

Article

A Multi-Module Information-Optimized Approach to English Language Teaching and Development in the Context of Smart Sustainability

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Abstract: With high-tech advancements, intelligent, sustainable development has become widespread in daily life. However, due to developmental differences among various regions, continuity in English language teaching can be challenging. The goal of teaching in the context of sustainable development is to tailor learning plans for students through intelligent intervention. In this paper, we address the issues of classifying students' interests and jointly assessing the listening, reading, and writing modules in online English teaching. Our results demonstrate that an autoencoder can accurately recognize students' interests in the four modules, with a recognition accuracy as high as 93.1%. Additionally, the mean squared error (MSE) between the comprehensive assessment and the teacher's given grade under GRUs is only 0.63, significantly outperforming other RNN-type methods. Therefore, the proposed framework in this paper is crucial in promoting future research development in the sustainable development of English teaching intelligence and the problems of multi-module assessment problem and multi-information integration.

Keywords: sustainable development; English teaching; multi-module fusion; intelligent teaching and assessment

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1. Introduction

Artificial intelligence has become a developing trend in society. Moreover, smart sustainable development has emerged with the deepening awareness of sustainable development [1]. Smart sustainable development refers to integrating smart technologies and sustainable development principles to achieve economic, social, and environmental sustainability. The primary objective of smart, sustainable development is to promote effective resource utilization, energy conservation, and environmental protection through the innovation of smart technologies. Smart, sustainable development is a shared concern of the international community, and many countries have proposed smart development strategies and policies to promote economic development and environmental protection [2]. Education is an essential component of smart, sustainable development, and the integration of sustainable development content into daily curricula, the use of artificial intelligence methods in curriculum design, the conservation of human resources, and the rapid development of curriculum design personalized to individual identities are new directions for educational development in the current sustainable context. The incorporation of smart technology in the field of English education is an essential part of this process.

The importance of English, one of the most widely spoken languages worldwide, cannot be overstated. With the development of globalization, English teaching has become increasingly crucial. English teaching has evolved, and English education institutions and teachers utilize intelligent teaching methods to better cater to students' needs

and enhance teaching effectiveness [3]. Among these methods, the application of artificial intelligence technologies such as deep learning has become a highlight of English teaching and learning, offering students a more personalized and efficient learning experience.

In English teaching, the concept of intelligent sustainability can be implemented in curriculum design, teaching methods, and the development of teaching resources. For instance, introducing intelligent technologies and sustainable development cases can cultivate students' innovative thinking and practical skills. Moreover, intelligent teaching platforms and educational resources can be utilized to personalize and differentiate teaching methods, thus improving the quality and effectiveness of learning [4]. English language teaching can also introduce students to the concept and application of intelligent sustainability, foster their social responsibility and environmental awareness, and promote their action and awareness for sustainable development.

By adopting an intelligent and sustainable approach to English language teaching, students can not only improve their language skills but also acquire sustainable knowledge and skills, which can help them better adapt to the future needs of society [5]. With the widespread application of multimedia and internet technology, analyzing and guiding students' learning interests, abilities, and methods through more intelligent means and providing more personalized learning plans for their comprehensive development are crucial. Specifically, the multi-module joint optimization technology based on deep learning effectively achieves intelligent and sustainable English teaching. Multi-module joint optimization technology can use intelligent methods to analyze relevant data based on student's interests, thereby improving learning efficiency and ensuring teaching effectiveness. This paper aims to achieve the ultimate intelligent and rapid evaluation of multimedia English teaching through data fusion through multi-module learning. The specific contributions to this article are as follows:

- User interest recognition was implemented based on an autoencoder for four modules typical of the English teaching process: listening, reading, writing, and listening;
- A joint multi-module intelligent assessment of English learning was implemented using GRUs with an MSE of only 0.63 between its score and the actual score;
- Practical testing was conducted on the proposed intelligent learning and evaluation framework, and the actual operating efficiency of the system exceeded 80%.

