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PAPER

Application of Mobile Technology-Based Learning Analytics in Educational Assessment

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ABSTRACT

With the rapid development of mobile technology, its application in the educational sector, particularly in learning analytics, has garnered increasing attention. The widespread adoption of modern mobile devices has introduced new opportunities for educational assessment. However, challenges remain in effectively utilizing these technologies for educational assessment. Current research predominantly focuses on data collection and analysis, yet the methods employed are limited in scope and application. This study aims to address these gaps by exploring data collection methods and teaching assessment approaches based on mobile technology. The objective is to contribute new perspectives and methodologies that modernize educational assessment. Through an in-depth analysis of the application of mobile technology in educational assessment, this study seeks to provide educators with scientifically grounded assessment tools and strategies, enabling more precise teaching management and personalized education.

KEYWORDS

mobile technology, learning analytics, educational assessment, data collection, teaching assessment methods

1 INTRODUCTION

With the rapid development of digital technologies, mobile technology has increasingly become a vital tool in the educational field, particularly in the area of learning analytics [1–3]. The application of mobile technology offers new perspectives and methods for educational assessment. Modern mobile devices, such as smartphones and tablets, alongside corresponding applications, enable students to engage in learning anytime and anywhere, while allowing teachers to monitor students' progress in real-time [4–6]. The widespread use of such technologies has not only transformed traditional teaching models but has also driven innovation in educational assessment methods. However, effectively utilizing these technologies for teaching assessment remains a pressing challenge.

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Research on the application of learning analytics in educational assessment holds significant theoretical and practical implications. On the one hand, it provides more accurate data support for educational decision-making, enabling teachers and educational administrators to better understand students' learning statuses and needs, thereby optimizing teaching strategies [7, 8]. On the other hand, the use of mobile technology can enhance students' engagement and self-directed learning capabilities, facilitating the realization of personalized education [9–14]. Therefore, exploring how learning analytics based on mobile technology can contribute to educational assessment will aid in advancing the modernization and scientific nature of educational assessment.

Although some studies have attempted to apply learning analytics in educational assessment, limitations remain in the methods and tools currently available. For instance, many studies focus solely on data collection, with insufficient emphasis on the in-depth analysis and interpretation of the data [15–17]. Other studies face issues of limited scope and methodological diversity. These shortcomings hinder the ability to comprehensively and accurately reflect students' learning outcomes and the effectiveness of teaching practices, thereby affecting the overall validity of educational assessment [18–20].

This study aims to explore the application of learning analytics based on mobile technology in educational assessment and is divided into two main research areas. First, the study focuses on data collection for teaching assessment using mobile technology, including the sources, types, and methods of data collection. Second, it investigates the methods of teaching assessment enabled by mobile technology, analyzing their effectiveness in practical teaching settings and potential areas for improvement. Through these two areas of research, this study seeks to provide new insights and methods for educational assessment, enhancing both its scientific rigor and practical utility.

2 DATA COLLECTION FOR TEACHING ASSESSMENT BASED ON MOBILE TECHNOLOGY

Due to the diverse behaviors of students, differences in learning progress, and the dynamic nature of learning environments in instructional settings, traditional static and singular data collection methods have struggled to fully and effectively capture students' learning processes and performance. An innovative data collection method was therefore proposed in this study, utilizing mobile technology to introduce models for environmental perception, behavior perception, and learning progress perception. These models enable real-time acquisition of student learning data, addressing the challenges and limitations associated with current data collection processes in educational assessment.

Specifically, this method was designed around the sensors and applications embedded in mobile devices, incorporating various data perception modules that monitor students' learning behaviors, activity environments, and learning states. For instance, the location perception module tracks students' movements within learning spaces, identifying their preferred learning zones. The speed perception module, on the other hand, analyzes students' focus duration and task completion speed, thereby assessing their learning efficiency. In addition, the environmental perception module collects real-time data on the impact of learning environments on students' learning states. These modules, leveraging the built-in sensors of mobile devices for data collection, facilitate detailed monitoring of the entire learning process. In the design of the data collection method, an incentive-based mechanism aimed at teaching assessment was also introduced. By monitoring and providing feedback on students' learning behaviors, various reward mechanisms were implemented to guide intelligent decision-making for data collection. Specifically, rewards can be set for task completion, learning engagement, and behavioral diversity. These reward mechanisms dynamically adjust the data collection strategy to maximize the acquisition of high-value data that can contribute to teaching assessment.

