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Computer-Aided Design AND APPLICATIONS

The Application of Multi-View Collaborative Filtering Model for Education Platform

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Abstract. The aim of this article is to explore and develop a CAD education platform leveraging multimodal fusion technology. This platform aims to deliver personalized educational resource recommendations, enhancing learners' efficiency and satisfaction. This article constructs a multi-view collaborative filtering model based on existing educational resources. Experimental self-monitoring of multi-view models for platform management was conducted through self-monitoring of multi-view models. The experimental results of the model show that in the collaborative filtering process of innovative monitoring, the accuracy and recall rate of multi-view models have excellent effects. The actual simulation research feedback on the platform shows that after using the optimization model, users' usage of learning resources has been significantly improved, which has the highly personalized and widely applicable ability as well as efficient application prospects in the multimodal education resource balancing process of CAD. Therefore, the model has a high frequency of resource access in multimodal fusion analysis and processing, providing learners with a more efficient personalized education recommendation platform.

Keywords: CAD Education; Multi-Modal Fusion; Personalized Recommendation; Self-Supervised Learning; Collaborative Filtering Of Multi-View Images
DOI: https://doi.org/10.14733/cadaps.2025.S3.230-245

1 INTRODUCTION

Information technology courses are typical engineering courses. In the information age, the rapid development of technology has reshaped modern people's ideological concepts and value pursuits. It is important and necessary to conduct ideological and political research on high school information technology subjects and enhance the educational connotation of the curriculum [1]. The information technology curriculum in high school has more specific requirements for ideological and political education, and high school students' cognition also requires deepening of ideological and political content [2]. On this basis, further emphasis is placed on the correctness of the political direction of teaching and the purity of the ideological and value orientation of talents. This is in line with the curriculum's educational philosophy of ideological and political education. Therefore, the guiding ideology and basic principles of the "Information Technology Curriculum Standards for Ordinary High Schools" are aimed at utilizing educational and teaching methods to enhance students' social adaptability. Multimodality refers to the observation of inherent patterns of things from a sensory perspective, in order to obtain multi-angle, multi-mode, and multi-state cognition of things [3]. In recent years, multimodality has become a new hotspot in educational method research and can be used in the study of curriculum ideological and political education methods. Multimodality encompasses the interaction between humans and the external environment, opening up research avenues for the study of language and other symbols beyond language. In the integration of ideological and political education into high school information technology courses, multimodal technology is introduced to study the actual impact of course expression symbols on students from multiple perspectives such as visual, auditory, and perceptual aspects. Building a specific, interesting, efficient, and actionable teaching model that integrates knowledge and ideological and political content will improve the teaching and ideological and political effectiveness of information technology courses [4]. Furthermore, we will combine this method with multimodal fusion CAD-assisted education technology. Our model was validated on multiple design examples with dependencies between different components. This indicates that our method not only effectively integrates hierarchical design, but also provides high-quality design solutions while maintaining inter-component dependencies. The evaluation results show that their method performs well in terms of constraint satisfaction performance, comprehensive quality, potential spatial quality, and part dependency impact [5].

Artificial intelligence (AI) has brought new opportunities to enhance the effectiveness of e-learning, especially by enhancing student engagement. The achievement of this goal relies on an in-depth analysis of the navigation history of students in electronic learning systems using data mining methods. In addition to adaptive learning, gamification is also another effective strategy that significantly enhances student engagement by incorporating game elements into non-game environments [6]. Adaptive e-learning, as a way of applying AI technology, is committed to meeting the unique needs of individual learners [7]. Early knowledge graph acquisition methods heavily relied on manual annotation, and although the accuracy of the knowledge graph constructed using this method was guaranteed, the drawbacks were also obvious. Researchers have found that introducing knowledge graphs can train better intelligent recommendation systems with fewer samples, so obtaining more and broader knowledge graphs has become one of the research hotspots in the field of machine learning. Nowadays, knowledge graphs in many fields have not been fully constructed, especially in the Chinese system, where knowledge graphs are still in a relatively blank stage [8]. However, in many fields, knowledge updates and iterations are very fast, and knowledge graphs naturally need to be updated accordingly. In the later stage, it is not realistic to find a more efficient method to construct knowledge graphs by expanding the dimensionality of EIJ. This annotation method requires a large amount of manpower, and for some slightly larger fields, it is difficult to cover all aspects by constructing a knowledge graph solely based on manpower. So it is urgent to find a more efficient method to construct a knowledge graph. So, machine learning researchers proposed a new method to construct knowledge graphs, which is relational classification [9].