The organization of this paper is as follows: Section 2 introduces related works for content pushing and intelligent evaluation; in Section 3, the model establishment process is given; we give the experiment result and analysis in Section 4; and the discussion is presented in Section 5. The conclusion is drawn at the end.

2. Related Works

2.1. Research on Content Pushing Based on Learning Habits

Recommendation systems have been developed from e-commerce to various other fields, and with the change in and development of digital education, recommendation systems are gradually being incorporated [6]. Khribi et al., based on the history of active learners and the similarities and differences between learners' preferences and the content of learning resources, provided learning resource recommendations [7]. In 2011, Katuk et al. [8] recommended appropriate learning paths for learners based on their learning experience and emotional engagement from the perspective of an "optimal learning experience". With the development of information technology, researchers have found differences between the recommendation of learning resources and the recommendation of commodities, and the recommendation of learning resources also needs to consider learners' preferences, learning styles, learning levels, cognitive abilities, etc. Klasnja et al. [9] discovered the existence of implicit labels for learning resources and clustered and ranked the labels to provide personalized learning resources for learners with different preferences based on the labels. Dascalu et al. designed and developed a personalized recom-

mendation system for learning resources and made recommendations in the virtual environment U-learn. The system recommends suitable learning resources for learners based on the similarity of their learning styles. For the recommended resources, learners can choose whether to accept the system's recommendations [10]. Yau et al. proposed a context-aware personalized m-learning application for the characteristics of different learners' learning preferences. Six learning scenario preferences were designed to recommend suitable learning objects for learners [11].

Through the above research, it is easy to see that with the development of artificial intelligence technology, the personalized pushing of courses is also more intelligent, and the recommendation methods for different scenarios and preferences are becoming increasingly mature, providing more convenient help for student learning.

2.2. Research on Intelligent Evaluation Techniques in the Context of Machine Learning and Deep Learning

Computers and artificial intelligence have flourished in recent years and have made important progress in numerous fields. Deep network models are widely used in various evaluation fields because they can handle multimodal information quickly and accurately. Mangalathua [12] proposed multi-parameter fragility using a neural network to establish the relationship between structural parameters and structural demand parameters, Karbassi et al. [13] proposed a decision tree CART algorithm-based seismic vulnerability analysis method. Saint et al. [14] proposed a support vector machine (SVM)-based method to assess the seismic fragility of reinforced concrete structures. In the risk assessment of emergency accidents, Jacek Skorupski proposed a fuzzy risk matrix to obtain the probability and severity of accident consequences and derived the probability of accidents by Petri nets, and applied this assessment method to achieve risk assessment of air traffic accidents [15]. Brandon Johnson proposed a Monte Carlo-based approach to assess the impact of earthquakes on large and complex power systems [16]. In the industrial field, Farzad Piadeh et al. proposed a combined tree analysis method and applied it to the risk assessment of ATUs for industrial wastewater treatment [17]. Autoencoders (AEs) are one of the most representative models in unsupervised learning and have received widespread attention. They can automatically learn potential features from many unlabeled sample data, then reconstruct the input sample data and train the model through reconstruction errors to obtain more accurate sample features. With in-depth research, many deformations of autoencoders have emerged, forcing them to be more robust by adding certain constraints to the model's hidden layer. Using automatic encoders for unsupervised clustering and classification of training data without labeling can reduce the cost and time of data labeling. Secondly, an automatic encoder can automatically learn useful representations and features of input data, which helps to discover patterns and structures in the data, thereby improving clustering. Therefore, automatic encoding methods can greatly improve efficiency in analyzing large amounts of learning-index-related data.

Through the above intelligent evaluation methods based on artificial intelligence, it is easy to see that the performance evaluation of most systems can be completed based on existing data and the integration of multimodal information. The same is true for English teaching. The daily teaching of English is often divided into four modules: listening, speaking, reading, and writing. The learning of each module is often done independently, so after personalized recommendations of learning materials are made based on users' habits, an overall learning assessment is completed for different learning situations, which is of great significance for future English language education.

