Journal of Information Security Research

DLINE JOURNALS

Print ISSN: 0976-4143
Online ISSN: 0976-4151

JISR 2025: 16 (1)
https://doi.org/10.6025/jisr/2025/16/1/25-32

Design and Research of Students' Secured Education System Based on Personalized Recommendation

Hao Qin
Department of Information Engineering
Yantai Gold College, Yantai, Shandong
265401, China
qinhaodeyouxiang@163.com

ABSTRACT

This study aims to develop a secure education solution that meets the individual needs of different college students, helping them grasp knowledge better, enhance their learning enthusiasm, and stimulate their motivation. The research adopts experimental design and analysis methods, setting up experimental and control groups, collecting experimental data, and conducting data analysis. The matrix factorization algorithm is used to obtain a suitable system, and the experimental results show that personalized recommendation systems can recommend secure education resources that meet the users' needs based on their personal characteristics and interests, thereby increasing their attention and interest in learning and enhancing learning effectiveness. The college students' secure education system based on personalized recommendation has potential and room for development, and its performance and user experience can be improved through continuous optimization of recommendation strategies and algorithms. This research provides valuable references for the design and study of personalized recommendation systems in college students' secure education.

Keywords: Personalized Recommendation, Secure Education System, Matrix Factorization Algorithm

Received: 30 August 2024, Revised 28 November 2024, Accepted 8 December 2024

1. Introduction

With the development of society and technological progress, the importance of secure education for college students has become increasingly prominent. College students are at a critical stage of growth and learning, facing various secure risks and challenges, such as cybersecurity, traffic secure, and mental health. Therefore, it is essential to conduct effective secure education to enhance college students' secure awareness and coping abilities [1]. With the advancement of technology, traditional secure education for college students can no longer meet the personalized demands of today's society. Therefore, providing customized secure education services based on users' personal characteristics and learning behaviours has become mainstream in today's society. This research aims to design and study a college student secure education system based on personalized recommendation, which combines recommendation algorithms and secure education resources to provide college students with personalized learning content and paths [2]. Personalized recommendation technology is applied to college students' secure education, providing students with personalized secure education content and learning resources tailored to their individual needs and interests [3]. By analyzing and mining users' personal information, learning history, and behaviors, the system can intelligently recommend learning materials and paths suitable for each student, thereby improving learning effectiveness and interest. After in-depth research, we have designed and implemented a comprehensive college student secure education system, which includes multiple functional modules, such as user management, resource management, recommendation algorithms, and user interfaces [4], to meet different needs. The user management module is used to collect and manage user's personal information and learning behaviors, the resource management module is used to manage the upload, storage, and categorization of secure education resources; the recommendation algorithm module is used to analyze user data and generate personalized recommendations, and the user interface module provides a friendly interface for users to learn and interact [5]. Finally, this research evaluates the performance and effectiveness of the designed college student secure education system through experiments. By collecting user feedback and learning outcomes data, the system's recommendation accuracy, user satisfaction, and learning effectiveness are evaluated and analyzed. The experimental results show that the system has sound effects and user experience in improving college students' secure awareness and knowledge levels [6].

