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PAPER

Evaluation of Learning Outcomes in Higher Education through the Integration of Interactive Mobile Technology and Big Data Analytics

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ABSTRACT

With the rapid advancement of mobile Internet technology, interactive learning platforms, and big data analytics, they have become essential tools in modern higher education, particularly in the evaluation of learning outcomes. Traditional evaluation methods primarily rely on offline testing and questionnaire surveys, which often lack real-time adaptability, specificity, and multi-dimensional analysis, making it difficult to comprehensively reflect learners' academic progress. Recent developments in big data technology and artificial intelligence have led researchers to explore data-driven approaches for evaluating learning outcomes. However, existing methodologies remain limited in feature selection, feature fusion, and model optimization, hindering their ability to fully capture learners' behavioral features and academic performance. To address these limitations, a learning outcome evaluation model based on multi-semantic feature interaction and big data analytics was proposed. The model was designed with a feature embedding module, a multi-semantic feature interaction module, a two-dimensional squeeze-and-excitation module, and a feature fusion module to enhance evaluation accuracy and comprehensiveness. The feature embedding module extracts latent features by embedding multidimensional learner behavior data. The multi-semantic feature interaction module captures complex learning patterns by facilitating interactions among various features. The two-dimensional squeeze-and-excitation module optimizes feature representation, improving evaluation sensitivity. The feature fusion module integrates diverse features to enhance evaluation accuracy. Through these innovations, this study not only introduces a novel perspective for evaluating learning outcomes in higher education but also provides valuable insights for further research in educational technology.

KEYWORDS

learning outcome evaluation, interactive learning, big data analytics, feature embedding, multi-semantic feature interaction, feature fusion

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1 INTRODUCTION

With the rapid advancement of information technology, particularly the widespread adoption of mobile Internet technology, interactive learning platforms, and big data analytics have become integral components of modern higher education [1–4]. As noted in previous studies [5–10], intelligent mobile devices enable learners to access educational resources, participate in interactive discussions, and track their learning progress and performance in real time. Additionally, big data technology offers the capability to comprehensively analyze learning behaviors, learning pathways, and learning outcomes, providing novel perspectives and methodologies for evaluating academic performance. However, the effective integration of interactive mobile technology with big data analytics to achieve more precise learning outcome evaluation remains a critical challenge in the field of education.

Existing learning outcome evaluation methods exhibit certain limitations [11–14]. Traditional evaluation approaches primarily rely on offline testing and questionnaire surveys, which are often characterized by single-dimensional evaluation metrics and a lack of real-time adaptability and specificity. With the proliferation of intelligent mobile devices, significant transformations have occurred in learner behaviors, which conventional evaluation methods fail to adequately capture [15–20]. Moreover, many big data-based evaluation approaches face challenges in feature selection and fusion strategies, making it difficult to effectively integrate data from diverse sources, thereby compromising the accuracy and comprehensiveness of evaluation results. Consequently, there is an urgent need to explore a novel evaluation framework that enables multidimensional and real-time evaluation of learning outcomes.

To address these challenges, a learning outcome evaluation model based on multi-semantic feature interaction and big data analytics was proposed in this study. This model was designed with four key modules to overcome the limitations of existing methodologies. First, the feature embedding module extracts latent learning features by embedding multidimensional learner behavior data. Subsequently, the multi-semantic feature interaction module facilitates in-depth interactions across different dimensions to capture complex learning patterns. Next, the two-dimensional squeeze-and-excitation module further optimizes feature representations, enhancing the model's sensitivity. Finally, the feature fusion module integrates diverse features to improve evaluation accuracy and comprehensiveness. By adopting this integrated approach, this study enhances the precision of learning outcome evaluation and provides valuable insights and methods for future research in educational technology applications.