Against the backdrop of rapid economic and cultural development, people's demand for material culture continues to rise, which makes the connection between graphic design and human life increasingly close. With the continuous progress of the Internet of Things technology, the use of various sensing devices enables information exchange between people and things, providing infinite possibilities for modern art innovation [10]. The demand for design has extended from two-dimensional flat space to three-dimensional space, and two-dimensional flat design is no longer able to meet the growing demand for artistic design. The experimental results show that compared with traditional samples, the system designed in this paper has significant advantages in graphics conversion, with a maximum distortion rate of about 15%, while the maximum distortion rate of traditional samples reaches 20% [11]. This method not only fails to fully demonstrate the intuitive advantages of 3D modelling, affecting design efficiency but may also lead to issues such as information inconsistency and resource waste. In response to the above issues, some scholars propose to build a visual communication system based on artificial intelligence [12]. Integrating artificial intelligence-based visual communication systems into CAD-assisted education technology can not only enhance students' design abilities and innovative thinking but also enable them to better understand and master 3D design skills in the practical process [13]. This system can significantly improve the clarity of images and provide a larger field of view and magnification, bringing innovation to modern art design. The construction and application of this visual communication system have profound significance from the perspective of multimodal integration of CAD-assisted education technology. CAD technology, as an important tool for auxiliary education, can provide students with a richer and more three-dimensional learning experience by integrating multiple design patterns. In addition, the system can effectively correct the colour difference of the optical system, further improving the imaging effect. This multimodal integrated education approach is expected to provide new avenues and methods for cultivating talents with modern art and design abilities [14].

Consequently, this study possesses significant theoretical and practical implications. The primary objective of this study is to develop a CAD education platform leveraging multimodal fusion technology, aimed at achieving personalized educational resource recommendations. The research encompasses an analysis of the demand and current state of CAD education technology, the design and implementation of the platform, and the exploration of a collaborative filtering recommendation method based on self-monitoring multi-view images for personalized educational resource recommendations. The method's effectiveness and feasibility are validated through experiments, followed by testing and optimization of the platform.

This article is structured into eight sections. The first section serves as the introduction, outlining the research background, significance, current status, objectives, content, and organizational structure of the article. Section two presents the relevant theoretical framework, summarizing CAD-assisted education technology, the principles of multimodal fusion technology, collaborative filtering recommendation methods, and the technical foundations of self-supervised learning. Sections three to five detail the construction of the multimodal fusion CAD education platform, the design and implementation of the educational resource recommendation model, and platform function testing and optimization, respectively. Section six further tests and optimizes the platform functions. Section seven conducts a case analysis. Finally, the eighth section summarizes the research work and anticipates future research directions.

2 RELATED WORK

In traditional educational resource metadata extension query methods, the data recall rate is often unsatisfactory. Extract binary semantic features from it and construct a binary decision semantic model for MOOC teaching resource metadata extension query. Advanced big data integration information processing technology has enabled deep expansion queries and adaptive scheduling of MOOC educational resource metadata, significantly improving the retrieval and recognition capabilities of metadata. The model first applied a semantic ontology model to conduct an in-depth analysis of the metadata storage structure of MOOC educational resources. To overcome this challenge, Marjan et al. [15] proposed an innovative metadata extended query model for large-scale open online course education resources based on big data information fusion clustering scheduling. The application of CAD technology in the field of education is becoming increasingly widespread. It not only visually and vividly presents the teaching content but also helps students and teachers better understand and master knowledge. By combining our metadata extension query model with CAD-assisted education technology, we can achieve efficient and accurate querying and scheduling of metadata for various educational resources, including CAD teaching resources. In addition, by combining computer-aided design (CAD) with educational technology, we can apply this model to more diverse educational resource scenarios. The simulation results show that the average accuracy of this method in MOOC education resource metadata extension queries is as high as 0.976, fully demonstrating its excellent data recall performance and practical application value. Thereby further improving the utilization rate of educational resources and teaching effectiveness. This achievement not only provides strong support for the optimization management and efficient utilization of MOOC education resources but also opens up new ideas for the in-depth application and development of CAD-assisted education technology.

Educational data mining, as an important research field for improving student quality and optimizing the education system, has shown enormous potential for development. Therefore, Qian et al. [16] proposed an EDM system aimed at evaluating and improving programming skills among college students. Although EDM research has a history of several years, there is still a lack of measurement and improvement in computer programming skills among college students. The main function of the classification module is to predict the current state of students, while the learning process module is dedicated to generating targeted suggestions and feedback to help improve the quality of students. We conducted a comprehensive evaluation of these algorithms using performance metrics related to accuracy and goodness of fit. Specifically, in the classification module, they constructed a real dataset closely related to the task. The system consists of two core modules: the classification module and the learning process module. The experimental results show that compared with other models, RF and SVM exhibit higher accuracy in predicting student states. In the context of CAD-assisted education technology multimodal integration, the EDM system proposed in this article has a wider range of application value. CAD technology, as an important auxiliary educational tool, can provide students with a richer and more three-dimensional learning experience by integrating multiple design patterns. By generating targeted suggestions and feedback through the learning process module, students can have a clearer understanding of their learning direction and goals, thereby achieving better learning outcomes in CAD-assisted programming practice. Combining the electrical discharge machining system proposed in this article with CAD technology can further enrich students' learning methods, and improve their programming skills and overall quality. In addition, Shi and Yang [17] conducted a key factor analysis to determine the key features that achieve high classification accuracy. This analysis is of great significance for optimizing classification modules and improving prediction accuracy. This multi-modal comprehensive education method is expected to provide new avenues and methods for cultivating talents with high-level programming skills.