Finally, by integrating deep learning algorithms and utilizing the computational capabilities of mobile devices, the strategy for data collection was optimized through a combination of centralized data collection and distributed analysis. Continuous training and feedback iteration were conducted throughout the data collection process, enabling the method to adapt to the evolving instructional environment, thereby improving the efficiency and accuracy of data collection.

2.1 Data collection process

Mobile devices utilize built-in sensors and applications to collect data on students' learning behaviors and environmental data. These devices continuously monitor and integrate various state information throughout the learning process, such as the time distribution of learning activities, interactions with learning content, and environmental variables. This information was used to generate the next stage of the data collection plan, akin to action-value generation in drone data collection. As mobile devices carry out data collection tasks, the system stores the real-time learning data in a central data buffer. This data includes real-time student feedback, learning progress records, and environmental perception data. The central data buffer is continuously updated to reflect the actual situation of the data collection, ensuring that subsequent analysis remains accurate. During the data collection process, key data samples were periodically extracted from the buffer for model updates. Specifically, these sample data were analyzed to optimize the learning analytics models and assessment algorithms, which in turn contribute to the refinement of teaching strategies. This process is comparable to experience replay and strategy updating in drone data collection. By continuously updating the analytical models, the data collection and teaching assessment strategies remain aligned with changes in the instructional environment and student behavior. This ensures the accuracy of data collection and enhances the effectiveness of educational assessment.

2.2 Model training and execution

The mobile device of each student i in the teaching assessment process was equipped with a policy network $\omega^i(\cdot)$, a critic network $W^i(\cdot)$, as well as their corresponding target networks $\omega'^i(\cdot)$ and $W'^i(\cdot)$. These networks are all composed of deep neural networks. The policy network is responsible for generating operational suggestions t^i_{s+1} for the device under the current teaching state t^i_{s+1}, while the critic network W^i evaluates the value of these actions. The target networks, which are replicas of the policy and critic networks, were used to stabilize the training process. During training, a centralized training approach was adopted, enabling each device's critic network to use the state and action information of other devices to evaluate the current state. Figures 1 and 2 illustrate the execution and training processes of the proposed network model.

During the data collection process, the data generated by the devices was stored in a central buffer. To train and update the network model, a random selection of experience groups was drawn from the buffer for training. The target policy network generates target operational suggestions based on the states in these experience groups.

The critic network updates its parameters by minimizing the loss function $M_p(\varphi^{Wi})$, thereby improving the accuracy of its operation value evaluations. The parameter update formulas are as follows:

$$M_p\left(\varphi^{W^v}\right) = R\left[\left(b_s^i - W^i\left(t_s, x_s \middle| \varphi^{W^i}\right)\right)^2\right] \tag{1}$$

$$b_s^i = \mu e_s^i + \varepsilon W'^i\left(t_{s+1}, x_{s+1} \middle| \varphi^{W'^i}\right) \tag{2}$$

To enhance the stability of the reward values, a scaling factor μ was applied to adjust the reward values, making them more suitable for the needs of teaching assessment. The policy network $\omega^i(\cdot)$ updates its parameters through the method of gradient ascent, optimizing the policy to improve the device's performance in the instructional environment. The formula is as follows:

$$\nabla_{\varphi^{\omega^i}} K \approx \nabla_{\varphi^{\omega^i}} \omega^i\left(t \middle| \varphi^{\omega^i}\right)_{t=t_s} \times \nabla_x W^i\left(t_s, x_s \middle| \varphi^{W^i}\right)\Big|_{x_s^i = \omega^i t\left(s_s^i\right)} \tag{3}$$