3. Multi-Module Joint Optimization of English Teaching Model Design

3.1. Autoencoder-Based Course Recommendation Model Design

The user learning recommendation process is essentially a kind of data mining based on student learning data, so deep learning models can extract the effective features of learning to help them make recommendations for learning interests accordingly. Various deep learning algorithms are available in content pushing research, such as neural network models, autoencoders, restricted Boltzmann machines, and deep belief networks [18]. Considering that the data used are related to students' learning times in the four modules of listening, reading, writing, and listening, the data dimension is not high, so a self-encoder is chosen for feature extraction of user interest in this paper. The self-encoder is an unsupervised learning algorithm that does not require labeled data, so it can handle a large amount of unlabeled data and save the cost of manual labeling. Secondly, the method has strong nonlinear fitting ability, can learn the nonlinear features of data, and has good applicability in complex push scenarios. Furthermore, the autoencoder can improve the robustness by denoising the original data, making the model more robust [19].

Autoencoder is an unsupervised learning algorithm for learning low-dimensional data representations [20]. In push, an autoencoder can be used for user interest modeling and recommendation. It can build a model of users' interests by learning patterns in their historical behavior sequences and predicting future content that may interest them. Specifically, the user's historical behavior sequence can be represented as a sparse matrix $X = [x_1, x_2, \dots, x_n]$, where each vector x_i represents a timestamped user behavior feature. For example, in an e-commerce recommendation system, x_i can represent the products the user purchases. These behavioral vectors can then be mapped into a low-dimensional coding space by training an autoencoder model [21]. Automatic encoders have significant advantages in processing time series data. Firstly, they can automatically learn key features and patterns in data without the need for manual feature engineering, which is crucial regarding the complexity and difficulty of capturing trends in time series data. Secondly, automatic encoders can compress time series data and extract the most important information, thereby reducing the dimensionality of the data and helping to reduce the impact of noise and redundant information. In addition, automatic encoders can also be used for anomaly detection and reconstruction tasks, helping to detect outliers or missing data in time series and perform interpolation or repair. Finally, the deep structure and recursive variants of automatic encoders can handle long-term dependencies, which are crucial in time series modeling. In summary, automatic encoders are powerful tools for processing time series data, which can improve the performance of tasks such as feature learning, dimensionality reduction, anomaly detection, and reconstruction. The automatic encoder method can help better understand the internal data correlation for the student learning time and related operational data extracted from the class.

The loss function of the autoencoder model can be expressed as the reconstruction error, which is the difference between the input data and the decoder output data. Specifically, the reconstruction error can be calculated using the mean square error function (MSE):

$$L(X, \hat{X}) = \frac{1}{N} \sum_{i=1}^N \|x_i - \hat{x}_i\|^2 \quad (1)$$

where X is the input data, $\hat{X}$ is the decoder output data, and N is the number of data samples.

During training, the autoencoder model minimizes the reconstruction error and thus learns a low-dimensional representation of the data. After training, the encoder can map the user's historical behavior vectors into the encoding space. These encoded vectors can be used to compute behavioral vectors that are similar to the user's interests, for example, by computing the similarity between two vectors using cosine similarity:

$$\text{sim}(x_i, x_j) = \frac{x_i \cdot x_j}{\|x_i\| \cdot \|x_j\|} \quad (2)$$

where x_i and x_j are two behavior vectors.

In a recommendation system, a vector of behaviors similar to the user's interests can be calculated using coding vectors, and similar behaviors can be recommended to the user. In the personalized, developable English course learning process, students' learning interests can be computed to highlight the courses that interest them and refine the learning process according to their learning situation. In addition, the autoencoder can solve the cold-start problem in collaborative filtering recommendation, i.e., how to recommend courses or articles for a new user when they join. The feature vector of the new user can be fed into the self-encoder model, and then courses similar to it can be recommended from the encoding space. The training process for the AutoREC model designed in this article is as follows (Algorithm 1):

Algorithm 1 The course push using autoencoder model

Step 1: Input user learning data $x_i = \{x_1, x_2, x_3, x_4\}$, where x_i represents the learning, speaking, reading and writing data.