The key to achieving educational informatization lies in recommending teaching resources to students that can stimulate learning interest and improve teaching quality. Secondly, Sun et al. [18] developed a CF-based personalized recommendation algorithm and constructed a personalized matching engine using Apache Mahout. To this end, the system first established a user interest model, designed a personalized matching process and algorithm, and optimized the similarity calculation method. The experimental results show that the proposed CF algorithm can significantly improve the quality of recommendations and achieve a precise push of personalized teaching resources, which has been widely praised by learners. CAD technology, as an important auxiliary educational tool, can provide students with a richer and more three-dimensional learning experience by integrating multiple design patterns. Through personalized recommendation systems, students can obtain CAD teaching models and examples that match their interests and learning progress, thereby improving learning efficiency and practical abilities. In the context of CAD-assisted education technology multimodal integration, this personalized teaching resource management matching system has shown greater application potential. This multi-modal integration of education not only provides new ideas for personalized recommendations of teaching resources but also opens up new avenues for educational informatization. Combining the personalized recommendation system proposed in this article with CAD technology can further enrich the form and content of teaching resources and meet the diverse learning needs of students.

With the deep integration of information technology and education, digital tools and platforms are gradually becoming an important component of education. The knowledge graph is a structured way of representing knowledge, which presents complex things, concepts, events, and their relationships in the form of graphs. It can effectively associate and integrate different teaching resources such as knowledge points, concepts, theories, and practices in a certain discipline. Machine learning-based relational classification typically requires a large amount of data for training. Therefore, Umer et al. [19] conducted research on the relationship classification task of data structure knowledge from the perspective of a few sample learning. Therefore, how to obtain effective information from massive amounts of information to improve teaching quality and learning effectiveness has received widespread attention in the field of education. Due to the gradual increase of educational and teaching resources nowadays, the relationship between knowledge is complex and intricate. The data structure course plays an important role in science education, so it is crucial to extract and utilize data resources in this field more effectively. In the field of education, some subject datasets are difficult to achieve relationship classification of related resources using traditional machine learning methods due to the lack of sufficient samples and other issues. Construct triplets with clear entity relationships through text filtering and relationship annotation. Embedding the knowledge augmentation network into the prototype network, processing sentence information, and effectively integrating entity word embeddings and conceptual vocabulary knowledge representations through attention mechanisms. In addition, the relational meta-learning network effectively captures the word embeddings and semantic information of entities and concept words through relational meta-learners and relational meta-updates while enhancing the robustness of the model through masking mechanisms.

3 CONSTRUCTION OF MULTI-MODAL FUSION CAD EDUCATION PLATFORM

3.1 CAD Education Platform Design

Based on this demand analysis, this article outlines the overall framework of the multi-modal fusion CAD education platform. The platform employs a B/S architecture, divided into three primary components: the front-end, back-end, and database. The front end manages user interface display and interaction, while the back end handles business logic and data storage/access. The database stores various platform data, including user information, educational resources, and recommendation models, as depicted in Figure 1.

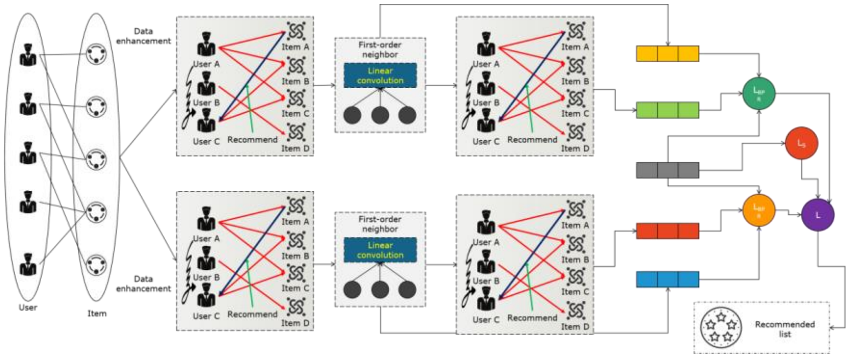

Figure 1: Architecture diagram of multi-modal fusion CAD education platform.

