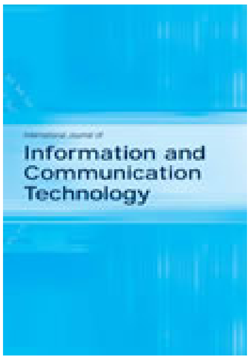

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Assessment of civic education in universities from a multidimensional perspective: the Integration of OBE and CIPP models

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Assessment of civic education in universities from a multidimensional perspective: the Integration of OBE and CIPP models

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Abstract: This study explores methods for assessing ideological and political education in higher education, proposing an innovative framework that combines outcome-based education (OBE) with the context, input, process and product (CIPP) model. By employing multimodal data fusion techniques, we integrated student learning behaviour data, affective-attitudinal surveys, and social media feedback to achieve a comprehensive assessment of learning outcomes. The study also employs multiple machine learning algorithms to systematically compare the effectiveness of the models. Through the design and implementation of comparative and fusion experiments, the results show that the fusion model significantly outperforms traditional methods in terms of assessment accuracy and reliability. The results of this study provide new ideas and practical basis for the assessment of ideological and political education in higher education, which has important theoretical value and application potential.

Keywords: outcome-based education; OBE; context, input, process and product; CIPP; civic education; multidimensional data fusion.

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1 Introduction

Ideological and political education (civic and political education) in colleges and universities plays a key role in cultivating students' values, enhancing their sense of social responsibility and improving their comprehensive quality (Luo and Qin, 2023). With the continuous development of globalisation and information technology, university students are faced with an increasingly complex social environment and multiculturalism, and the importance of ideological and political education in shaping their ideology and behavioural norms has become more and more prominent. Therefore, how to scientifically assess the effectiveness of civic education has become an important issue in education research and management (Condon and Wichowsky, 2018).

Traditional methods of assessing Civic Education rely mostly on qualitative analyses, such as teachers' subjective evaluation and students' self-feedback (Claassen and Monson, 2015). Although these methods provide some reference, they have many deficiencies in objectivity, systematicity and assessment efficiency, making it difficult to accurately reflect the changes in students' thinking and the actual effectiveness of civic and political education (Galston, 2001).

In recent years, with the booming development of big data and artificial intelligence technology, the education assessment model has gradually shifted towards data-driven and intelligent. Through data mining and machine learning technologies, education administrators can mine valuable information from a large amount of data, which provides powerful support for improving the science and efficiency of assessment (Yang and Zhang, 2022). Especially in the field of civic education assessment, the application of technological means enables administrators to more comprehensively grasp the ideological dynamics of students, so as to optimise teaching strategies.

Numerous studies have been conducted to show the promising applications of data technologies in educational assessment. For example, Asif et al. (2014) developed an affective computing-based model that dynamically tracks and predicts students' affective responses as a means of assessing their learning performance. In addition, Romero and Ventura (2020) used a framework of educational data mining to analyse the main factors affecting teaching and learning effectiveness using large-scale student behavioural data, and Siemens (2013) proposed learning analytics, which provides accurate educational assessment by tracking and analysing all aspects of students' learning behaviours. The basis of the study is to track and analyse students' learning behaviours.

Although these techniques have achieved remarkable results, most of the existing research focuses on a single dimension or a specific field, and fails to effectively meet the comprehensive needs of civic education assessment. For this reason, this paper proposes a multi-dimensional intelligent assessment framework based on big data and machine learning by combining outcome-based education (OBE) (Evans and King, 1994) and context, input, process and product (CIPP) models (Aziz et al., 2018). The framework not only focuses on learning outcomes, but also provides an all-encompassing assessment solution for civic education in colleges and universities by dynamically monitoring the educational process, achieving intelligent and data-driven assessment.

The main innovations and contributions of this work include:

1 Innovation in model integration: OBE and CIPP are effectively integrated to form a more comprehensive education assessment framework. This integration not only enhances the systematic nature of assessment, but also enables the effective use of different dimensions of educational data.

2 Multimodal data fusion approach: Multimodal data fusion technology is used to comprehensively analyse student learning by combining learning behaviour data, emotional attitude surveys and social media feedback. This approach breaks through the limitations of traditional assessment and provides a deeper understanding of students' learning status.