2 LEARNING OUTCOME EVALUATION MODEL BASED ON MULTI-SEMANTIC FEATURE INTERACTION AND BIG DATA ANALYTICS

The proposed learning outcome evaluation model, which integrates multi-semantic feature interaction and big data analytics, consists of four primary modules: the feature embedding module, the multi-semantic feature interaction module, the two-dimensional squeeze-and-excitation module, and the feature fusion module. The feature embedding module is designed to extract and map learners' behavioral features from diverse learning data. The multi-semantic feature interaction module is designed based on the implementation of interactive mobile technology to capture multidimensional semantic information embedded in learner behavioral data, deeply exploring latent learning patterns within the learning process. The two-dimensional squeeze-and-excitation module further optimizes feature representation, ensuring enhanced perceptual capability in learning outcome evaluation and capturing subtle variations in learner behavior in a timely manner, thereby improving the sensitivity of the evaluation process. Finally, the feature fusion module effectively integrates features from multiple sources, strengthening the model's robustness and evaluation accuracy. This ensures that the final evaluation results are more precise and holistic, thereby providing educators with personalized learning feedback and recommendations.

The proposed model primarily relies on large-scale learning data collected from intelligent mobile learning platforms, learning management systems, and online education platforms. The data encompasses various dimensions of student learning behavior, interaction records, and academic performance. For instance, clickstream data, page navigation behavior, participation frequency and duration in discussions, and video engagement metrics on mobile devices serve as valuable behavioral features for evaluation. Additionally, assignment scores, online quiz results, course participation levels, and interactive feedback provide insights into learners' proficiency levels and learning outcomes. The collection and analysis of the data sources offer a comprehensive and dynamic perspective for learning outcome evaluation.

In the context of learning outcome evaluation, various feature types—including learner behavioral data, learning content, and learning environment—can be considered. These features can be either continuous, such as learning duration and task completion time, or discrete, such as discussion participation frequency and assignment submission records. The primary function of the feature embedding module is to transform these high-dimensional and sparse features into low-dimensional and dense representation vectors through embedding techniques. This transformation enables different types of learning features to be effectively processed by neural network models. During this process, discrete features, such as learning pathways, video engagement records, and interaction frequencies, are transformed using one-hot encoding or categorical embedding techniques. Meanwhile, continuous features, such as learning duration and task completion progress, undergo standardization or normalization to ensure consistent scaling and relative importance across different features. Let the total number of features be represented by v, and let the u-th input feature be denoted as a_u (where $1 \leq u \leq v$). The model input is formulated as follows:

$$a = [a_1, a_2, \ldots, a_v] \tag{1}$$

In the feature embedding module, all learning-related features are transformed into low-dimensional embedding vectors through an embedding layer, enabling the vectors to capture deep behavioral patterns of learners during the learning process. The structure of this module is illustrated in Figure 1. For example, learners' demographic information, such as age, gender, and subject interests, is embedded into vectors, which are further integrated with interaction-based data, including the frequency of video views and peer interactions, to construct a comprehensive representation of learner behaviors. For multi-attribute features, such as interests in sports, reading, and programming, each interest is independently embedded, and the resulting vectors are either concatenated or aggregated to generate a unified representation of the learner's multi-dimensional interest features. Let the embedding vector of the u-th input feature be denoted as $r_u \in E^f$ (where $1 \le u \le v$), and let f represent the length of each embedding vector. The output of the feature embedding layer is expressed as:

$$R = [r_1, r_2, \ldots, r_v] \tag{2}$$

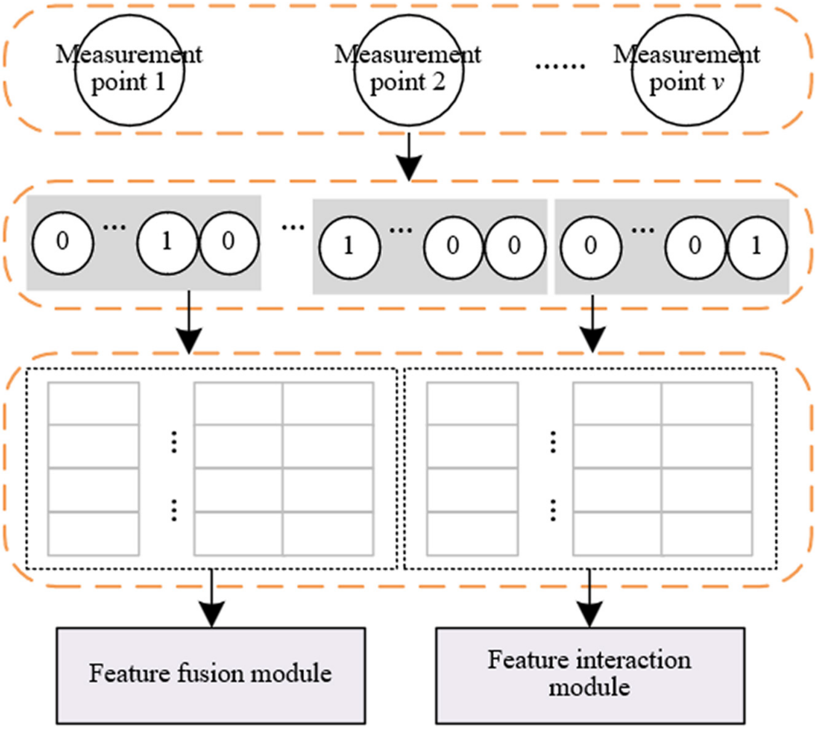

Fig. 1. Structure of the feature embedding module

In traditional learning outcome evaluation models, feature interactions are often confined to a single semantic space, which may fail to capture the diverse behaviors and dynamic responses of learners in complex learning environments. With the increasing prevalence of interactive mobile technology, behavioral data collected from learning platforms exhibit significant diversity and complexity. Learners' behaviors are influenced not only by learning content but also by factors such as learning environment, emotional state, and social interactions. To address these challenges, this study introduces the multi-semantic feature interaction module, which integrates information from multiple semantic spaces, including learning content, learning pathways, and social interactions, to enable a more comprehensive analysis of learner behaviors and learning outcomes. To achieve this, the proposed model incorporates the concept of convolutional kernels from convolutional neural networks (CNNs) into multi-semantic feature interaction. Multiple convolutional kernels are utilized to extract distinct feature patterns. For ease of representation, let $s = v(v - 1)/2$, where the number of input features in the convolutional layer is $2s$. The final input representation for the convolutional layer is given by:

$$A_z = \left[r'_1, r'_2, r'_1, r'_3, \ldots, r'_{v-1}, r'_v\right] \tag{3}$$

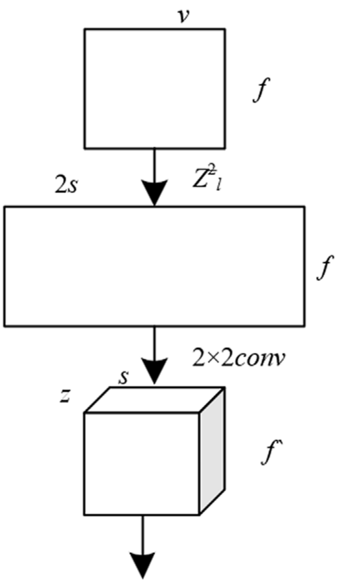

Fig. 2. Structure of the multi-semantic feature interaction module

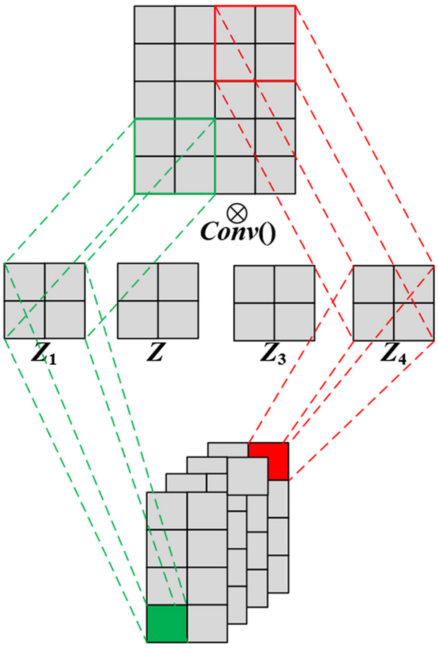

Fig. 3. Schematic representation of the multi-semantic feature interaction process

The first step in multi-semantic feature interaction involves expanding the input feature vectors to meet the input requirements of CNN. Learner behavior data typically consist of multiple features, such as learning duration, task completion progress, and interactions with instructors or peers, each possessing distinct data types and dimensions. The structure of the multi-semantic feature interaction module is illustrated in Figure 2, while Figure 3 provides a schematic representation of the multi-semantic feature interaction process. During this process, the input feature vector A_z is first expanded into a three-dimensional matrix to facilitate convolutional operations. The expanded feature matrix encapsulates learning data across different dimensions, which are subsequently transformed into enriched semantic interaction features through convolution. A sliding window operation is performed using convolutional kernel j, where the kernel height and width regulate both the order of feature interactions and the vector dimensionality. Additionally, the number of convolutional kernels determines the number of semantic spaces involved in feature interactions. This design enables the model to adjust the hierarchy and complexity of feature interactions, allowing for the extraction of meaningful interaction features across different semantic spaces, which consequently achieves a more refined modeling of learner behaviors.