Step 2: Obtaining h that is the interest prediction of the model

Step 3: Model training using MSE the interest vector Equation (2) to minimize the loss function θ

Step 4: Input the feature data of the learning user in sequence to obtain the user's interest classification;

Step 5: Obtaining the rating of user n 's interest in the course, sort it, and obtain a recommendation list for user n .

3.2. Intelligent Assessment Model Integrating Multi-Module Course Information

After completing user interest and recommendation algorithm modeling according to the autoencoder conducted in Section 3.1, in this study, we perform user interest recommendation and student learning quality assessments according to the divided listening, reading, and writing modules. The optimization strategy of multi-module synergy should focus on the correlation between modules, the integration of teaching resources, the integration of teaching assessments, and the optimization of the teaching process to achieve a comprehensive and effective English teaching and cultivation effect. It is not difficult to see that the essence of multiple listening, reading, and writing modules is a regression technique based on time series. Considering the multimodal characteristics of the data and the amount of data in the current study, this paper intends to use the RNN method to evaluate multi-module course information [22].

Recurrent neural networks (RNNs) processes sequential data by considering the current input and incorporating previous information into the model [23]. Specifically, RNNs capture contextual information sequentially by passing an implicit state at each time step. The value of the hidden state depends on the input of the current time step and the hidden state of the previous time step. The mathematical formulation of an RNN can be expressed as

$$h_t = f(x_t, h_{t-1}) \quad (3)$$

where x_t is a vector representation of the input sequence at the time step t , h_{t-1} is the hidden state vector of the previous time step, h_t is the hidden state vector of the current time step, and f is a nonlinear function, usually tanh or ReLU.

RNNs can capture contextual information in sequence data during multimodal data evaluation, which is crucial for full-process evaluation; secondly, RNNs are end-to-end

trainable models that can learn features directly from the raw data without the need to design features manually. In addition, since RNNs have a recurrent structure, they can handle sequence data of arbitrary length.

Although RNNs have been successfully applied to time-series-like problems, there are some challenges and limitations. For example, due to their long-range dependence on sequence data, RNNs may suffer from gradient disappearance or gradient explosion during training, leading to difficulties in learning long-term contextual information. In addition, RNNs need to handle sequence data of arbitrary lengths, which can lead to increased computational complexity and longer training times. To overcome these limitations, researchers have proposed various improved RNN models, such as Long Short-Term Memory Networks (LSTM) and Gated Recurrent Units (GRUs), which can be more effective in handling long-term contextual information [24].

This paper uses the GRU method for collaborative data analysis with multiple modules, considering the data computation requirements. GRUs are a modified recurrent neural network that control the flow of information by adding two gating units to reduce the occurrence of gradient disappearance and explosion problems. GRUs contain a reset gate and an update gate to control the flow of information in the memory cell. Compared to traditional RNNs and LSTM, GRUs have a higher efficiency and fewer parameters, making them the preferred choice in many sequence modeling tasks. The gating mechanism of GRUs is more straightforward, but it can still effectively capture long-distance dependencies while reducing gradient vanishing issues, making training more stable. This means GRUs are widely used in fields such as natural language processing and time series data, providing high-performance sequence modeling capabilities. In particular, the reset gate controls the past information, and the update gate controls the current flow of information.

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (4)$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (5)$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \quad (6)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (7)$$

where r_t denotes the reset gate, z_t denotes the update gate, $\tilde{h}_t$ denotes the candidate hidden state vector, and h_t denotes the hidden state vector of the current time step. After recommending courses based on the user's interests, we conducted data analysis based on the recommended student data. The data input of the GRU model is also the user's learning time series. Based on this, we fitted and output the actual final grades of the student users, thus completing the data training. The autoencoder and GRU models both have a single-layer network structure and determine the number of units based on batch size optimization. Based on this, we completed the training of the model. Therefore, in this paper, the automatic English learning assessment process is completed for multi-module English teaching using an autoencoder for interest recognition pushing, as shown in Figure 1.