3 Application of machine learning algorithms: A variety of advanced machine learning algorithms are applied in the assessment process, including random forest, support vector machine (SVM), long-short-term memory network (LSTM), and gradient boosting machine (GBM), which provide a diverse perspective on the assessment results. By comparing the performance of different algorithms, the most suitable algorithm for the assessment of civic education is explored.

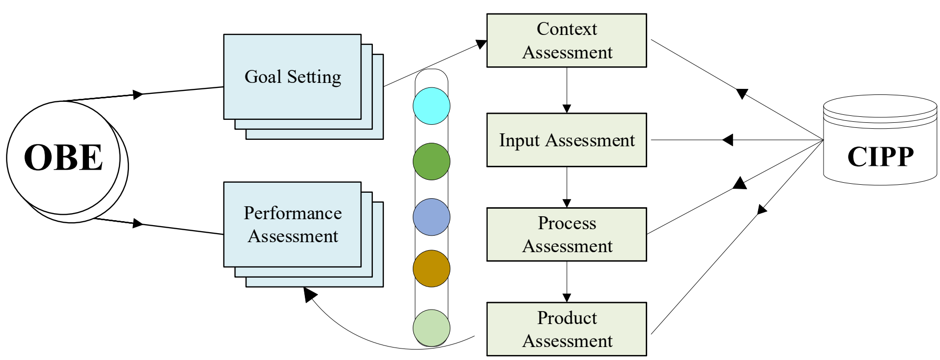
4 Systematic experimental design: Systematic comparison and fusion experiments are designed to assess the effects of different models in the assessment of ideological and political education. Through the detailed experimental process and data analysis, the effectiveness of the fusion model in improving the accuracy and reliability of assessment is verified.

2 Relevant technologies

2.1 Technical realisation of OBE and CIPP models

Two models are particularly prominent in the field of modern educational assessment: the OBE and the CIPP, as shown in Figure 1.

Figure 1 Structure of OBE and CIPP (see online version for colours)



The technical implementation of the OBE model is centred on target outcomes and aims to assess educational effectiveness by comparing actual student performance with predefined pedagogical goals. In order to quantify this process, several assessment indicators can be used, such as achievement rates, skill mastery and student satisfaction (Kaliannan and Chandran, 2012). The core idea of OBE is reflected in the setting of goals and measuring their achievement through quantitative methods.

We apply weights to each modal feature based on their predictive relevance, which is ascertained by means of a combination of correlation analysis and expert input, for the multimodal data fusion method described previously in this section. This guarantees that the weights fairly represent statistical significance as well as pragmatic usefulness.

It is assumed that student learning outcomes consist of multiple modules, and that the performance of each module can be assessed by a composite assessment score (Schmidt et al., 2000). The model uses a weighted average formula to calculate the overall score:

$$T_{total} = \sum_{i=1}^{n} w_i \cdot S_i \tag{1}$$

where T_{total} is the total assessment score, w_i is the weight of the i^{th} module and S_i is the student's score in the module. This formula can be applied to assess the quality of teaching and learning as well as the degree of improvement in students' competence.

We used an approach combining statistical analysis with domain knowledge to ascertain the weights for the weighted average formula. Adjusting for pedagogical relevance, the weights are obtained from the association between the performance of every module with the general educational objectives.

The implementation of OBE also allows for dynamic assessment through student learning trajectories. For example, student learning outcomes are tracked over time and learning progress is predicted using curve fitting or time series analysis methods. Learning progress can be modelled using linear regression or polynomial regression:

$$y(t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \ldots + \beta_k t^k \tag{2}$$

where $y(t)$ is the student's learning effect at time t, β_i is the regression coefficient, and t_k is the higher-order term at time, which applies to the case where the learning effect grows nonlinearly.

The CIPP model is a comprehensive assessment framework for analysing all stages of education in a multidimensional way (Zhang et al., 2011). The CIPP model achieves its technical application through the following four stages:

For every level of the CIPP model, we include thorough implementation guidelines as follows: Contextual analysis examines student perspective and the learning environment. Input evaluation of course materials and teaching tools evaluates Record of process assessment notes student actions and instructional activities. Measures of product assessment track student learning results and ideological growth.

