for learners. Therefore, the accurate detection and identification of these abrupt behavioral changes and anomalies are essential for improving the precision and timeliness of lifelong education evaluations for highly skilled professionals.

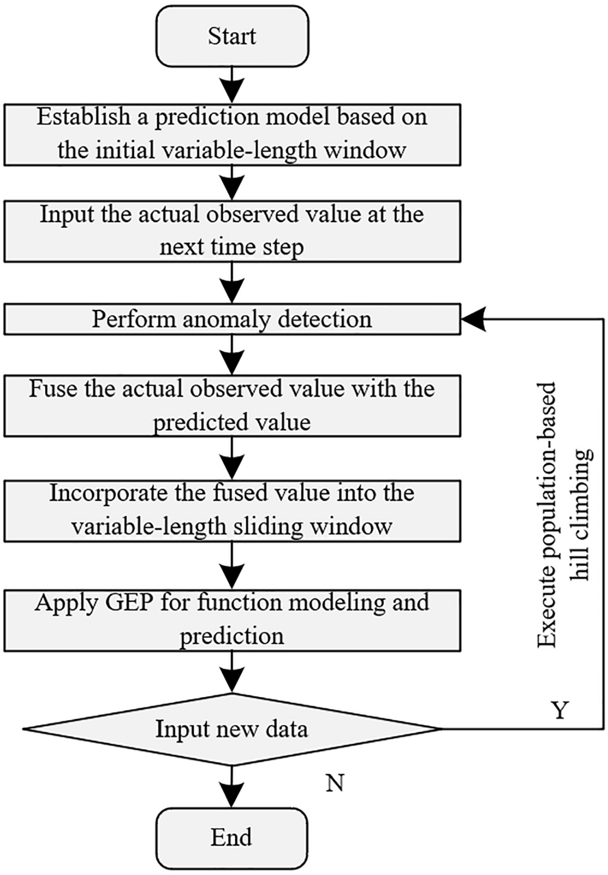


Fig. 3. Flowchart of the abrupt change and anomaly detection algorithm for learning behavior in lifelong education for highly skilled professionals

The core of the proposed abrupt change and anomaly detection method lies in learning from historical learning behavior data to establish a prediction model that aligns with actual behavioral change patterns. By detecting deviations between current data points and predicted values, abnormal fluctuations in learning behavior can be identified in real time. For example, a sudden and significant fluctuation in a learner's study time may indicate external disturbances, which typically deviate from historical patterns. Therefore, anomaly detection in univariate time series can effectively identify such abrupt behavioral changes. Figure 3 presents the flowchart of the anomaly detection algorithm for learning behavior in lifelong education for highly skilled professionals.

First, the difference between the predicted and actual values in the time-series streaming data at time *s* was computed, and this absolute value is denoted as *s*. Specifically, a time-series model was established to predict the learning behavior data of highly skilled professionals, generating the predicted value at time *s*. Simultaneously, the actual learning behavior data point, denoted as b_s, was collected. The absolute difference between the predicted value and the actual observed value was then calculated using the following equation:

$$t_s = \left| b_s - \bar{b}_s \right| \tag{6}$$

The difference in the above equation reflects the magnitude of the deviation between the model prediction and actual behavior, serving as an indicator for potential anomalies in learning behavior. For instance, if a highly skilled professional has exhibited stable learning time patterns over a given period but, at a particular time step, the actual learning time is significantly lower than the predicted value, such a deviation may indicate an abrupt change or anomaly in learning behavior.

Further, the principle of the normal distribution was applied to establish an anomaly detection threshold and determine whether the data at time $s + 1$ constitute an anomaly. Specifically, within a fixed-length window of width l at time s, the dataset $T_s = \{T_1, T_2, T_3 \ldots, T_l\}$ was modeled as a Gaussian distribution with a mean ω and variance δ^2, where $\omega = 1/l\Sigma_{s=1}^{l} t_s$, and $\delta^2 = 1/l\Sigma_{s=1}^{l}(t_s - \omega)^2$. In a normal distribution, the probability that a data point falls within the range of the mean (ω) plus or minus three standard deviations (δ) is 99.81%. Therefore, the distribution of past deviation values can be used to compute the mean ω and standard deviation δ, based on which the anomaly detection threshold λ is set with $\lambda = 3\delta$. If the deviation value at time t_{s+1} at time $s + 1$ exceeds this threshold ($|t_{s+1} - \omega| > \lambda$), the learning behavior data at time $s + 1$ are classified as anomalous. Let X_{s+1} represent the state of the data at time $s + 1$, which is determined as follows:

$$X_{s+1} = \begin{cases} 1, if \ \ t_{s+1} > \lambda \\ 0, else \end{cases} \tag{7}$$