Through convolutional operations, the input high-dimensional sparse features are mapped into a low-dimensional, dense semantic space, thereby reducing computational complexity and improving model training efficiency. For each input feature, the convolutional operation generates an interaction feature representation denoted as W. The total number of features obtained through convolutional processing is represented by s, while f indicates the feature dimensionality after convolution, and z denotes the number of convolutional kernels, which corresponds to the number of semantic spaces. This approach not only captures local interactions among features but also preserves information complementarity across different semantic spaces, thereby enhancing the model's representational capacity. Let the convolutional operation be denoted by $O_{CO}(\cdot)$, with the parameters of the z-th convolutional kernel represented as j_z. The set of all interaction features in the z-th semantic space is expressed as $w_z = [w_{z1}, w_{z2}, \ldots, w_{zs}]$, where the u-th interaction feature in the z-th semantic space is denoted as w_{zu}. The interaction feature representation for a single semantic space is formulated as follows:

$$w_z = O_{CO}(j_z, A_z) \tag{4}$$

Traditional feature interaction modules often rely solely on simple feature fusion and weighted aggregation, which are insufficient for capturing the variability and interdependencies of features across different semantic spaces. To address this limitation, this study introduces a two-dimensional squeeze-and-excitation module based on SENet, enabling dynamic adjustment of feature weights from both the semantic and feature dimensions. This ensures that the model can automatically prioritize relevant features based on the complex relationships between features and the target variable.

Figure 4 shows the structure of the two-dimensional squeeze-and-excitation module. The fundamental principle of this module is based on two operations: the squeeze operation and the excitation operation. First, the squeeze operation performs global aggregation of multi-semantic interaction features, extracting global information from each semantic space—referred to as the semantic descriptor. This process is implemented by computing either the sum or the average of features within each semantic space, ultimately generating a global representation of multi-semantic spaces. Such an approach is crucial for learning outcome evaluation, as real-world learning data contain diverse features originating from different semantic spaces, including behavioral data, affective data, and environmental data. These features exert varying degrees of influence on learning outcomes depending on their semantic space. Through global aggregation, heterogeneous features can be effectively unified, facilitating further analysis. Let the scalar value be represented as $\hat{x}_{(z,u)}$, and let the set of semantic descriptors for the u-th feature across all spaces be denoted as $\hat{x}_u = [\hat{x}_{(z,u)}, \hat{x}_{(z,u)}, \ldots, \hat{x}_{(z,u)}]$. The global semantic descriptor is then expressed as $X = [\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_u]$. The fundamental computation of the semantic descriptor unit is formulated as follows:

$$\hat{x}_{(z,k)} = O_{tw}\left(w_{z_u}\right) = \frac{1}{f'}\sum_{k=1}^{f'} w_{z_u}^{k} \tag{5}$$