- Context (situational assessment): analysing the current educational context, the socio-cultural environment and the students' state of mind. Contextual data can be modelled by students' background characteristics, school resources and social factors (Karatas and Fer, 2009). Assuming that the contextual characteristics are the vector $C = \{c_1, c_2, \ldots, c_m\}$, the impact of the context can be comprehensively assessed by a multidimensional weighting formula:

  $$C_{total} = \sum_{i=1}^{m} \alpha_i \cdot c_i \tag{3}$$

  where α_i is the weight of each factor and c_i is the context-specific characteristic value.

- Input (input assessment): This stage assesses the quality of teaching resources, teacher competencies and course content. The input data can be represented as a matrix I with columns representing different resources, competencies or tools and rows representing different groups of students or time periods. Assuming that the input matrix is $I \in R^{n \times m}$ the input data can be simplified by principal component analysis (PCA) or feature selection methods to reduce the impact of noise on the assessment results.

- Process (process assessment): Recording and assessing teaching activities and learning behaviours. This can be done through learning activity logs, class participation data, assignment submissions, etc. In order to model the behavioural characteristics of the process, Markov chain (MCC) can be introduced to describe the state transfer process of students. Let the student's learning state be $S = \{s_1, s_2, \ldots, s_k\}$ and the state transfer probability matrix be P. The prediction formula for the next state is:

  $$P\left(S_{t+1} = s_j \middle| S_t = s_i\right) = p_{ij} \quad (4)$$

  where p_{ij} denotes the probability of transferring from state s_i to s_j.

- Product (output assessment): Assesses students' learning outcomes, including test scores, skill acquisition and ideological and political improvement. The future performance of students can be estimated through prediction methods based on regression modelling. The commonly used formulas for output assessment are as follows:

  $$P_{outcome} = f\left(C_{total}, I_{total}, P_{total}\right) \quad (5)$$

  where $P_{outcome}$ is the predicted value of output assessment C_{total}, I_{total} and P_{total} are the comprehensive evaluation results of context, input and process respectively.

Through the multi-dimensional comprehensive assessment, the CIPP model can provide education managers with more detailed analysis, so as to optimise the teaching strategies and the practical effects of civic education.

2.2 Application of data mining and machine learning in educational assessment

As the size of data in education continues to grow, data mining and machine learning techniques play an increasingly important role in educational assessment. These technologies are not only able to mine useful information from large amounts of student data, but also to predict students' learning behaviours and thought dynamics through automated models.

Based on their capacity to manage challenging educational data and their success in forecasting student outcomes – as confirmed by past studies in educational technology – machine learning algorithms are chosen. Data mining is the extraction of useful information from massive data through pattern discovery, clustering and classification techniques (Fayyad and Stolorz, 1997). In the assessment of civic education, commonly used data mining techniques include clustering, association rule mining and decision trees. For example, cluster analysis can group students according to different patterns of thought and behaviour:

$$D = \{x_1, x_2, \ldots, x_n\} \quad (6)$$

Assuming that the student behaviour dataset is D, where each x_i is a set of feature vectors, the commonly used k-means clustering algorithm iteratively updates the centre of mass of each cluster by using the following formula:

$$\mu_j = \frac{1}{|S_j|} \sum_{x_i \in S_j} x_i \tag{7}$$

where μ_j is the centre of mass of the j^{th} cluster and S_j is all data points in the j^{th} cluster.

In addition, association rule mining can be used to find correlations between students' behaviour and changes in thoughts, and commonly used association rule metrics are support and confidence. The goal of association rule mining is to find frequently occurring behavioural combinations $A \rightarrow B$, where support is calculated as:

$$Support(A \rightarrow B) = \frac{|A \cap B|}{|D|} \tag{8}$$

The confidence level is calculated by the formula:

$$Confidence(A \rightarrow B) = \frac{|A \cap B|}{|A|} \tag{9}$$

Common tasks when machine learning models are used for educational assessment include classification, regression and prediction. The core problem in the assessment of civics education is the prediction and classification analysis of students' ideological dynamics. Classification models can be constructed to predict students' performance in the civics program. For example, the classification model based on XGBoost can effectively handle high-dimensional datasets and has good generalisation ability (Ogunleye and Wang, 2019). Its objective function consists of the following two parts:

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{10}$$

where L is a loss function that measures the error between the model's predicted value and the true value y_i, and $\Omega(f_k)$ is a regularisation term that controls the complexity of the model.