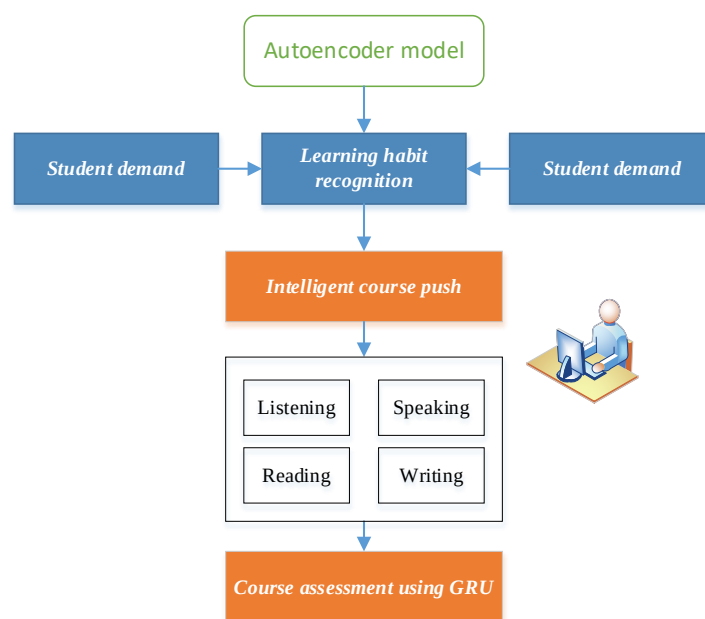


Figure 1. Framework for the intelligent course push and assessment.

As shown in Figure 1, after collecting relevant data, we feed them into the autoencoder model and push relevant courses based on the student's needs, information, and collected learning features. After completing the four modules of listening, reading, and writing based on data pushing, the GRU method is used to evaluate student learning data and predict their academic performance.

4. Experiment Result and Analysis

We tested the model using the data from four modules of an English course: listening, reading, writing, and writing. In the test, we first identified the modules preferred by students using an autoencoder, completed the modeling of push information, and determined the student satisfaction survey statistics. After that, we analyzed the students' online learning performance in recent years to form the data statistics, and the difference between the performance results was measured using the *MSE* index, which is calculated as shown in Equation (8):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (8)$$

where n represents sample number, y_i is the sample's true value, $\hat{y}_i$ denotes the sample's predicted value.

4.1. Student Interest Identification Based on Autoencoder

The model's training process is shown in Figure 2, where the red line represents the recognition accuracy of the model and the black line represents the loss function output of the model. Due to the inherent characteristics of the data, we conducted research on classification and clustering and analyzed it based on quantitative data features. At the input end of the model, we used quantified student questionnaire analysis results and specified clustering data. Then, we compared the results of the interest categories based on the actual data collected, thus completing the evaluation of the model's accuracy. In this experiment, more than 350 students from a school were surveyed and analyzed for their English learning data and an informed consent form was obtained from the subjects. We have provided a detailed explanation of the overall data training process in Section 3.

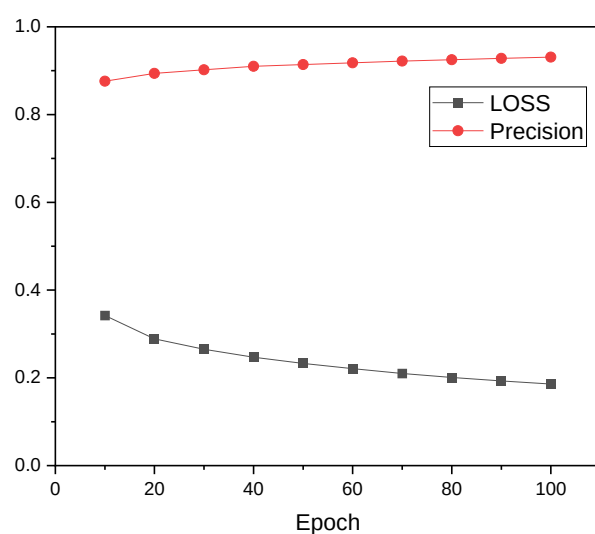


Figure 2. The result of the model training.