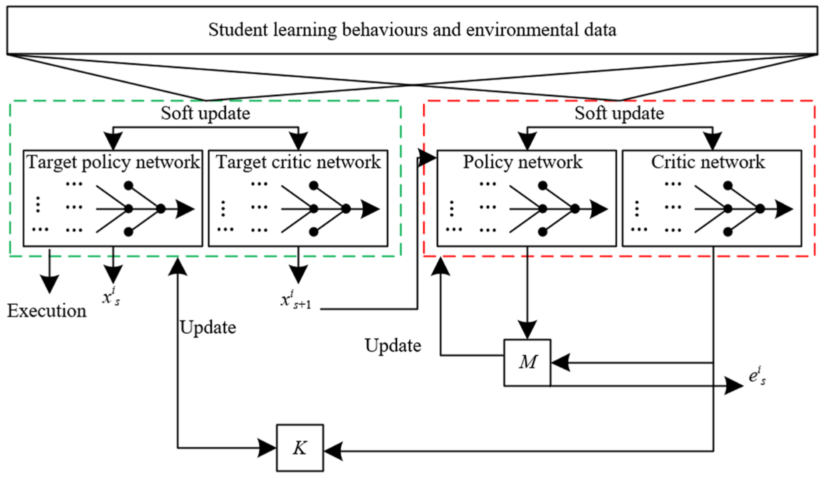

Fig. 1. Execution process of the proposed network model

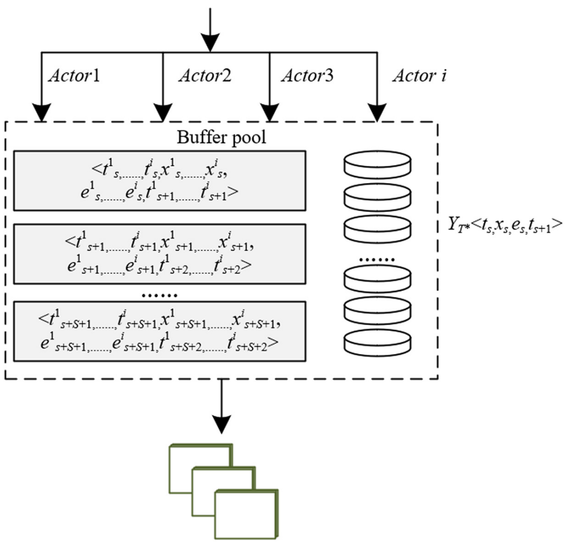

Fig. 2. Training process of the proposed network model

2.3 Algorithm discussion and analysis

In the proposed data collection method, the teaching data collection task was divided into H rounds, with each round lasting S time steps. Each student's mobile device selects the appropriate operational strategy based on the current teaching state and introduces a certain level of random noise to encourage exploration. Once all devices have completed their actions, the system updates the global teaching state based on the feedback and operational outcomes from the devices and assigns rewards to each device. These data (t_s, x_s, e_s, t_s), including the device's state t_s, operation x_s, reward e_s, and the updated state t_{s+1}, were stored in a central experience pool. At each time step, the system randomly samples T_{SI} data points from the experience pool for model updating. Specifically, the critic and policy networks undergo parameter updates. The critic network was optimized by minimizing the loss function to improve the accuracy of evaluating teaching operations, while the policy network updates its parameters via gradient ascent to optimize device performance in the instructional environment. The target networks were adjusted through soft updates to maintain stability during the training process. In terms of model design, both the policy and target policy networks adopt neural networks with three hidden layers, while the critic and target critic networks utilize neural networks with four hidden layers. All hidden layers were activated using the ReLU function. This network structure is particularly suited to handling complex teaching data, thereby enhancing the accuracy and personalization of teaching assessment.

The proposed algorithm exhibits strong generalization capabilities, particularly in dynamic scenarios. Specifically, the algorithm effectively manages the dynamic changes in instructional environments, owing to its state-space design, which incorporates elements of dynamic data. In the context of teaching assessment, students' learning behaviors and feedback are constantly changing, akin to dynamic data points. Key information included in the algorithm's state space, such as the changing distance and speed between the student and the task, reflects trends in the learning process. For example, elements in the state space can represent the degree of alignment between students' learning progress and teaching tasks, or the speed at which students complete different learning tasks. By capturing these dynamic factors, the proposed algorithm can adjust the operational strategies of mobile devices in real time to better support personalized teaching assessment.

The proposed algorithm employs a centralized training with decentralized execution (CTDE) framework to address the dynamic and uncertain nature of the teaching assessment environment. In the CTDE framework, each student's mobile device does not operate in isolation during data collection. The behavior of each device is not only influenced by its own learning state and data needs but is also guided by a global "critic," which incorporates the state and behavior information of other devices. This means that each device can adjust its strategy by observing the operations and feedback of other devices, facilitating intelligent collaboration in data collection. For instance, when multiple student devices are collecting evaluation data, one device may choose a different learning task or question type based on the feedback from other devices, thereby improving the diversity and quality of the data collected. This implicit information interaction enhances the comprehensiveness and effectiveness of teaching assessment data.