Random forest modelling is another common machine learning method, particularly suitable for classification tasks in educational assessment (Adetunji et al., 2022). By constructing multiple decision trees and integrating the predictions of each tree, Random Forest can effectively reduce the overfitting problem of the model. The prediction process of Random Forest can be expressed by the following equation:

$$\hat{y} = \frac{1}{m} \sum_{i=1}^{m} T_i(x) \tag{11}$$

where $T_i(x)$ is the prediction result of the i^{th} decision tree and m is the number of decision trees.

By combining data mining and machine learning techniques, the evaluation of civic education can be automated and intelligent, helping educational administrators to better understand the changes in students' thoughts and optimise teaching strategies.

3 Multi-dimensional data fusion and system architecture

3.1 Multimodal data fusion

The use of multimodal data fusion technology is particularly important in the assessment of civic education in colleges and universities, taking into account students' ideological dynamics, learning behaviours and social environments. This technique not only provides a comprehensive view of students' overall performance, but also digs deeper into their ideological changes and learning motivations. By integrating data from different modalities, such as behavioural data from online learning platforms, classroom participation records and social media feedback, educators are able to better understand and assess the effectiveness of civic education (Zhang et al., 2022).

In this study, we choose a specific multimodal data fusion approach, which consists of the following techniques:

- Data-level fusion: Directly integrating data from different modalities to generate a unified data representation. The specific formula is as follows:

$$X_{fused} = \left[X_{learning}, X_{survey}, X_{classroom}, X_{social}\right] \quad (12)$$

  where $X_{learning}$ denotes online learning behaviour data, X_{survey} denotes questionnaire data, $X_{classroom}$ denotes classroom performance data and X_{social} denotes social media data.

- Feature-level fusion: Integration by extracting the features of each modality. In this study, weighted feature fusion is used to assign weights to each modal feature using a priori knowledge with the formula:

$$F_{fused} = W_1 \cdot F_{learning} + W_2 \cdot F_{survey} + W_3 \cdot F_{classroom} + W_4 \cdot F_{social} \quad (13)$$

  where $F_{learning}$, etc. denotes the feature vector extracted from each modality and W_i denotes the corresponding weight.

- Decision-level fusion: Independently train the data models of different modalities, and finally make a comprehensive decision by voting or averaging to ensure that the information of different modalities is fully utilised:

$$\hat{y} = \frac{1}{m}\sum_{i=1}^{m} y_i \quad (14)$$

- Deep learning fusion: Deep learning models, such as convolutional neural networks (CNNs) and LSTMs, are used to synthesise and analyse multimodal data. These models are able to extract complex features more efficiently and provide in-depth analysis of the relationship between students' learning behaviours and the dynamics of their thoughts:

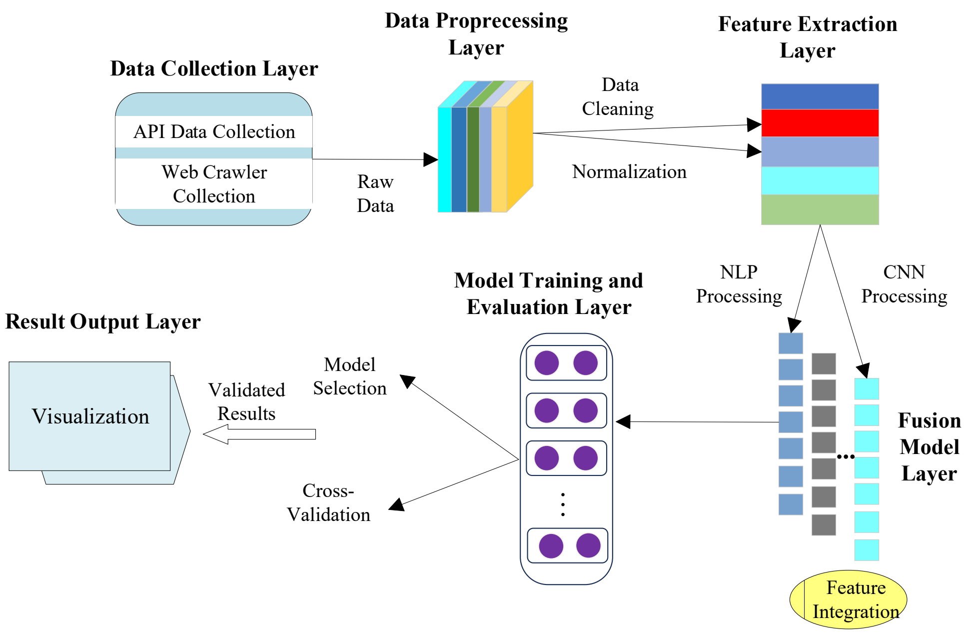
$$H = f\left(X_{fused}\right) \quad (15)$$