Through this threshold-setting and decision-making mechanism, learning data points that significantly deviate from normal behavioral patterns can be effectively identified. For instance, if a highly skilled professional exhibits a sudden and substantial decline in learning engagement at a particular time step, and this decline exceeds the expected range of historical data fluctuations, the data point is flagged as an anomaly. This enables educational administrators to implement timely interventions and adjustments.

4 EXPERIMENTAL RESULTS AND ANALYSIS

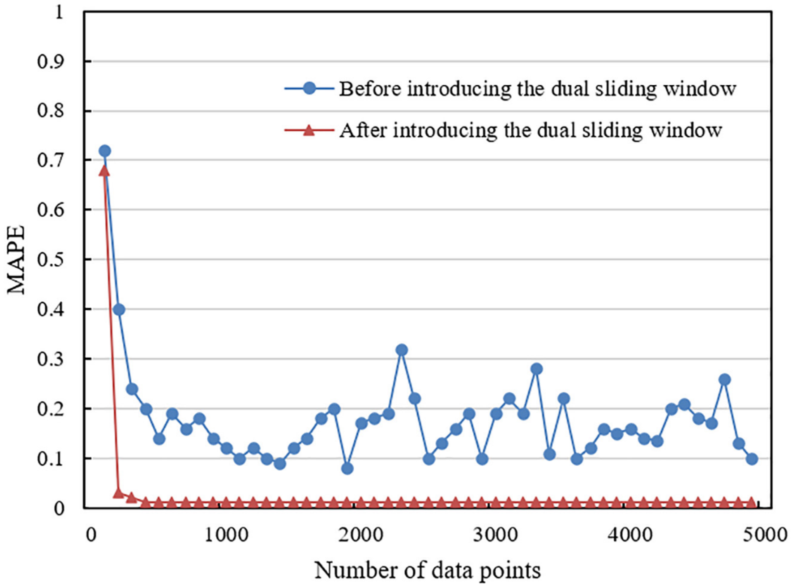


Fig. 4. MAPE of learning engagement real-time monitoring before and after introducing the dual sliding window

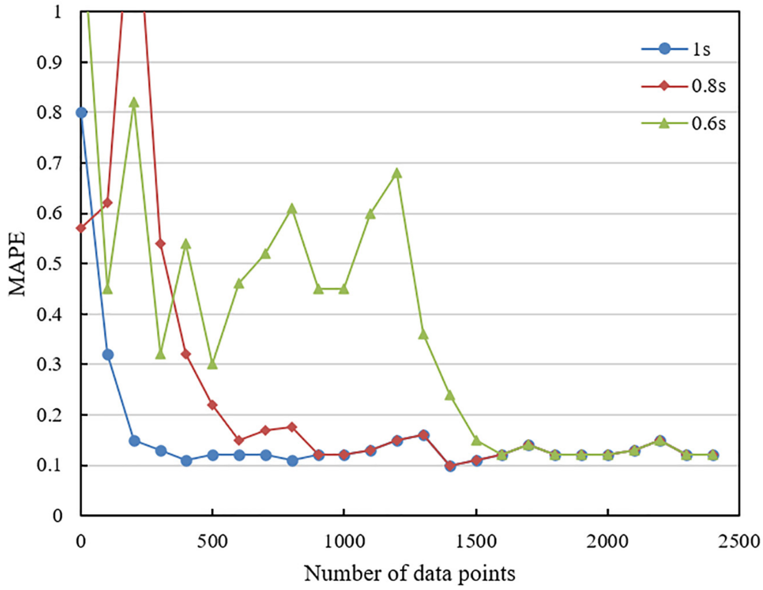
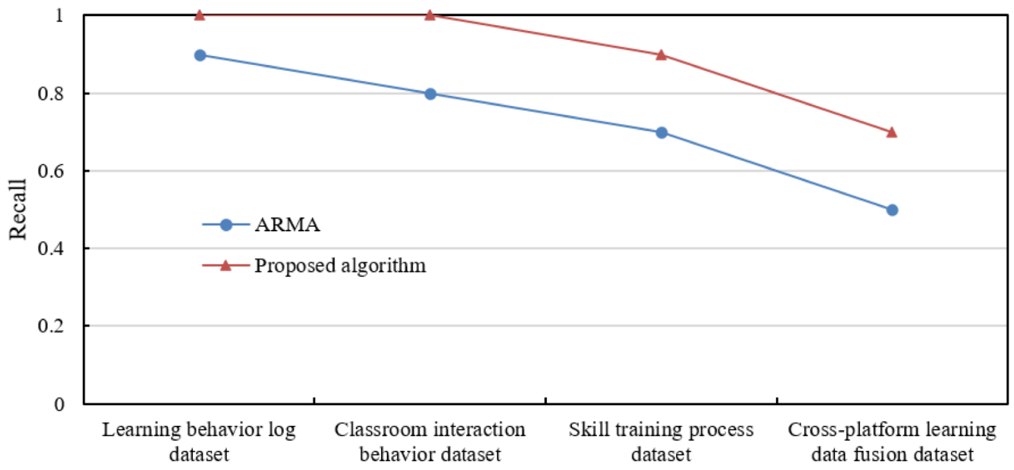