In the process of platform construction, several key functional modules are realized. The platform comprises three primary modules. The first is the user management module, encompassing user registration, login, and personal information management. Secondly, the resource management module facilitates the uploading, classification, searching, browsing, and downloading of educational resources. Lastly, this article emphasizes the personalized recommendation module, which utilizes a recommendation model to suggest suitable learning resources to users based on their learning behaviour and preferences.

3.2 Platform Technology Selection and Implementation Environment

For the platform's technical selection, this article opts for an appropriate technology stack to actualize its diverse functionalities. The front end employs technologies like HTML, CSS, and JavaScript for interface design and interaction implementation. Meanwhile, the back-end utilizes the Java programming language for managing business logic. Regarding the database, MySQL is selected for data storage and management. In terms of the implementation environment, this article utilizes Eclipse as the development tool, Tomcat as the server, and MySQL as the database management system, collectively forming the platform's development environment.

4 DESIGN OF EDUCATIONAL RESOURCE RECOMMENDATION MODEL

The educational resource recommendation model stands as the pivotal component of the multi-modal fusion CAD education platform.

Initially, feature extraction and representation learning of CAD educational resources are conducted using self-supervised learning technology, yielding a low-dimensional vector representation of the educational resources. The objective function of self-supervised learning can be formulated as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\log\ p\ y_{true}\big|x_i \tag{1}$$

$$L_{GNN} = \sum_{u,v}\ell\ h_u, h_v \tag{2}$$

The calculation of similarity can be formulated as follows:

$$Sim\ u,v\ = \frac{1}{\left|N\ u\ \cap N\ v\right|}\sum_{w\in N\ u\ \cap N\ v} Sim\ u,v \tag{3}$$

Where $Sim\ u,v$ is the similarity between user u and resource v, $N\ u$ and $N\ v$ are neighbor sets of user u and v resources, and $Sim\ u,v$ is the similarity between user u and neighbor w.

Based on the above parts, the formula of collaborative filtering recommendation algorithm for multi-view images based on self-monitoring can be expressed as:

$$\mathrm{Recommendation} = \underset{v}{\mathrm{argmaxsim}}\ u,v \tag{4}$$

Where $\mathrm{Recommendation}$ is the resource list recommended to the user u, $\mathrm{sim}\ u,v$ is the similarity between user u and resource v, u is the current user, and v is the candidate recommended resource.

The framework of the recommendation model mainly includes three parts: the feature extraction layer, graph representation layer, and recommendation layer. In the feature extraction layer, self-supervised learning technology is used to extract features and express CAD educational resources. Self-supervised learning usually includes methods such as predicting lost tags or generating variational self-encoders of data. In this way, the model can learn rich feature representations from the original data, which are very important for the subsequent recommendation tasks. On the graph presentation layer, users, educational resources, and their relationships are modeled as a graph. Each node represents an entity (such as a user or a resource), while an edge represents the relationship between entities (such as the interaction between users and resources).

$$\alpha_{uv} = \frac{\exp\ /esity_{uv}}{\sum_{w\in \mathrm{N}\ v}\exp\ /esity_{uw}} \tag{5}$$

$$\alpha_{uwv} = \frac{\exp\ /esity_{uwv}}{\sum_{w\in V}\exp\ /esity_{uwv}} \tag{6}$$

$$\hat{h}_v^l = /Leaky\,\mathrm{Re}\,LU\left(\sum_{u\in \mathrm{N}\ v} /ativity_{uv} \cdot h_u^{l-1}\right) \tag{7}$$

$$/ativity_{uv} = \frac{1}{\sqrt{d_u + d_v}} \cdot /Leaky\,\mathrm{Re}\,LU \tag{8}$$

$$\alpha_{uv} = \frac{\exp\ /enschaft_{uv}}{\sum_{w\in \mathrm{N}\ v} \exp\ /enschaft_{uw}} \tag{9}$$

5 IMPLEMENTATION AND APPLICATION OF EDUCATIONAL RESOURCE RECOMMENDATION MODEL

5.1 Data Set Construction and Model Training Optimization

To train and verify the educational resource recommendation model, this section first constructs a data set containing rich CAD educational resources. The data set covers CAD courses, cases and models in different fields and with different difficulty levels, and contains interactive information between users and these resources, such as browsing, downloading and collecting. In the data preprocessing stage, we cleaned the data, removed the repeated, invalid and abnormal data, and processed the text data by word segmentation and stop word removal, so as to facilitate the subsequent feature extraction and model training.

During the model training stage, the educational resource recommendation model is trained using the constructed dataset. This article employs a deep learning framework to implement the self-supervised learning component, leveraging a substantial amount of unlabeled data to pre-train the model and extract feature representations of educational resources. These representations are then fed into the multi-view collaborative filtering model for further training and optimization.