The fusion model in this study combines the above techniques to ensure that the best results are achieved in the assessment of civic education.

3.2 System architecture

In response to the needs of the assessment of civic education in higher education, it is crucial to design a system architecture that integrates multimodal data processing, analysis and visualisation specifically for the integration of the OBE and CIPP models. The architecture should cover the following core modules as shown in Figure 2, ensuring that each module is closely integrated with computer science and technology, and providing innovative support for the assessment of civic education.

Figure 2 Structure of system model (see online version for colours)



3.2.1 Data acquisition layer

This layer is responsible for collecting multimodal data related to civic education in real-time, mainly through the API interface to obtain behavioural data from the online learning platform and using web crawler technology to capture student feedback on social media. In addition, online questionnaires are used to collect students' emotional and ideological states to ensure the diversity and comprehensiveness of the data.

$$D_{raw} = \{D_{learning}, D_{survey}, D_{classroom}, D_{social}\} \tag{16}$$

where D_{raw} denotes the original dataset containing the inputs for each modality.

3.2.2 Data pre-processing layer

In this layer, the raw data are cleaned and normalised to remove missing values and outliers to ensure the quality of the data. Specifically, methods such as mean-filling or median-filling are used to deal with missing data, followed by the use of Z-score standardisation to transform the modal data to the same scale for subsequent analysis.

$$D_{cleaned} = \{D_{raw} - Outliers\} \tag{17}$$

$$D_{normalised} = \frac{D_{cleaned} - \mu}{\sigma} \tag{18}$$

where μ is the mean and σ is the standard deviation.

3.2.3 Feature extraction layer

This layer uses deep learning models to extract representative features from each modal data. Text data is analysed using natural language processing techniques (e.g., BERT) for sentiment analysis, while image or video data is feature extracted using CNN to generate feature vectors containing multimodal information.

$$F_{text} = BERT(D_{text}) \tag{19}$$

$$F_{fused} = [F_{learning}, F_{survey}, F_{classroom}, F_{social}] \tag{20}$$

where F_{fused} denotes the fused feature set.

3.2.4 Data pre-processing layer

In this layer, the feature vectors of each modality are integrated through weighted fusion to form a unified assessment feature. Based on the elements of the OBE and CIPP models, the integrated assessment is achieved through the weighting function to ensure that the importance of each modality is fully reflected and utilised in the assessment process.

$$E_{total} = f(OBE, CIPP) = \sum_{i=1}^{n} W_i \cdot OBE_i + \sum_{j=1}^{m} V_j \cdot CIPP_j \tag{21}$$

where OBE_i and $CIPP_j$ denote the elements in the OBE and CIPP models, respectively, and V_j denotes the weight of each element in the CIPP model.

3.2.5 Model training and evaluation layer

This layer uses traditional machine learning algorithms such as random forest and XGBoost, as well as deep learning models such as LSTM for training and evaluation. K-fold cross-validation methods are used to ensure the stability and generalisation ability of the models, thus improving the accuracy and reliability of the evaluation results.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{22}$$

where *TP*, *TN*, *FP* and *FN* stand for true examples, true negative examples, false positive examples, and false negative examples, respectively.