Before executing the teaching assessment data collection task, each student's mobile device must initialize network parameters. The time complexity of the initialization process is represented as $P_1 = P\left(\sum_{i=1}^{I} 1\right) = P(I)$, where I represents the number of devices involved in data collection. During task execution, each device generates actions based on the policy network, which involves the computation of a deep neural network. The time complexity of a deep neural network is assumed to be $P\left(\sum_{d=1}^{D} v_d \cdot v_{d-1}\right)$ in this study, where v_d is the number of units in the fully connected layer. Therefore, the time complexity for each device to perform a task is $P_2 = P(I) \cdot \left(\sum_{d=1}^{D} v_d \cdot v_{d-1}\right)$. During data collection, devices must also randomly sample experience from the buffer for network learning and parameter updating, with the time complexity for this process being $P_3 = P(I) \cdot P\left(Y_{SI}\right) \cdot P\left(\sum_{d=1}^{D} v_d \cdot v_{d-1}\right)$. Overall, the training process of the proposed algorithm consists of H rounds, each containing S time steps, resulting in the total time complexity: $P = P(I) + P(H) \cdot P(S) \cdot (P_2 + P_3)$.

In the process of collecting teaching assessment data, the total time it takes for the algorithm to run is affected by several factors. These include the number of devices involved, the number of training rounds, the steps in each round, the complexity of the neural network, and the sample batch size. Specifically, more devices and a more complex network structure led to a significant increase in time complexity.

3 TEACHING ASSESSMENT METHOD BASED ON MOBILE TECHNOLOGY

The proposed teaching assessment method based on mobile technology draws from the ensemble empirical mode decomposition normalization (EEMDN) technique and the bidirectional gated recurrent unit (BiGRU) model to enhance the accuracy and effectiveness of data analysis in teaching assessment. Specifically, this method utilizes EEMDN to process data sequences in teaching assessment. Evaluation data often exhibit non-stationarity, such as significant variations in student learning progress and feedback, along with notable differences in numerical values. EEMDN effectively handles these non-stationary data and addresses the issue of reduced prediction accuracy caused by large numerical discrepancies. Furthermore, a spatial attention mechanism was introduced to capture the features of each teaching area or task. Spatial regularities in teaching assessment data can be reflected through the weighting of teaching activity hotspots. In instructional contexts, spatial attention mechanisms can be designed based on indicators such as the density of teaching activities in different regions or the frequency of student interactions. This allows the model to more accurately capture the regional characteristics within teaching data and to prioritize those areas or tasks of greater significance during analysis, thereby improving the comprehensiveness and precision of evaluation. The BiGRU algorithm is employed within this method to improve the accuracy of feature extraction. In teaching assessment data analysis, student learning behaviors and feedback often exhibit temporal dependencies. The proposed method based on BiGRU can simultaneously capture both forward and backward information, leading to a more comprehensive understanding of the students' learning processes and performance, ultimately enhancing the accuracy of predictions and analysis. Figure 3 illustrates the framework of the proposed network model.

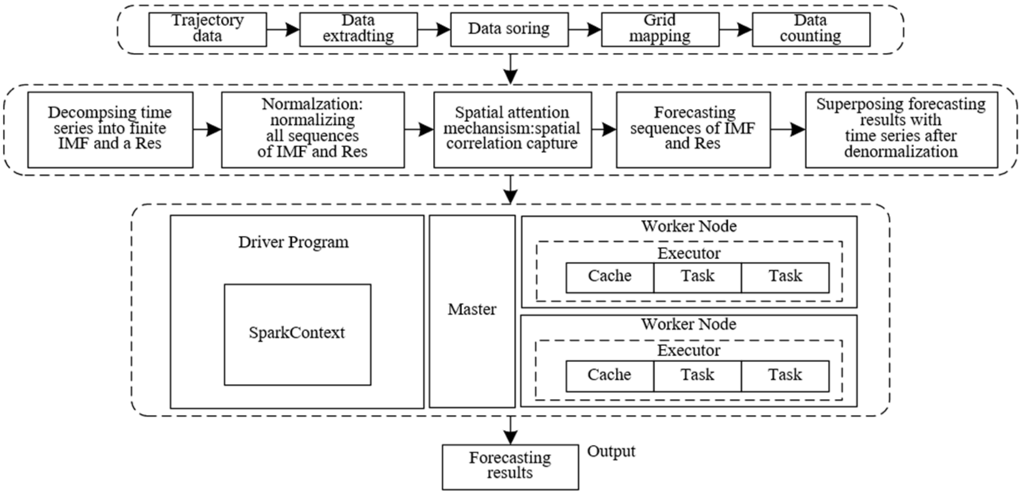

Fig. 3. Framework of the proposed network model

The specific design of this method incorporates the ensemble empirical mode decomposition (EEMD) algorithm, aimed at addressing complex non-linear and non-stationary features in teaching data. Initially, a white noise signal with a standard normal distribution was added to the original teaching data to generate augmented noise signals. This step stabilizes the decomposition process, allowing for more effective extraction of IMFs from the data. Assuming the total number of iterations is L, the original signal is denoted as $a(s)$, the white noise sequence in the u-th iteration is represented as $v_u(s)$, and the augmented noise signal in the u-th iteration is expressed as $a_u(s)$. Thus, the following equation holds:

$$a_u(s) = a(s) + v_u(s), u = 1, 2, \ldots, L \tag{4}$$

Subsequently, the noisy signals were subjected to empirical mode decomposition (EMD), resulting in the extraction of intrinsic mode functions (IMFs). This process was repeated M times, with each iteration using white noise signals of different magnitudes, thereby generating a set of IMFs. By averaging these IMFs, the final result of the EEMD decomposition was obtained. Let $z_{u,k}(s)$ represent the k-th IMF from the u-th iteration after adding white noise, and let $e_{u,k}(s)$ denote the residual function, with K representing the number of IMFs. The following equation can be derived:

$$a_u(s) = \sum_{k=1}^{K} z_{u,k}(s) + e_{u,k}(s), u = 1, 2, \ldots, K; k = 1, 2, \ldots, K \tag{5}$$

The aforementioned steps were repeated L times to obtain the set of IMFs:

$$z_{1,k}(s), z_{2,k}(s), z_{3,k}(s), \ldots, z_{L,k}(s), k = 1, 2, \ldots, K \tag{6}$$

By averaging the corresponding IMFs, the final result of the EEMD was produced, which was then mapped to the range [0, 1]. Let $z_k(s)$ represent the k-th IMF after decomposition, resulting in the following formula:

$$z_k(s) = \frac{1}{L} \sum_{u=1}^{L} z_{uk}(s), u = 1, 2, \ldots, K \tag{7}$$

Specifically, feature values were extracted based on student engagement, test results, or interaction frequency within each region or task. To enhance the model's spatial perception, these feature values were first processed through MaxPool and AvgPool operations to extract the maximum and average values from each region. This allows for the consideration of both prominent features and overall trends in each region or task. Further, the pooled features were input into a convolutional layer for additional processing. The convolutional layer effectively captures local patterns within regional features, enabling the model to identify key features of each teaching task or module. In teaching assessment, this operation helps the model better understand student performance across various learning scenarios and improves the model's overall predictive capabilities. Finally, the features processed by the convolutional layer were passed through a sigmoid activation function. The sigmoid function maps the output values to the (0, 1) range, which serves as the weight for each region or task. These weights reflect the relative importance of different instructional regions or tasks and guide the BiGRU model to focus more on regions or tasks with higher weights when processing data. Let D represent the feature map, AP denote average pooling, MP denote max pooling, d represent the convolution operation, δ represent the sigmoid activation function, and $L_t D$ represent the spatial attention parameter matrix. The construction process of the spatial attention mechanism is given by the following equations:

$$L(D) = [AP(D); MP(D)] \tag{8}$$

$$L_T D = \delta(d(L(D))) \tag{9}$$

The BiGRU model processes time-series data by combining two directions of GRU: a forward GRU and a backward GRU. For teaching assessment applications, the BiGRU model can fully capture the temporal dynamics of student learning behaviors, enhancing both the accuracy and comprehensiveness of the evaluation. In the BiGRU model, the forward GRU ($h \rightarrow t - 1$) and the backward GRU ($h \leftarrow t - 1$) process data from the forward and backward directions of the sequence, respectively. The forward GRU captures information from the past to the present, while the backward GRU captures information from the future to the present. This bidirectional processing allows the model to fully leverage the entire time-series data, leading to a more accurate understanding of student learning processes and behavioral patterns. When analyzing students' learning progress, the forward GRU processes past learning behaviors, while the backward GRU provides predictions for potential future learning behaviors. Let the update gate be represented by C_s, the reset gate by e_s, the output value at time step $(s - 1)$ by g_{s-1}, the input value at time step s by a_s, the activation functions by δ and tanh, and the weight matrices by Q, with the update gate weights represented by Q_c, the reset gate weights by Q_e, the tanh output value by $\tilde{g}_s$, and the output result by g_s. The equations are as follows:

$$C_s = \delta(Q_c \cdot [g_{s-1}, a_s]) \tag{10}$$

$$e_s = \delta(Q_e \cdot [g_{s-1}, a_s]) \tag{11}$$

$$\tilde{g}_s = \tanh(Q \cdot [e_s * g_{s-1}, a_s]) \tag{12}$$

$$g_s = (1 - C_s) * g_{s-1} + C_s * \tilde{g}_s \tag{13}$$

Figure 4 presents the flowchart of the proposed network model. At time t, the hidden layer state of the BiGRU model involves the weighted sum of the hidden states from the forward GRU $\left(\overrightarrow{g_{s-1}}\right)$ and the backward GRU $\left(\overleftarrow{g_{s-1}}\right)$. This weighted sum operation integrates both forward and backward information, allowing the final hidden layer state to reflect the full scope of the time-series data. In teaching assessment, this mechanism helps the model better synthesize past student behaviors and future trends, thus providing more accurate evaluation results. Let the non-linear transformation of the input word vectors be represented by the *GRU* () function, the input value at time s by a_s, the forward output by $\overrightarrow{g_s}$, the backward output by $\overleftarrow{g_s}$, and the forward and backward outputs at time (s – 1) by $\overrightarrow{g_{s-1}}$ and $\overleftarrow{g_{s-1}}$, respectively. The forward hidden state of the BiGRU at time s is denoted by $\overrightarrow{g_s}$, and the backward hidden state is denoted by $\overleftarrow{g_s}$, with their respective weights represented by q_s and n_s, and the bias of the hidden state at time s by y_s. The equations are as follows:

$$\overleftarrow{g_s} = GRU\left(a_s, \overleftarrow{g_{s-1}}\right) \tag{14}$$

$$g_s = q_s \overrightarrow{g_s} + n_s \overleftarrow{g_s} + y_s \tag{15}$$

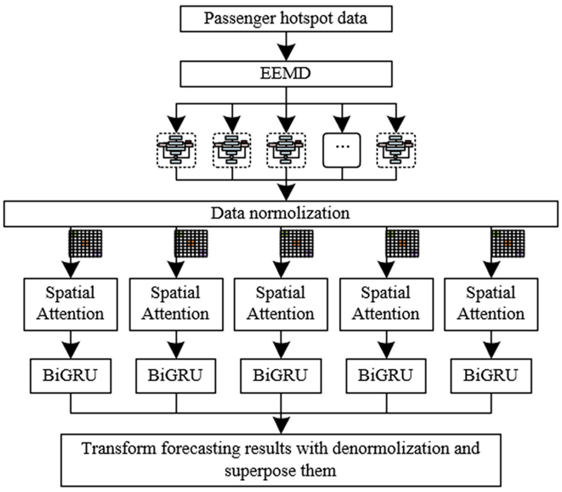

Fig. 4. Process flow of the proposed network model

4 EXPERIMENTAL RESULTS AND ANALYSIS

It can be observed from Table 1 that there are significant differences in the data collection proportions across various data types and scenarios. For learning behavior data, the proposed method achieves a high proportion of 77.26% in Scenario 4, significantly higher than other scenarios and methods. This indicates that the proposed method has a notable advantage in collecting learning behavior data in specific scenarios. In contrast, the proportions for Deep Q-Network (DQN) and Transformers in learning behavior data are relatively low, with DQN achieving 3.58% and Transformers reaching 4.69% in Scenario 4, and 4.69% and 7.75%, respectively, in Scenario 6. For environmental and contextual data, the proposed method reaches a proportion of 130.25% in Scenario 4, significantly exceeding other methods, which demonstrates the effectiveness of this approach in collecting environmental and contextual data. Regarding teaching content data and course feedback data, the proposed method achieves proportions of 148.26% and 181.26% in Scenario 4, respectively, indicating its strong advantage in these types of data collection as well. Overall, the proposed method demonstrates a higher proportion of data collection across all data types, particularly in Scenario 4, where the proportions for learning behavior, environmental and contextual data, teaching content data, and course feedback data are significantly higher than those achieved by other methods. This suggests that the proposed method is capable of effectively covering a wide range of data types in specific instructional environments, providing a more comprehensive evaluation perspective. In comparison, the lower data collection proportions for DQN and transformers across multiple scenarios may limit their effectiveness in certain applications.

Table 1. Proportion of data collection for different data types

Data Type	Method	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Learning behavior data	Proposed method	3.52%	0.75%	17.12%	77.26%	4.56%	52.36%
	DQN	0.82%	1.12%	0.33%	3.58%	0.07%	4.78%
	Transformers	0.18%	0.03%	0.36%	4.69%	0.33%	7.75%
	Random	0.32%	0.52%	0.58%	6.56%	0.81%	12.36%
Environmental and contextual data	Proposed method	32.36%	33.75%	63.25%	130.25%	27.56%	126.35%
	DQN	0.02%	2.03%	0.27%	15.26%	1.71%	11.85%
	Transformers	0.15%	2.08%	0.41%	4.87%	0.12%	8.26%
	Random	0.32%	0.53%	0.61%	6.56%	0.81%	12.36%
Teaching content data	Proposed method	41.23%	7.88%	58.23%	148.26%	40.56%	60.31%
	DQN	1.72%	2.54%	1.82%	14.87%	1.78%	7.06%
	Transformers	0.04%	5.89%	0.26%	0.76%	1.06%	26.54%
	Random	0.33%	0.53%	0.64%	6.59%	0.81%	12.26%
Course feedback data	Proposed method	27.36%	36.16%	23.14%	181.26%	37.45%	122.36%
	DQN	0.00%	1.87%	2.51%	131.24%	7.26%	82.31%
	Transformers	0.03%	1.95%	7.25%	70.23%	3.21%	43.26%
	Random	0.31%	0.53%	0.63%	0.63%	0.81%	12.56%