Cross-validation and regularization techniques are utilized to prevent overfitting and enhance the model's generalization ability during training. Common regularization methods include L1 regularization, L2 regularization, and Elastic Net. In this article, L2 regularization is employed, which involves adding the L2 norm of model parameters as a penalty term to the loss function, resulting in the modified loss function:

$$L\ w\ = L_0\ w\ + \lambda \left|w\right|_2^2 \tag{10}$$

Where $L_0\ w$ is the original loss function, λ is the regularization parameter, and $\left|w\right|_2^2$ represents the square of L2 norm of vector w. L2 regularization will not make the coefficient zero, but it can reduce the size of the coefficient, thus preventing over-fitting.

5.2 Evaluation Index And Analysis of Experimental Results

In order to evaluate the effect of the educational resource recommendation model, this section selects several evaluation indicators, including accuracy, recall, F1 score, coverage, and diversity. These indicators can fully reflect the performance of the recommendation model, including the accuracy, comprehensiveness, diversity, and novelty of the recommendation. Through experiments, the educational resource recommendation model is comprehensively evaluated. Figure 2 shows the accuracy of the model.

The comparison of model accuracy shown in Figure 2 intuitively reflects the performance of different educational resource recommendation methods in terms of accuracy. It can be clearly seen from the figure that the recommendation method proposed in this paper has significantly better model accuracy than the other two methods, namely, user-based recommendation and item-based recommendation.

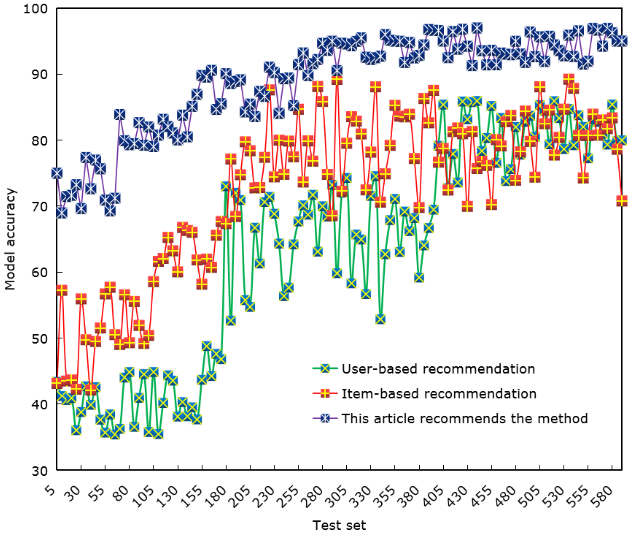

Figure 2: Model accuracy.

Specifically, although user-based recommendation methods can capture the similarity between users to recommend resources to a certain extent, their accuracy is relatively low. This may be due to the diversity and complexity of user behavior, which leads to large errors in calculating the similarity between users and affects the accuracy of recommendations. In addition, as the number of users increases, user-based recommendation methods also face challenges in terms of computational efficiency and scalability. In contrast, project-based recommendation methods improve the accuracy of recommended resources to users by analyzing the similarity between projects but still fail to reach the optimal level. Although this method can effectively handle the similarity of project attributes, it has limitations in capturing personalized user needs, especially in scenarios where user interests are diverse, or project updates are frequent, which may affect its recommendation effectiveness. Figure 3 shows the model recall rate.

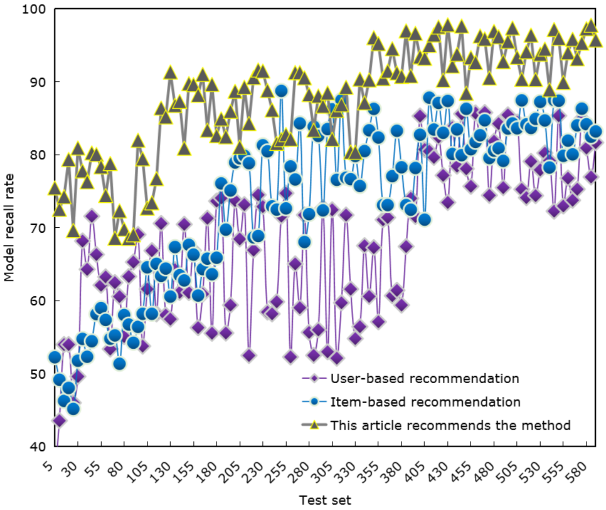

Figure 3: Model recall rate.