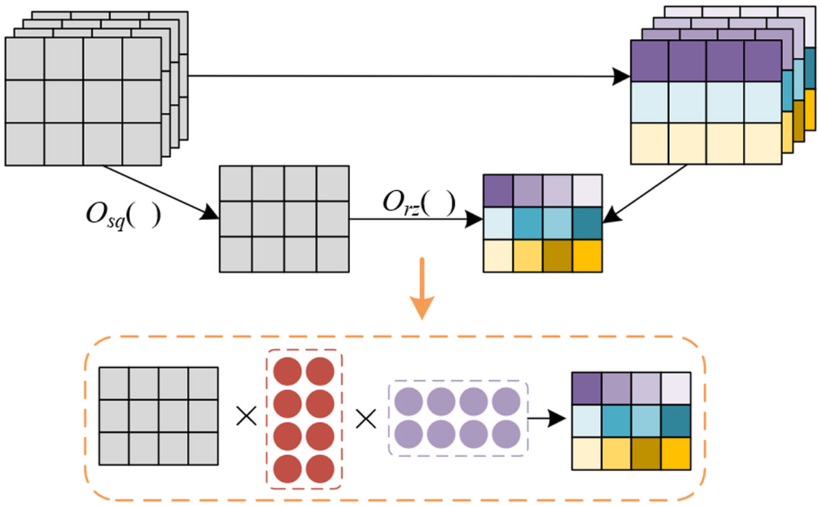

Fig. 4. Structure of the two-dimensional squeeze-and-excitation module

The two-dimensional squeeze-and-excitation module dynamically learns the weights of different semantic spaces through an excitation operation, enabling the model to assign importance to features that exhibit strong correlations with the target variable while suppressing those with weaker relationships. In learning outcome evaluation, different features hold varying degrees of significance across different semantic spaces. For example, learners' online interactions may be more critical during one phase, whereas learning duration or assignment completion may serve as more reliable indicators in another. To achieve this adaptive weighting, two weight matrices, $\hat{Q}_1$ and $\hat{Q}_2$, are employed. The matrix $\hat{Q}_1$ is utilized for dimensionality reduction, minimizing the dimensionality of the feature space and reducing computational cost. Meanwhile, $\hat{Q}_2$ restores the reduced-dimension features to their original dimensions. This operation facilitates efficient attention allocation across different semantic spaces. By leveraging this dimensionality reduction and reconstruction process, the model dynamically learns the importance of features across semantic spaces and adjusts their contributions to learning outcome evaluation accordingly. Let $\hat{y}_u$ denote the set of weights for the *u*-th interaction feature across all semantic spaces, and let the Tanh function be represented by δ_1. The implementation of this weighting process is expressed as follows:

$$\hat{y}_u = O_{rz}(\hat{x}_u, \hat{Q}) = \delta_1(\hat{Q}_2 \times (\hat{Q}_1 \times \hat{x}_u)) \tag{6}$$

Finally, the module enhances feature correlations through a re-weighting and aggregation operation, producing the final output features. During this process, the multi-semantic interaction features *W* are multiplied by the corresponding attention scores *Y*, generating a weighted feature matrix *T*.

$$T = O_{eq}(W, Y) = W * Y \tag{7}$$

Subsequently, the model aggregates the re-weighted features, integrating critical information from various semantic spaces to produce the final output features A_t in the feature interaction module. This process enables the refined integration of multi-semantic feature interaction information, effectively capturing inter-feature relationships and providing a more precise basis for personalized learning outcome evaluation. Let the aggregation operation be denoted as O_{AG} (·), and let the final representation of the u-th interaction feature be represented as a_{tu}, formulated as follows:

$$A_t = O_{AG}(T) = [a_{t1}, a_{t1}, \ldots, a_{ts}] \tag{8}$$

In learning outcome evaluation, data often encompass multiple types of features, such as learners' behavioral data, learning progress, and assignment completion records. These features exhibit complex and diverse interaction relationships, making it difficult for low-order feature interactions to capture deep patterns and correlations effectively. To enhance the representational capacity of the model, the feature fusion module first integrates multi-semantic interaction features with the original embedded feature vectors.

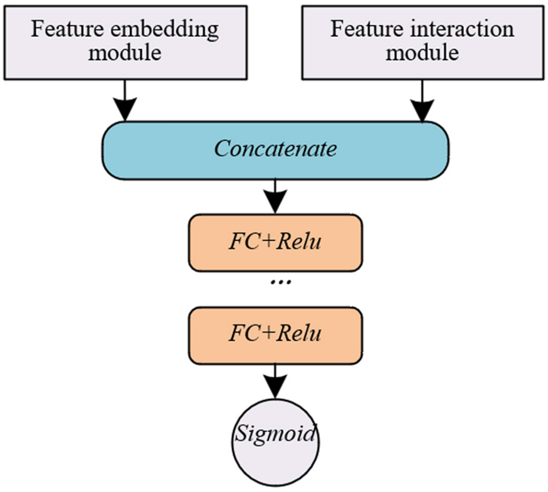

Fig. 5. Structure of the feature fusion module

This fused representation serves as the input to the neural network, which progressively extracts higher-order feature interaction information through successive neural network layers. Figure 5 shows the structure of the feature fusion module.