Based on the data provided in Figure 5 on data collection quality in dynamic scenarios, significant differences are observed in the performance of different methods regarding the number of training rounds for learning behavior data and environmental and contextual data. For learning behavior data, the proposed method shows an increase in training rounds from 400 to 1020, indicating high stability and progressively improved performance during training. In contrast, DQN and Transformers exhibit relatively lower training rounds at higher iterations, with DQN reaching 920 rounds after 2400 iterations and Transformers at 150. For environmental and contextual data, the proposed method consistently demonstrates a clear advantage across all training rounds, ranging from 5000 to 24000 rounds, showcasing strong data collection capabilities. Comparatively, DQN performs well at higher iterations, achieving 27500 rounds after 2400 iterations, while the rounds for Transformers and

Random methods remain significantly lower, with Transformers reaching 10200 and Random at only 800 after 2400 iterations. Overall, the proposed method exhibits superior performance in data collection quality in dynamic scenarios, particularly during higher training rounds, highlighting its significant advantage in continuous and stable data collection. This suggests that the method is well-suited for applications requiring long-term data tracking and analysis. In comparison, while DQN achieves higher training rounds during later stages, its performance in the early stages of learning behavior data and environmental and contextual data collection is relatively weak. The Transformers and Random methods demonstrate clear disadvantages in terms of training rounds, especially in maintaining high-quality data collection during extended training periods.

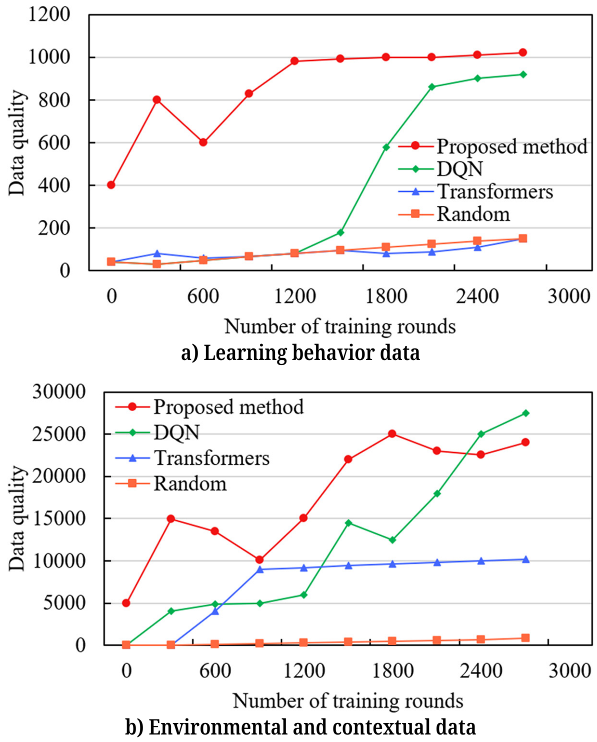

Fig. 5. Analysis of data collection quality in dynamic scenarios

Based on the data presented in Figure 6, the fitting of the EEMD algorithm to the real data shows general consistency across different quantity ranges. The variations in total EEMD and real data are quite similar within the 0–50 quantity range. For example, when the quantity is 10, both the total EEMD and the real data are four. Between the 60–80 quantity range, there are noticeable fluctuations between the total EEMD and the real data, though the overall trends remain closely aligned. From 100 to 150, the gap between the two narrows further, with a particularly strong fit at a quantity of 104, where both EEMD and the real data reach 104. This suggests that the algorithm performs well within this range. In general, the EEMD algorithm demonstrates strong consistency in fitting the real data across most quantity ranges, indicating its effectiveness in handling data fitting tasks. While fluctuations occur in certain intervals, the overall trends and patterns of variation remain consistent with the real data, suggesting that the EEMD algorithm can accurately reflect the distribution of real data in most cases. This good fit suggests that the EEMD algorithm is well-suited for data processing in mobile technology-based learning analytics, enabling effective comparisons and analyses with actual data to support more precise teaching assessments and improvements.