3.2.6 Results output layer

The final layer is responsible for visualising the assessment results, using data visualisation tools (e.g., Tableau and Matplotlib) to show students' performance in civic education. By designing interactive dashboards, educators can understand students' learning status and ideological dynamics in real-time.

$$R_{visualised} = Visualise(E_{total}) \tag{23}$$

where $R_{visualised}$ denotes the assessment results after visualisation.

Because of its sophisticated data visualisation features and capacity to produce interactive and easy-to-use dashboards that help to analyse difficult educational data, we chose tableau for result visualisation.

Through a specified data exchange mechanism, the modules communicate; each module contributes to and draws from a central data repository, therefore guaranteeing a consistent operation and data integrity throughout the system.

4 Experimental results and analyses

4.1 Datasets

The experimental dataset was derived from the following sources to ensure diversity and representativeness, as shown in Table 1. In this study, we choose a specific multimodal data fusion approach, which consists of the following techniques:

Table 1 Datasets for the experiment

Data source	*Data type*	*Feature description*	*Data volume*
Online learning data	Learning behaviour data	Student ID, login count, learning duration (hours), course completion percentage (%), periodic assessment scores	1,000
Survey data	Student emotion and attitude	Student attitude ratings towards ideological and political courses, participation level, self-assessment of learning outcomes	1,000
Social media data	Comments and feedback	Comment content, timestamp, sentiment score (positive, negative, neutral)	5,000 comments
Teacher evaluation data	Teacher assessments	Evaluations of student participation, learning status, and ideological state	1,000

4.2 Experimental procedure

This section describes in detail the design and implementation process of the comparison and fusion experiments and their results.

In the comparison experiments, we evaluated the performance of a variety of models to ensure that we can fully reflect the performance of different algorithms in the assessment of Civic Education. The selected models include random forest, SVM, LSTM, and GBM.

The implementation of the comparison experiments firstly consisted of dataset partitioning, where the entire dataset was randomly divided into a training set (80%) and a test set (20%). Stratified sampling was performed to ensure that the distributions of the training and test sets were consistent. Then, training was performed for each model. The random forest model was set to 100 trees with Gini coefficients as the splitting criterion; the SVM used a linear kernel function with hyperparameters optimised by grid search; the LSTM model was designed as a two-layer model with 128 hidden units, and was trained using Adam's optimiser; and the GBM was set to 100 trees with a learning rate of 0.1. All the models were used for K-fold cross validation for performance evaluation to improve the reliability of the results.

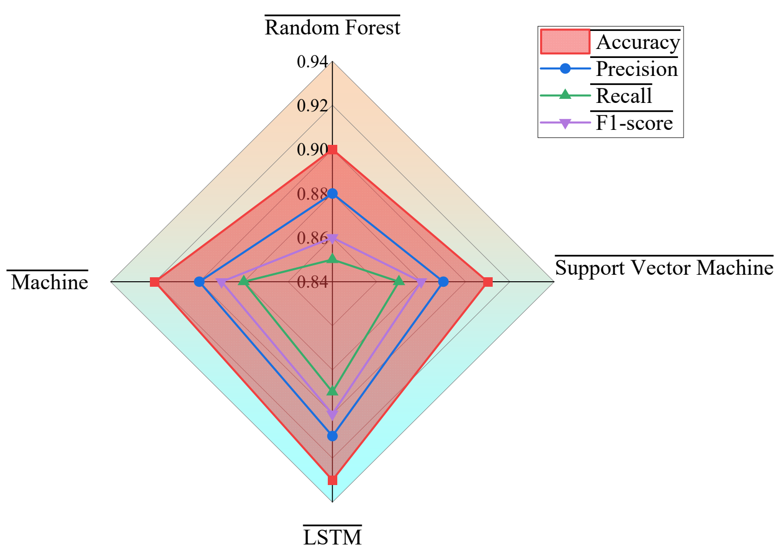
In order to comprehensively evaluate the effectiveness of the model, we use the metrics of accuracy, precision, recall and F1-score (Chicco and Jurman, 2020). The specific F1-score calculation formula is:

$$F1\text{-}score = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \tag{24}$$

Since they reveal information on the efficacy of teaching tactics and the effects on student learning outcomes, thereby guiding future educational strategies and interventions, the performance indicators given in our study directly affect educational practice.