The feature fusion module integrates multi-semantic interaction features A_t with the original feature embedding vectors R, forming the first-layer input of the deep neural network. These fused features encapsulate information from multiple semantic spaces and feature dimensions, enabling deep nonlinear transformations within the neural network. Through processing in the first neural network layer, low-order feature interactions are transformed into high-order interactions, which better capture complex dependencies among features. The input expression for the first layer is formulated as follows:

$$x^{(0)} = concat(R, A_t) \tag{9}$$

In subsequent layers, each layer's output is dependent on the feature representation from the preceding layer and is continuously optimized through the neural network. As the number of layers increases, the network progressively learns higher-order and more abstract feature interactions. These interactions not only reflect the relationships among various features but also uncover latent patterns and trends within large-scale data. For instance, learning outcomes in specific contexts may be influenced by multiple factors, such as learning methods, emotional states, and external environments. Low-order feature interactions may fail to capture these multidimensional influences, whereas deep feature interactions allow for a more accurate prediction of learning outcomes through the combination of high-order features. Let the ReLU activation function be represented by δ. The output, weight, input, and bias term of the m-th layer are denoted as $x^{(m)}$, $Q^{(m)}$, $x^{(m-1)}$, and $y^{(m)}$, respectively. The output $x^{(m)}$ of the m-th neural network layer is formulated as follows:

$$x^{(1)} = \delta(Q^{(1)} x^{(0)} + y^{(1)}) \tag{10}$$

$$x^{(m)} = \delta(Q^{(1)} x^{(m-1)} + y^{(m)}) \tag{11}$$

In the final stage, the output of the feature fusion module is processed using the sigmoid activation function to generate the final prediction results. The sigmoid function compresses the model's output values into the range of 0 to 1, making it well-suited for binary classification tasks, such as predicting the effectiveness of learning outcomes. Through the multi-layer processing of the feature fusion module, information from different semantic spaces is integrated at the input layer, and high-order feature interactions are progressively learned through deep network training. This process ultimately enhances the accuracy of learning outcome evaluation. Specifically, let the total sample size be represented by F, the ground truth value of the u-th instance in the dataset be denoted as b_u, and the predicted value be represented as $\hat{b}_u$. The prediction process is formulated as follows:

$$\hat{b} = sigmoid(Q^{(m+1)} x^{(m)} + y^{(m+1)}) \tag{12}$$

$$LOSS = -\frac{1}{F}\sum_{u=1}^{F}\left(b_u \log(\hat{b}_u) + (1-\hat{b}_u)\log(1-\hat{b}_u)\right) \tag{13}$$

3 EXPERIMENTAL RESULTS AND ANALYSIS

The results presented in Table 1 indicate that the proposed method consistently outperforms the comparative approaches across all three datasets. On the classroom big data dataset, the proposed method achieves an area under the curve (AUC) of 0.8892 and a Logloss of 0.3107, exceeding the performance of all other methods. On the online big data dataset, the AUC of 0.8336 and Logloss of 0.4105 attained by the proposed method are the best among all evaluated approaches. Similarly, on the hybrid big data dataset, the AUC of 0.7890 and Logloss of 0.3816 represent the highest predictive performance. In comparison, the other methods exhibit varying levels of performance across different datasets. However, the proposed method consistently demonstrates significant advantages in terms of both AUC and Logloss, highlighting its effectiveness in learning outcome evaluation.