According to the model training process in Figure 2, it can be seen that the training process of the proposed model is more consistent and the changes are more uniform. The final model recognition result is 93.1%, and the recognition results for the course categories under different interests of students are shown in Figure 3.

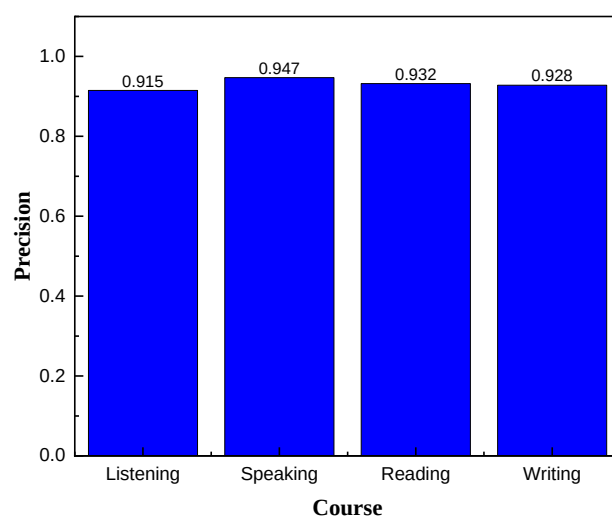


Figure 3. The recognition precision among different courses.

In Figure 3, the chosen autoencoder method has a more balanced recognition performance, and its interest recognition accuracy exceeds 90% for all four types of modules.

4.2. GRU-Based Course Evaluation

After completing the classification of course interests, we advised the students to study according to the course and gave the final grade by integrating the study time and quizzes and comparing this grade with the actual final grade of the students to complete the intelligence analysis. The training results of the GRU model are shown in Figure 4.

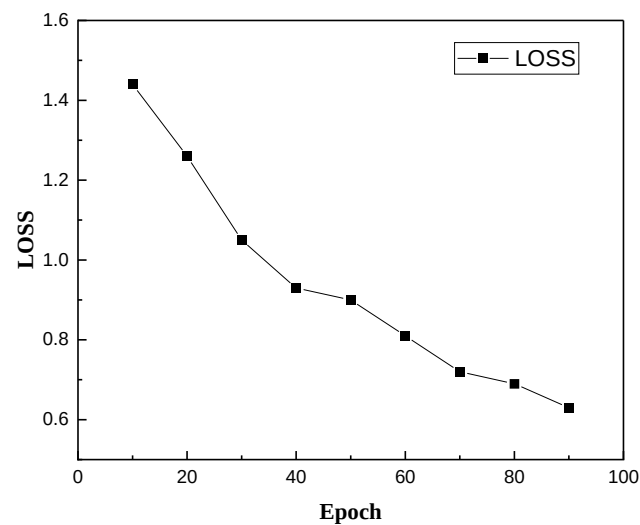


Figure 4. The training loss for the assessment training using GRUs.

In the model training, we first used the students' final grades of this semester as the true values of the GRU model sequence regression, completed the model training, and then conducted relevant sequence analyses. In the model training loss shown in Figure 4, it can be seen that the final average MSE of this article is 0.63. The percentage system's final error is already less than 1%, meaning it can effectively evaluate the course score for the current sample. To better illustrate the course evaluation under multi-module writing, we conducted a comparison of typical neural network methods.

4.3. Comparison of Multi-Module Learning Evaluation under Different Methods

To better illustrate the assessment of courses under multi-module writing, a comparison of typical neural network approaches was conducted, and the results are shown in Figure 5.