After model training and evaluation, the results of the comparison experiment are shown in Figure 3.

Figure 3 Results of the comparison experiment (see online version for colours)



The experimental results show that the LSTM model performs best in metrics such as accuracy and F1-score, indicating that it has a clear advantage in processing complex data. In contrast, SVMs and GBMs also perform quite well, while random forest has the weakest performance among all evaluation metrics.

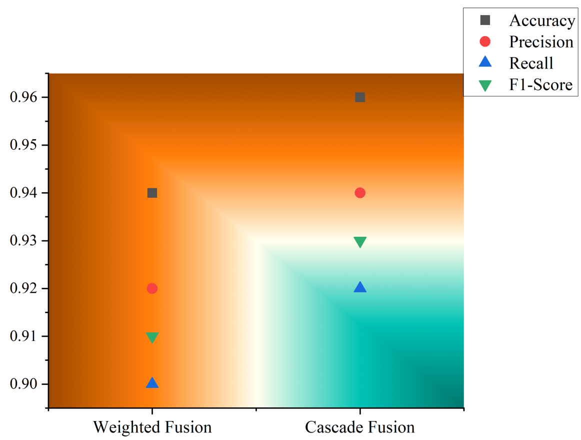
In the fusion experiments, we aim to improve the evaluation performance by combining different models. Two strategies, weighted fusion and cascade fusion, were used. The weighted fusion method assigns weights to different models and performs weighted summation based on the performance of each model on the validation set:

$$F_{fused} = W_1 \cdot F_{LSTM} + W_2 \cdot F_{RF} + W_3 \cdot F_{SVM} + W_4 \cdot F_{GBM} \tag{25}$$

The cascade fusion approach then takes the outputs of multiple models as inputs and constructs a new meta-model (e.g., logistic regression) to further improve prediction performance. In this process, the same dataset and evaluation metrics as the comparison experiments are used.

The results of the fusion experiment are shown in Figure 4.

Figure 4 Results of the fusion experiment (see online version for colours)



The results show that the cascade fusion model performs best on all assessment indicators, especially showing significant improvement in accuracy and F1-score. This result validates the effectiveness of multimodal data fusion in the assessment of civic education and highlights the importance of using different models in combination. Through these experiments, we can conclude that the multimodal data fusion approach can not only improve the accuracy of assessment, but also provide educators with more comprehensive decision support.

5 Conclusions

This study proposes an integrated framework that combines OBE and CIPP to enhance the assessment of ideological and political education in higher education. By employing advanced data mining techniques and machine learning algorithms, we demonstrate the potential of a multidimensional approach that takes into account student engagement and learning outcomes in the assessment process. Experimental results show that integrating these models, especially through a multimodal data fusion approach, significantly improves the accuracy and reliability of educational assessment.

Despite the encouraging findings, there are some limitations to this study. Firstly, the data used in the experiment were derived from a specific educational setting, which may limit the applicability of the findings to other educational scenarios or cultural contexts. In addition, although the models used, such as random forest, SVMs, LSTM, and GBMs, showed varying degrees of effectiveness, it is possible that there are other emerging algorithms or techniques that could further enhance the effectiveness of the assessment process. Finally, the reliance on available datasets may introduce bias, especially if certain population groups are underrepresented.

Going forward, research should focus on several key areas. Expanding the dataset to encompass more diverse educational settings and student populations will help to more fully understand the applicability of the proposed model. In addition, exploring the combination of other advanced machine learning techniques, such as integrated methods or deep learning architectures, may result in a more robust evaluation framework. Finally, the implications of these findings for educational practice should be examined to ensure that these technological advances translate into substantial improvements to the teaching and learning experience.

We intend to increase our dataset to cover other educational environments and investigate new machine learning approaches to improve the resilience of our evaluation framework in order to overcome the restrictions of our research.

In summary, this study adds a new contribution to the educational assessment literature by proposing an innovative approach that combines established educational models with cutting-edge data analysis techniques. By addressing the identified limitations and exploring future research directions, we can continue to enhance the assessment process in higher education, ultimately creating more effective learning environments for students.

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