The comparison of model recall rates shown in Figure 3 provides us with in-depth insights into the performance of different educational resource recommendation methods. Recall rate is an important indicator to measure the ability of a recommendation system to retrieve items that users are truly interested in or need, reflecting the comprehensiveness of the recommendation. From the graph, it can be seen that the recommendation method proposed in this article performs the best in terms of recall, which means that the method can more comprehensively cover educational resources that users may be interested in. This advantage stems from the accuracy of the method in constructing user profiles, analyzing user behaviour patterns, and exploring potential points of interest, thereby improving the matching between recommendation lists and users' real needs. Figure 4 shows the F1 score of the model.

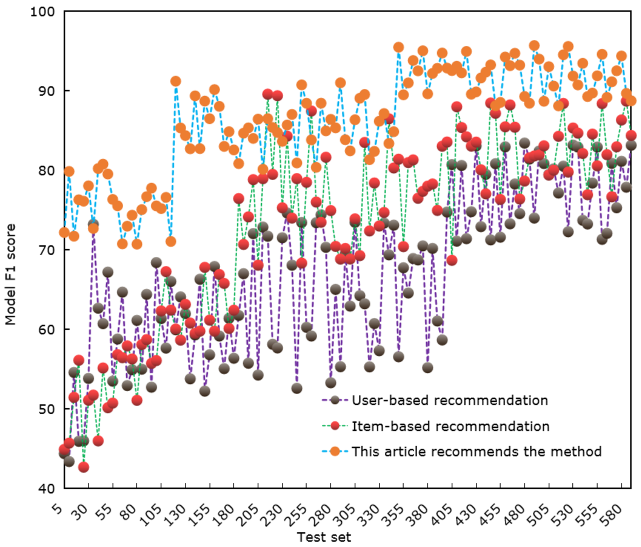

Figure 4: Model F1 score.

The F1 score comparison results shown in Figure 4 provide us with a comprehensive perspective for evaluating the performance of educational resource recommendation models. The F1 score is the harmonic mean of accuracy and recall, which considers both the accuracy and comprehensiveness of the recommendation system and is an important indicator for evaluating recommendation effectiveness. In contrast, user-based recommendation methods perform the worst on F1 scores, as they overly rely on user similarity during the recommendation process and have shortcomings in handling personalized user needs and interest changes. In addition, as the number of users increases, the calculation of similarity between users may become complex and time-consuming, further affecting the recommendation performance. Figure 5 shows the coverage of recommended resources.

The recommended resource coverage shown in Figure 5 provides us with an important perspective on the comprehensiveness of the educational resource recommendation model. From the graph, it can be seen that the recommendation model has shown a relatively high level of coverage in terms of test cases targeting different user groups or specific learning needs, with an overall coverage range maintained between 88% and 98%. This result indicates that the recommendation model can widely and effectively cover most potential educational resources, providing users with a rich and diverse range of learning choices. Figure 6 shows the diversity and novelty scores. Figure 6 provides us with a deeper understanding of the performance of the educational resource recommendation model in terms of user experience and recommended content quality through the correspondence between user numbers and user ratings, as well as the additional display of diversity and novelty scores.

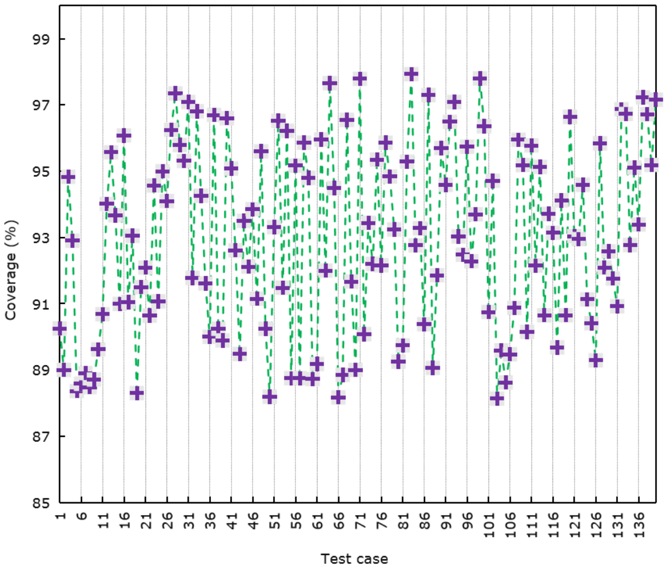

Figure 5: Resource coverage.