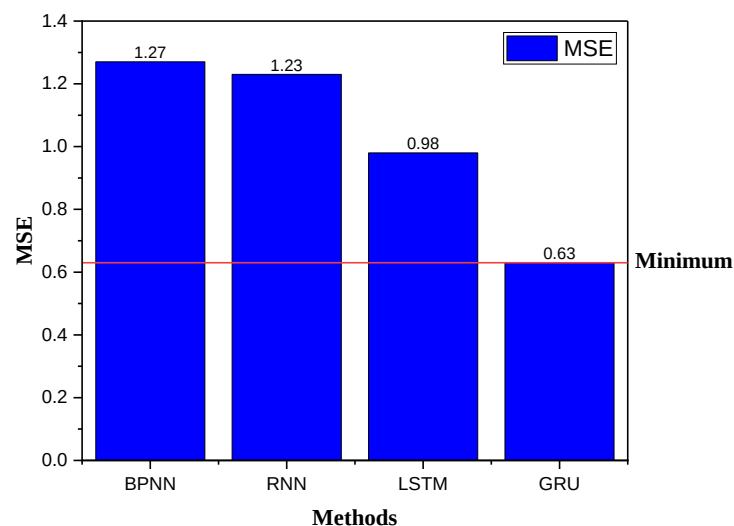


Figure 5. Comparison of different methods.

We selected the classical BPNN, RNN, and LSTM for contrast in the method comparison. We can see that the overall effects of recurrent neural network class methods are all better. In contrast, the GRU method greatly improves the efficiency and accuracy of the model due to its memory modulation with only reset gates and update gates.

4.4. System Operation Efficiency Test

For the personalized development of the course, in addition to accurately identifying students' interests in each module, it is necessary to fully understand students' learning habits and ensure their efficiency during multi-user use. Therefore, in this study, we conducted a system operation efficiency test through simultaneous online learning among students. During the testing process, students completed the interest test presented by the system in the shortest possible time. Based on this result, we observed the system's efficiency in pushing first-hand information quickly and the student's satisfaction. It was marked as valid if it was consistent with the student's interest classification results before the experiment. Our test results after several days are shown in Figure 6.

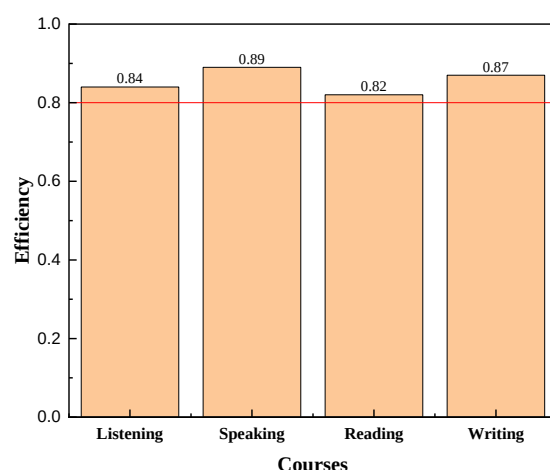


Figure 6. Investigation results for the student satisfaction.

According to the findings shown in Figure 6, it can be seen that we can coordinate each module through interest identification after students push learning for their English courses. The framework has more than 80% efficiency in multi-user use, and the highest push efficiency for the speaking module system is close to 90%. This result shows that the proposed framework has some advantages with a limited computer computing power.

5. Discussion

Smart sustainability integrates intelligent technology and sustainable development principles to achieve sustainable economic, social, and environmental development. It encompasses three main areas: smart economy, smart society, and a smart environment. Education is critical to social life, and improving its quality and sustainability is essential. This paper proposes an intelligent recommendation algorithm based on students' learning history information and using an autoencoder. This algorithm enables intelligent assessment of English teaching in four modules: listening, reading, writing, and speaking. This framework can significantly enhance teaching efficiency and ensure its continuity to achieve the sustainable development of English teaching in diverse schools. Intelligent teaching evaluation is crucial for sustainable development, as it plays a role through multiple channels, such as personalized education support, resource optimization, increased student participation, improved education quality, and adaptation to future needs. Personalized education support ensures that every student fully unleashes their potential; resource optimization improves the efficiency of the education system, increases student participation, and cultivates learning interest [25]. Improving education quality helps ensure that students receive a high-quality education. In addition, intelligent assessment also helps the education system adapt to constantly changing social and economic needs, thereby supporting the sustainable development of human resources. The comprehensive

effects of these aspects not only enable education to meet current needs, but help shape a more sustainable future [26].