Table 1. Performance of different methods across three datasets

Models	Classroom Big Data		Online Big Data		Hybrid Big Data	
	AUC	*Logloss*	*AUC*	*Logloss*	*AUC*	*Logloss*
Decision Tree	0.8562	0.3415	0.7789	0.4251	0.7326	0.4126
Random Forest	0.8741	0.3126	0.7745	0.4158	0.7458	0.4128
Support Vector Machine	0.8795	0.3258	0.7892	0.4162	0.7589	0.4158
Long Short-Term Memory	0.8862	0.3126	0.8125	0.4256	0.7652	0.3896
CNN	0.8852	0.3169	0.8263	0.4123	0.7641	0.3854
Gradient Boosting Decision Tree	0.8862	0.3152	0.8245	0.4126	0.7625	0.3826

(Continued)

Table 1. Performance of different methods across three datasets *(Continued)*

Models	Classroom Big Data		Online Big Data		Hybrid Big Data	
	AUC	*Logloss*	*AUC*	*Logloss*	*AUC*	*Logloss*
Generative Adversarial Network	0.8862	0.3125	0.7892	0.4236	0.7652	0.3874
Variational Autoencoder	0.8856	0.3169	0.8124	0.4259	0.7641	0.3852
Proposed method	0.8892	0.3107	0.8336	0.4105	0.789	0.3816

The results in Table 2 illustrate the impact of different modules on model performance, demonstrating their significance. On the classroom dig data dataset, the complete model achieves an AUC of 0.8856 and a Logloss of 0.3125. When the two-dimensional squeeze-and-excitation module is removed, the AUC decreases to 0.8815, and the Logloss increases to 0.3158, indicating a slight performance decline. Similarly, the removal of the feature interaction module results in an AUC of 0.8826 and a Logloss of 0.3126, showing only a marginal decrease in performance. However, when the feature fusion module is excluded, a notable drop is observed, with the AUC decreasing to 0.8796 and the Logloss rising to 0.3269, suggesting that the feature fusion module is crucial, particularly in minimizing Logloss. On the online big data dataset, the complete model attains an AUC of 0.8357. When the two-dimensional squeeze-and-excitation module is removed, the AUC declines to 0.8263. A further reduction to 0.8241 is observed when the feature interaction module is excluded. The most significant performance degradation occurs when the feature fusion module is removed, with the AUC dropping sharply to 0.7895, highlighting its critical role. A similar trend is observed in the hybrid big data dataset. When the feature fusion module is removed, the AUC declines to 0.7562, and the Logloss increases to 0.3896, indicating a substantial negative impact on model performance. These findings further reinforce the essential contribution of the feature fusion module to the overall effectiveness of the model.

Table 2. Performance of different modules in the proposed method

Models	Classroom Big Data		Online Big Data		Hybrid Big Data	
	AUC	*Logloss*	*AUC*	*Logloss*	*AUC*	*Logloss*
Complete model	0.8856	0.3125	0.8357	0.4103	0.7899	0.3815
Without the two-dimensional squeeze-and-excitation module	0.8815	0.3158	0.8263	0.4125	0.7892	0.3852
Without the feature interaction module	0.8826	0.3126	0.8241	0.4126	0.7842	0.3846
Without the feature fusion module	0.8796	0.3269	0.7895	0.4356	0.7562	0.3896

Table 3. Normality test results for learning outcomes and multi-semantic feature interaction metrics

	K-S Test			S-W Test		
	Statistic	df	Significance	Statistic	df	Significance
Overall score	0.114	33	0.215*	0.957	33	0.332
In-degree	0.126	33	0.118*	0.962	33	0.624
Out-degree	0.081	33	0213*	0.961	33	0.745
Closeness centrality	0.126	33	0.214*	0.968	33	0.578
Betweenness centrality	0.318	33	0.216*	0.658	33	0.423
Eigenvector centrality	0.115	33	0.218*	0.963	33	0.549

Note: *is significant at the 10% level.

The normality test results for multi-semantic feature interaction metrics in Table 3 indicate that none of the examined metrics reach statistical significance ($p > 0.05$) in either the Kolmogorov-Smirnov (K-S) test or the Shapiro-Wilk (S-W) test. Specifically, the overall score yields a K-S statistic of 0.114, with 33 degrees of freedom (df) and a p-value of 0.215, while the corresponding S-W statistic is 0.957, with a p-value of 0.332. Similarly, for in-degree, the K-S statistic is 0.126 ($p = 0.118$), and the S-W statistic is 0.962 ($p = 0.624$). The results for out-degree, closeness centrality, betweenness centrality, and eigenvector centrality also exhibit comparable non-significant findings. This shows that the data of these indicators follows an approximately normal distribution. These results confirm that the proposed feature embedding and multi-semantic feature interaction modules effectively capture latent learning features and complex learning patterns.