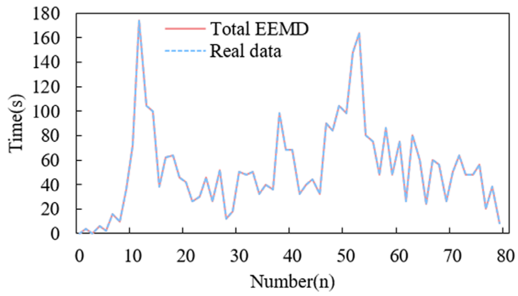

Fig. 6. Fitting analysis of the proposed algorithm

Table 2. Performance of the proposed algorithm after normalization for teaching assessment

IMF	MOEs			
	MAPE(%)	MAE	RMSE	ME
IMF1	3.601%	0.865	1.112	2.236
IMF2	1.301%	0.325	0.356	0.654
IMF3	4.000%	0.234	0.265	0.421
IMF4	3.902%	1.035	1.325	2.652
IMF5	0.024%	0.032	0.033	0.048
IMF6	0.021%	0.007	0.009	0.026
IMF7	3.401%	1.265	1.523	2.895

Based on the data in Table 2, the performance of each IMF shows significant variation across the teaching assessment metrics. IMF1 displays a mean absolute percentage error (MAPE) of 3.601%, a mean absolute error (MAE) of 0.865, and a root mean square error (RMSE) of 1.112, indicating a higher level of error. In contrast, IMF2 exhibits superior accuracy, with a MAPE of 1.301%, an MAE of 0.325, and an RMSE of 0.356. IMF3 and IMF4 have MAPEs of 4.000% and 3.902%, respectively, MAEs of 0.234 and 1.035, and RMSEs of 0.265 and 1.325, placing their performance between that of IMF2 and IMF1. IMF5 and IMF6 demonstrate particularly low error metrics, with IMF5 achieving a MAPE of 0.024%, an MAE of 0.032, and an RMSE of 0.033, while IMF6 has a MAPE of 0.021%, an MAE of 0.007, and an RMSE of 0.009, indicating excellent fitting performance. IMF7, with a MAPE of 3.401%, an MAE of 1.265, and an RMSE of 1.523, exhibits higher error levels, but still outperforms IMF1 and IMF4. According to the data analysis, IMF5 and IMF6 deliver the best performance in teaching assessment, with the lowest MAPE, MAE, and RMSE, suggesting they provide the highest accuracy in data prediction and fitting. The low error metrics of these IMFs indicate that their use can yield more precise teaching assessment results, making them suitable for teaching data analysis requiring high accuracy. In contrast, IMF1 and IMF4 show higher error metrics, particularly IMF1, suggesting that larger prediction errors may occur in some application scenarios. Therefore, selecting IMF5 and IMF6 as evaluation tools is likely to result in more reliable and precise outcomes, while the use of IMF1 and IMF4 may require further optimization or consideration of their limitations in specific applications.

5 CONCLUSION

The application of mobile technology in learning analytics for educational assessment was explored in this study, revealing the significant potential and advantages of mobile technology in modern teaching assessment. The first part of the study focuses on the diverse methods of data collection for teaching assessment. The results demonstrated that the proposed method significantly outperformed other traditional approaches in terms of data collection quality and efficiency, particularly excelling in the collection of learning behavior data and environmental and contextual data. The comprehensive coverage and efficient collection of these data types provide more abundant and accurate data to support subsequent teaching assessments. The second part of the study validates the effectiveness and superiority of the proposed algorithm by comparing the performance of various algorithms after fitting and normalization in teaching assessment. The experimental results indicated that the proposed algorithm, especially IMF5 and IMF6, exhibited lower error levels and higher accuracy, making it more suitable for mobile technology-based teaching assessments, thereby enhancing the precision and reliability of educational analytics.

However, several limitations exist within the study. First, the experimental results were primarily based on specific scenarios and datasets, and the algorithm's performance may be influenced by data characteristics and sample distribution, which limits the generalizability of the findings. Secondly, while this study made progress in data collection and evaluation methods, the detailed implementation of mobile technology and the use of specific tools were not explored in depth. Future research should further expand the adaptability and generalizability of the algorithm across diverse educational scenarios and datasets, explore more diverse implementations of mobile technology, and investigate how effective evaluation applications can be conducted in different educational systems and teaching environments, thereby promoting the broader and deeper application of mobile technology in educational assessment.

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