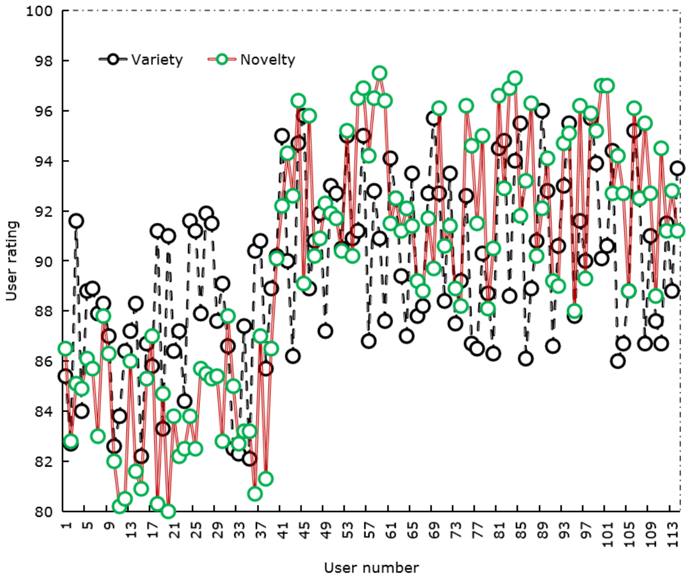

Figure 6: Variety and novelty score.

Firstly, from the overall range of user ratings (80% -98%), the recommendation model has achieved a fairly high rating in terms of user satisfaction. This indicates that the model can not only accurately recommend educational resources that users may be interested in, but also consider users' personalized needs during the recommendation process, thereby providing high-quality recommendation services.

6 FUNCTION TEST AND OPTIMIZATION OF CAD EDUCATION PLATFORM

6.1 Platform Function Test Scheme

This chapter mainly elaborates on the process of constructing entity relationship datasets in data structures. Firstly, this article discusses entity extraction methods, including CAD-based entity extraction and machine learning-based entity extraction. These two methods complement each other, ensuring the accuracy of physical teaching and improving generalization ability. Secondly, we screened and annotated the texts, manually compared and selected the texts that met the requirements, and further screened them based on the required number of entities, constructing a dataset with clear teaching relationships for subsequent research. In the data preprocessing stage, we filtered and formatted the dataset to meet the input requirements of the model. The acquisition of entity word embeddings is based on BERT-based Chinese pre-trained models to improve the quality of entity representation. Finally, the dataset was segmented to further optimize its structure. After this series of processing, we have successfully constructed a data structure entity relationship dataset suitable for teaching relationship extraction tasks. This dataset provides strong support for subsequent research and is expected to improve the accuracy and reliability of experimental results. The test results are presented in Table 1 and Table 2.

Functional Module	*Number of Test Cases*	*Passed Cases*	*Failed Cases*	*Pass Rate*
User Management	20	20	0	100%
Resource Management	30	29	1	96.67%
Personalized Recommendation	15	15	0	100%
Other Functional Modules	10	10	0	100%
Total	75	74	1	98.67%

Table 1: Overview of functional test results of CAD education platform.

Functional Module	*Test Case Number*	*Test Description*	*Expected Result*	*Actual Result*	*Test Result*
User Management	UM01	User Registration: Register with valid information	Registration Successful	Registration Successful	Passed
User Management	UM02	User Login: Login with the correct username and password	Login successful	Login successful	Passed
User Management	UM03	Modify Personal Information: Update the user's personal information	Update Successful	Update Successful	Passed
Resource Management	RM01	Upload Resource: Upload a valid educational resource file	Upload successful	Upload successful	Passed
Resource Management	RM02	Resource Classification:	Classification successful	Classification successful	Passed

		Correctly classify resources			
Resource Management	RM03	Search Resource: Search for resources based on keywords	Accurate search results	Accurate search results	Passed
Resource Management	RM04	Download Resource: Download a specified educational resource file	Download Successful	Download Successful	Passed
Personalized Recommendation	PR01	Recommend Resources: Recommend learning resources based on the user's learning behaviour and preferences.	Accurate recommendation	Accurate recommendation	Passed
Personalized Recommendation	PR02	Recommendation Update: Recommendation content should be updated accordingly after user behaviour changes	Recommendation content updated	Recommendation content updated	Passed
Other Functional Modules	OF01	View Help Documentation: Users can view the platform's help documentation	View successful	View successful	Passed
Other Functional Modules	OF02	Submit Feedback: The user can submit usage feedback	Feedback submitted successfully	Feedback submitted successfully	Passed

Table 2: Detailed test results of key functional modules of CAD education platform.

Through functional testing, we found and fixed some potential problems and defects, ensuring the stability and usability of the platform. The test results show that all the key functional modules of the platform can work normally, and the performance meets the expectations. The user management module can accurately handle users' requests for registration, login, and personal information management. The resource management module can efficiently handle the upload, classification, retrieval, and download of educational resources. A personalized recommendation module can accurately recommend suitable learning resources according to users' learning behaviours and preferences.