Table 4. Comprehensive principal component scores of learners' learning outcomes

ID	*S*1-01	*S*1-02	*S*1-03	*S*1-04	*S*1-05	*S*1-06	*S*1-07	*S*1-08
Score	91.26	88.24	85.64	83.28	74.61	81.26	84.59	84.23
ID	*S*1-09	*S*1-10	*S*1-11	*S*1-13	*S*1-14	*S*1-15	*S*1-16	*S*1-17
Score	85.26	74.24	81.28	81.25	83.59	82.57	77.59	81.23
ID	*S*1-18	*S*1-19	*S*1-20	*S*1-21	*S*1-22	*S*1-23	*S*1-24	*S*1-25
Score	74.26	82.16	82.59	85.64	75.26	84.21	77.59	82.36
ID	*S*1-26	*S*1-27	*S*1-28	*S*1-29	*S*1-30	*S*1-31	*S*1-32	*S*1-33
Score	82.34	82.56	84.98	78.23	82.16	82.45	84.23	78.63

Table 4 presents the comprehensive principal component scores of learners' learning outcomes, corresponding to individual learner IDs. The results indicate that the scores exhibit fluctuations within a certain range, with the highest score recorded at 91.26 for *S*1-01 and the lowest at 74.24 for *S*1-10. The majority of learners' scores fall within the 80 to 85 range, such as *S*1-03 (85.64), *S*1-08 (84.23), and *S*1-20 (82.59). Only a few learners have scores below 75, including *S*1-05 (74.61) and *S*1-10 (74.24). These findings suggest that overall learning performance is relatively balanced, with most learners achieving a high level of proficiency. However, a small number of learners exhibit lower scores, which may indicate potential learning deficiencies in specific areas. The ability of the model to identify such discrepancies provides valuable data support for subsequent personalized instructional interventions.

Table 5. Correlation analysis between comprehensive principal component scores and overall classroom learning effectiveness of learners

			Comprehensive Principal Component Score	Learning Effectiveness
Spearman's Rho	Comprehensive principal component score	Correlation coefficient	1	0.67
		Significance (two-tailed)	–	0.004
		N	32	32
	Learning effectiveness	Correlation coefficient	0.68	1
		Significance (two-tailed)	0.074	–
		N	32	32

The correlation between comprehensive principal component scores and overall classroom learning effectiveness was analyzed using Spearman's rank correlation coefficient, as shown in Table 5. The correlation coefficient between these two variables is 0.68, indicating a moderate positive correlation. The two-tailed significance test yields a p-value of 0.004, which is less than 0.05, confirming that the correlation is statistically significant. These findings suggest that the learning outcome evaluation model exhibits a strong association with overall classroom learning effectiveness. This result supports the proposed model's effectiveness in evaluating classroom learning performance.

4 CONCLUSION

A learning outcome evaluation model based on multi-semantic feature interaction and big data analytics was proposed to address the limitations of traditional evaluation methods. The model operates through the collaborative functioning of four key modules. First, the feature embedding module performs multi-dimensional embedding of learner behavioral data, extracting latent learning features. Second, the multi-semantic feature interaction module enables deep interactions among features from different dimensions, capturing complex learning patterns and enhancing both accuracy and comprehensiveness in evaluation. Third, the two-dimensional squeeze-and-excitation module optimizes feature representation, improving the model's sensitivity and enhancing performance in complex learning environments. Finally, the feature fusion module integrates diverse features, further improving the accuracy and comprehensiveness of learning outcome evaluation. Experimental results demonstrate that the proposed model exhibits superior performance across multiple datasets, with the feature fusion module playing a particularly significant role in improving evaluation capability.

This study introduces a novel learning outcome evaluation model that overcomes the constraints of traditional evaluation methods, offering substantial research value. The model effectively extracts effective features from multi-dimensional and multi-sample data while optimizing the evaluation process through a modular design, thereby improving both accuracy and comprehensiveness. Specifically, the feature fusion module is identified as the most critical component in enhancing model performance, particularly in complex data environments, where it significantly strengthens comprehensive evaluation capability. Furthermore, the flexibility and scalability of the model allow for its application across a wide range of educational settings, demonstrating strong potential for practical implementation.

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