Fig. 5. MAPE for real-time monitoring of learning engagement under different data transmission intervals

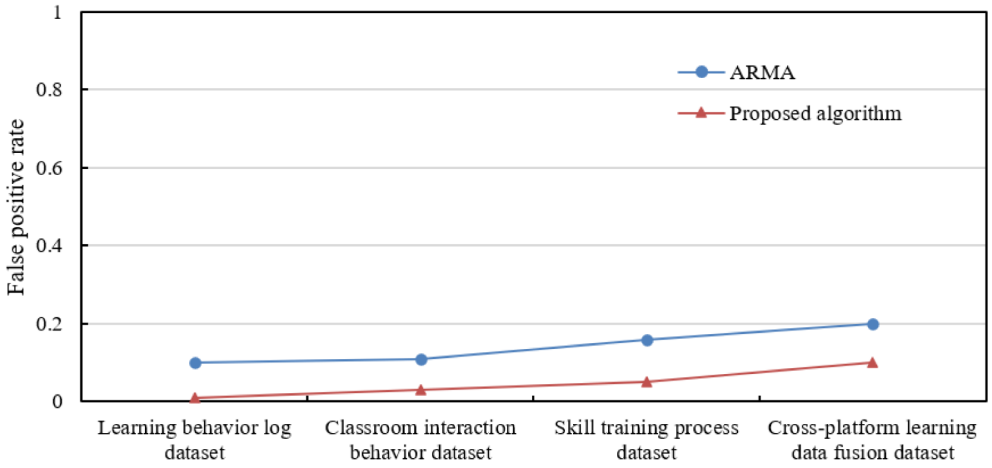
Figure 4 presents a comparison of the mean absolute percentage error (MAPE) values in real-time monitoring of learning engagement before and after the introduction of the dual sliding window, demonstrating the effectiveness of this method. Prior to implementing the dual sliding window, the MAPE value was relatively high in the initial stage, reaching 0.72 and 0.4, before gradually decreasing. However, fluctuations persisted within a certain range. For instance, in the time interval between 2000 and 3000 data points, the MAPE value ranged between 0.2 and 0.14, indicating some reduction but with continued instability. After the introduction of the dual sliding window, the MAPE value rapidly decreased from 0.68 to 0.03 in the early phase and remained at an extremely low level of 0.01 across all subsequent time intervals, indicating enhanced stability and accuracy. The results indicate that the incorporation of the dual sliding window substantially improves both the predictive precision and the robustness of the algorithm.

As shown in Figure 5, the algorithm exhibits different learning and prediction performance under varying data transmission intervals. When the data transmission interval is relatively large, the internal model of the data is learned at an earlier stage, leading to a rapid decrease in the MAPE value over time and a significant improvement in prediction accuracy. Conversely, under smaller data transmission intervals, the initial learning process of the algorithm is slower, resulting in higher MAPE values at the beginning. However, as the experiment progresses, the algorithm gradually learns the internal data model, and the MAPE value decreases progressively to a lower level. These results indicate that although shorter data transmission intervals limit the modeling time of the algorithm and lead to higher initial prediction errors, the accumulated learning process enables the algorithm to enhance its predictive accuracy over time. Ultimately, stable and desirable prediction performance can still be achieved.