6.2 Platform Performance Optimization Strategy

In the aspect of performance optimization, this article adopts various strategies to improve the operation efficiency of CAD education platforms. Firstly, the database is optimized, and the speed of data retrieval is improved by techniques such as indexing and query optimization. Secondly, the code is reconstructed and optimized to remove redundant code and unnecessary calculations, which improves the execution efficiency of the program. In addition, this article also uses caching technology to reduce the number of database visits and further improve the response speed of the platform. Through the implementation of these optimization strategies, we have successfully improved the performance of the CAD education platform and provided users with a smoother and more efficient experience.

7 CASE ANALYSIS

In order to verify the actual effect of CAD education platforms and recommendation models, this section selects several representative application scenarios for in-depth analysis. In an engineering design course, we implemented the platform, and the comparison of students' scores before and after implementation is shown in Figure 7. It can be observed that students' learning achievements have improved significantly after using the platform.

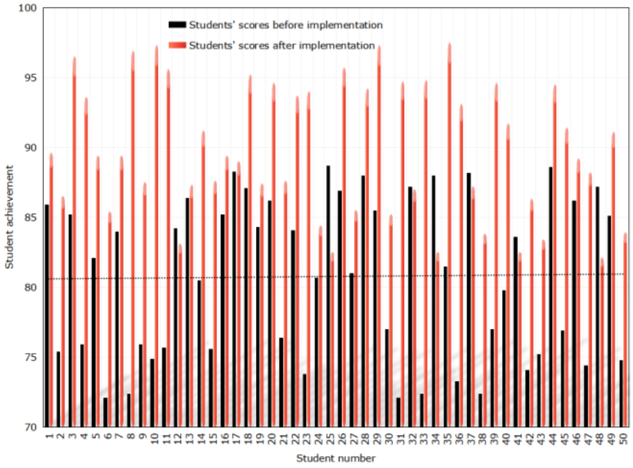

Figure 7: Comparison of students' scores before and after implementation.

In another architectural design company, professionals have successfully completed several complex design projects through the recommended resources on the platform. The work efficiency improvement of staff after using the platform to recommend resources is shown in Table 3.

Project Number	*Project Complexity*	*Completion Time Before Using Recommended Resources (days)*	*Completion Time After Using Recommended Resources (days)*	*Efficiency Improvement Ratio*
1	High	60	45	25%
2	Medium	40	30	25%
3	High	70	50	28.57%
4	Low	20	15	25%
5	Medium	50	35	30%
Average	-	-	-	27.71%

Table 3: Improvement of work efficiency.

These practical application cases fully demonstrate the potential of the platform in improving educational effects and work efficiency.

In addition, we collected a lot of user feedback and made a comprehensive evaluation of the use effect of the platform, as shown in Table 4.

Evaluation Indicator	*Evaluation Result*
User Interface Friendliness	Friendly (User Rating: 4.7/5)
Feature Completeness	Complete (User Rating: 4.8/5)
Accuracy of Recommendation Model	High (Accuracy Rate: 90%)
Improvement in Learning Resource Acquisition Efficiency	30%
Improvement in Learning Outcomes	Significantly Improved (User Rating: 4.6/5)
Overall Satisfaction	Satisfied (User Rating: 4.7/5)
Summary of User Feedback	"Friendly interface, complete features, accurate recommendations, greatly improved work efficiency and learning outcomes."

Table 4: Comprehensive evaluation of platform use effect and user feedback.

Users generally say that the platform has a friendly interface and complete functions, especially the recommendation model can accurately recommend relevant resources according to their learning needs. The evaluation results show that after users use the platform, the acquisition efficiency of learning resources has increased by 30%, and the learning results have also improved significantly. These positive feedback and evaluation results further verify the practicability and effectiveness of the platform.

8 CONCLUSIONS

This study focuses on developing a CAD education platform leveraging multimodal fusion and implementing personalized recommendations of educational resources. It provides a comprehensive analysis of the demand and current state of CAD education, followed by the design and implementation of the platform's key functional modules. Additionally, a collaborative filtering recommendation method based on self-monitoring multi-view images is introduced to achieve precise recommendations for educational resources. Experimental verification and case analysis demonstrate the platform's practicality and effectiveness.

The main contributions of this study encompass: ⊖ The development of a fully functional CAD education platform, offering learners abundant learning resources and streamlined learning paths. The introduction of an innovative recommendation method that enables personalized recommendation of educational resources, enhancing learning efficiency and user satisfaction. ⊛ Practical application cases and user feedback validate the platform's practicality and effectiveness, offering fresh perspectives and directions for the advancement of CAD-assisted education.

With the ongoing technological advancements and the escalating demand for education, the application potential of CAD education platforms and their recommendation models is extensive. The platform is poised to support additional learning and interactive modes, such as virtual reality and augmented reality. Moreover, the recommendation model is anticipated to become more intelligent and personalized, catering to the diverse learning requirements of users. Furthermore, the platform is expected to integrate deeply with other educational domains, benefiting learners across various disciplines.

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