However, it is essential to note that the autoencoder model has some limitations. For instance, it may not be as effective as other algorithms when dealing with high-dimensional, sparse data. Additionally, training the autoencoder model requires pre-processing and normalizing input data; otherwise, it may be negatively affected [27]. Regarding the GRU model of intelligent assessment, the introduction of reset and update gates enhances its recognition rate while maintaining the same model complexity, making it highly applicable in future multi-module and multi-information assessments. We have conducted practical application tests on the currently designed framework, as discussed in Section 4. In addition to testing the accuracy of the proposed algorithm framework, we have also conducted system efficiency tests on relevant frameworks. Through real-time testing with nearly one hundred volunteers, the system has achieved over 80% efficiency in pushing while ensuring student satisfaction, indicating that the system framework has broad prospects in practical applications.

With the continuous evolution of artificial intelligence technology, English teaching models in a sustainable context are gradually showing diverse prospects. In this constantly changing educational landscape, we can further expand the model proposed in this article to meet students' individual needs better. This extension includes intelligently recommending various learning resources, such as textbooks, questions, exercises, etc., based on students' learning history and preferences to achieve extensive and in-depth personalized recommendations, thereby improving learning outcomes. In addition, based on massive learning data, we can also achieve the vision of adaptive learning. By analyzing students' learning performance, the system can dynamically adjust learning content, difficulty, and teaching methods to ensure that each student can better understand and master knowledge, achieving a more efficient learning process. This personalized educational method is expected to play a key role in sustainable English teaching [28]. In the future, with the popularization of online learning, intelligent-assisted education will become mainstream. Applying deep learning technology will make natural language processing, intelligent dialogue, and question answering more advanced and intelligent. Students can interact and learn with virtual robots through intelligent teaching platforms and gain personalized educational experiences. This vision represents the future development direction of sustainable English education, providing students with richer and more attractive learning opportunities and promoting the continuous improvement of education quality and sustainability.

6. Conclusions

This study delves into the issues of English teaching in the context of intelligent, sustainable development and successfully proposes a method with significant contributions. We have innovatively constructed a learning interest recognition and intelligent evaluation framework based on autoencoders and GRUs. This framework can accurately classify students' interests based on their learning history data, achieving an astonishing 93.1% classification accuracy. This high-precision interest classification provides multi-dimensional information for automatic course recommendations, significantly improving learning satisfaction. Furthermore, we combined the GRU model to complete a joint analysis of the four typical listening, speaking, reading, and writing modules in English teaching, evaluating intelligent learning effectiveness. It is worth noting that the mean square error between our evaluation results and the teacher's final score is only 0.63, indicating our method has accuracy and reliability in evaluating students' learning outcomes. Compared with traditional methods such as RNNs and LSTM, our GRU method has a higher efficiency and a significantly lower MSE, further demonstrating the superiority of our approach. In summary, the framework proposed in this article performs well in modeling student user interests and multi-module joint intelligent assessment tasks, providing new

ideas and technical references for future research on the sustainable development of English teaching.

However, there are also some problems with the research in this paper. In this paper, we evaluate a small amount of students' learning history data, meaning the results are limited by the sample size, and the interest modeling in this paper only identifies and classifies the general modules in the learning process. Thus, in future research, expanding the sample size to improve the user picture will be the focus of study.

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Institutional Review Board Statement: This study did not involve humans or animals.

Informed Consent Statement: This study did not involve humans.

Data Availability Statement: The dataset can be accessed upon request.

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Conflicts of Interest: The authors declare no conflict of interest.

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