As shown in Figure 6, notable differences in recall and false positive rate are observed between the auto-regressive integrated moving average (ARIMA) algorithm and the proposed algorithm across the four datasets when 2% anomalous data are introduced. In terms of recall, the proposed algorithm consistently demonstrates superior anomaly detection capability across all datasets. Specifically, on the learning behavior log dataset, the recall of the proposed algorithm reaches 1.0, significantly higher than the 0.9 achieved by the ARIMA algorithm. In the classroom interaction behavior dataset, the recall of the proposed algorithm remains at 1.0, outperforming the 0.8 recorded by the ARIMA algorithm. Similarly, in the skill training process dataset, the recall of the proposed algorithm is 0.9, exceeding the 0.7 achieved by ARIMA. On the cross-platform learning data fusion dataset, the proposed algorithm attains a recall of 0.72, compared to 0.5 for the ARIMA algorithm, demonstrating a substantial improvement. Regarding the false positive rate, the proposed algorithm also exhibits consistently lower values. Notably, in the learning behavior log dataset, the false positive rate of the proposed algorithm is only 0.01, in contrast to 0.1 for the ARIMA algorithm. In the classroom interaction behavior dataset, the proposed algorithm achieves a false positive rate of 0.03, which is significantly lower than the 0.11 recorded by ARIMA. Likewise, in the skill training process dataset, the false positive rate of the proposed algorithm is 0.05, outperforming ARIMA's 0.16. Finally, in the cross-platform learning data fusion dataset, the false positive rate of the proposed algorithm is 0.1, lower than ARIMA's 0.2. These results indicate that the proposed algorithm not only identifies anomalous data with higher accuracy but also significantly reduces the likelihood of false detections.

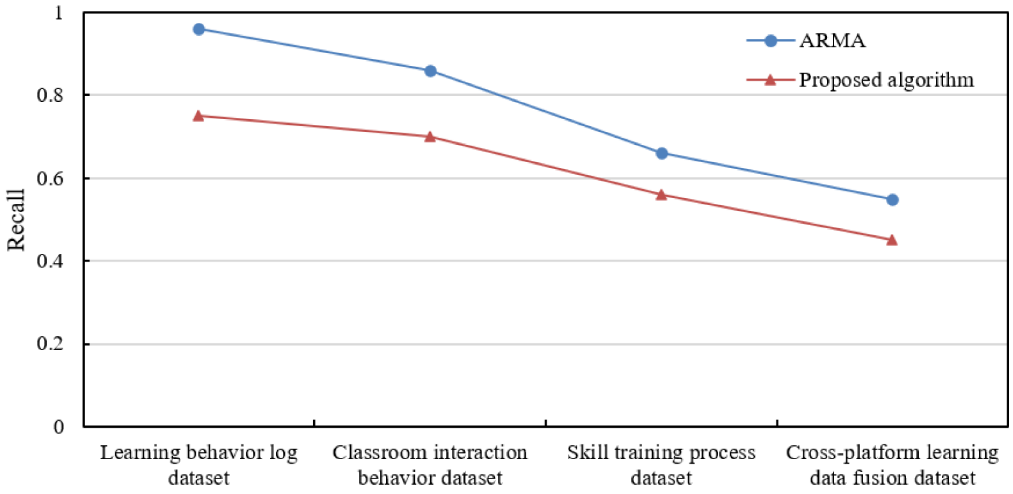


a) Recall

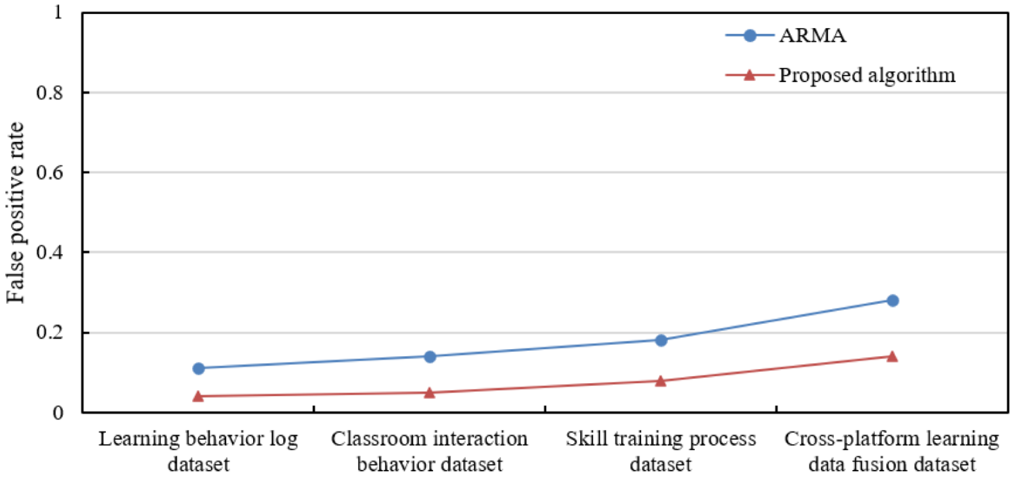


b) False positive rate

Fig. 6. Comparison of recall and false positive rate between two algorithms across four datasets with 2% anomalous data



a) Recall



b) False positive rate

Fig. 7. Comparison of recall and false positive rate between two algorithms across four datasets with 4% anomalous data

As shown in Figure 7, significant differences are observed in the recall and false positive rate between the ARIMA algorithm and the proposed algorithm across the four datasets when 4% anomalous data are introduced. In terms of recall, the ARIMA algorithm demonstrates superior performance across all datasets. For instance, in the learning behavior log dataset, the recall of the ARIMA algorithm reaches 0.96, substantially higher than the 0.75 achieved by the proposed algorithm. In the classroom interaction behavior dataset, the recall of the ARIMA algorithm is 0.86, outperforming the 0.7 obtained by the proposed algorithm. Similarly, in the skill training process dataset, the recall of the ARIMA algorithm is 0.66, exceeding the 0.56 recorded by the proposed algorithm. Finally, in the cross-platform learning data fusion dataset, the ARIMA algorithm attains a recall of 0.55, higher than the 0.45 achieved by the proposed algorithm. However, in terms of false positive rate, the proposed algorithm demonstrates a significant advantage by effectively reducing the probability of incorrect detections. Specifically, in the learning behavior log dataset, the false positive rate of the proposed algorithm is 0.04, substantially lower than the 0.11 of the ARIMA algorithm. In the classroom interaction behavior dataset, the proposed algorithm achieves a false positive rate of 0.05, outperforming the 0.14 recorded by ARIMA.

Likewise, in the skill training process dataset, the proposed algorithm achieves a false positive rate of 0.08, lower than ARIMA's 0.18. Finally, in the cross-platform learning data fusion dataset, the proposed algorithm records a false positive rate of 0.14, which is lower than ARIMA's 0.28. These results indicate that although the ARIMA algorithm outperforms the proposed algorithm in terms of recall, the proposed algorithm demonstrates significantly better control over false positive rates.

5 CONCLUSION

This study aims to achieve real-time monitoring and prediction of learning engagement in lifelong education for highly skilled professionals, as well as the detection of abrupt changes and anomalies in learning behavior through data mining and intelligent analysis techniques. The core contribution of this research lies in providing educational administrators and learners with a quantitative monitoring and predictive tool, enabling decision-makers to better understand fluctuations in learning engagement, promptly identify abnormal behavioral changes, and facilitate timely interventions. This enhances the effectiveness of education for highly skilled professionals and optimizes education management. The findings of this study offer data-driven support for more precise decision-making, contributing to the advancement and refinement of education.

However, certain limitations remain in this study. First, while the proposed algorithm improves predictive accuracy and detects anomalous fluctuations to some extent, its performance is constrained in scenarios with short data transmission intervals, where initial prediction errors tend to be larger due to limited time for model training. Second, this research does not comprehensively account for complex multi-factor influences, such as individual differences and external environmental changes, which may affect learning behavior. Future research could explore the integration of these multidimensional factors to further enhance the adaptability and predictive capability of the algorithm. Additionally, this study primarily focuses on data analysis and model prediction, and future work could expand its application by incorporating more diverse data sources to improve the accuracy and reliability of learning behavior anomaly detection. Future research directions may focus on several key aspects. First, to address the challenges posed by short data transmission intervals, more efficient modeling techniques could be explored to enhance algorithmic performance in scenarios requiring high real-time responsiveness. Second, a more comprehensive analysis integrating diverse data sources could be conducted to further improve the accuracy and completeness of anomaly detection. Additionally, research efforts could be directed toward the intelligent optimization of the algorithm by employing adaptive learning mechanisms, enabling the model to continuously update itself in response to novel and previously unknown learning behavior patterns, thereby further enhancing the practical application of the proposed approach in lifelong education.

6 ACKNOWLEDGEMENT

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