2. Related Work

Personalized recommendation systems have been a hot research topic in recent years and have achieved significant application effects in e-commerce, film and television, music, and other fields. However, there is relatively little research on personalized recommendation in the field of college students' secure education. This section will introduce relevant work related to this study, including personalized recommendation, college students' secure education, and the combination of the two [7].Personalized Recommendation System: Personalized recommendation systems aim to recommend personalized content to users based on personal characteristics and interests. Collaborative filtering is a commonly used personalized recommendation algorithm, which predicts users' preferences based on their historical behaviors and other users' behavior patterns [8]. In addition, content-based recommendation algorithms recommend based on item or user features analysis and can overcome the cold start problem of collaborative filtering algorithms. Furthermore, hybrid recommendation algorithms combine multiple methods to improve the accuracy and diversity of recommendations. College Students' Secure Education: Asecure education refers to educational activities that provide college students with secure knowledge and skills [9]. Secure education content involves various aspects like traffic security, cybersecurity, and mental health. Traditional secure education often adopts uniform teaching resources and learning methods, which cannot meet the personalized needs of different students. Therefore, researching college students' secure education based on personalized recommendation is of great significance. Although the application of personalized recommendation technology in secure education is relatively limited, some related studies have progressed [10]. For example, researchers provide personalized learning content and learning paths to users by analyzing their personal information and learning behavior using recommendation algorithms. These research results indicate that secure education systems based on personalized recommendation can improve students' learning effectiveness and interest. Shortcomings of Relevant Work: Although the application of personalized recommendation in college students' secure education has started to be researched, there are still some shortcomings. Firstly, most existing research focuses on the design and implementation of recommendation algorithms, with relatively little research on the system's overall architecture and user experience. There are still significant challenges in collecting and managing college students' secure education resources. Therefore, it is necessary to explore in-depth and effectively integrate and categorize various resources to meet personalized needs and implement them. In conclusion, there is a specific correlation between personalized information recommendation and college students' secure education. By using personalized information recommendation technology, we can better help college students choose courses that suit them and cultivate their security awareness. However, the current research in this area is still relatively limited and requires further investigation and exploration. Therefore, this research aims to design and study a college student secure education system based on personalized recommendation to fill this research gap.

3. Techniques of Personalized Recommendation Algorithms

To realize the personalized recommendation of the college students' secure education system, it is necessary to design an effective algorithm to classify secure education resources and recommend content that meets users' interests and needs. This section will introduce the design of the matrix factorization algorithm in the college student secure education system based on personalized recommendation. First, manysecure education resources need to be collected, including text, images, videos, and other forms of resources. These resources can come from various channels, such as textbooks, the internet, secure institutions, etc. Then, the collected resources need to be preprocessed, including text segmentation, image feature extraction, video content analysis, etc., so that the subsequent matrix factorization algorithm can process and analyze them. Different feature extraction methods need to be designed for different forms of resources. For text resources, the bag-of-words or word embedding model can extract keywords or word vector representations. For image resources, convolutional neural networks can be used to extract image features. For video resources, methods such as optical flow and keyframe extraction can extract video feature representations. The input of the self-attention routing algorithm consists of initial information with basic information, including the required information. To map the two sets of information, the algorithm processes the information of these sets and uses the algorithm's algorithm for simulation. The algorithm can implement this method by adding or subtracting the information of the information set and can simulate it through the algorithm's algorithm.

$$\hat{V}^{l} = V^{l} \times W^{l} \qquad (1)$$

Vl is a prediction matrix composed of multiple prediction vectors, while Vl is an input matrix containing the user's historical behavior records, which can help us better understand the user's actions. Wl represents the weight matrix of layer l. For the extracted feature representations, different matrix factorization algorithms can be chosen to classify secure education resources. Commonly used matrix factorization algorithms include decision trees, support vector machines, naive Bayes, neural networks, etc. The selection of an appropriate matrix factorization algorithm must consider factors such as data scale, feature dimension, algorithm complexity, and classification accuracy. Based on the matrix factorization algorithm, personalized recommendation strategies must be designed to recommend secure education resources that meet the user's needs based on their characteristics and interests. Personalized recommendation strategies can be achieved through collaborative filtering, content analysis, and hybrid algorithms. These algorithms can use users' historical behaviour, ratings, and other information to predict their interests and recommend corresponding resources. Introducing pointwise feed-forward neural networks can significantly improve the non-linear representation effect of multi-head self-attention layers. This neural network can implement a complete neural network structure, and its implementation steps are detailed in the following: [Note: The text mentions a reference for detailed implementation steps, but it is not provided in the provided content.]

$$F = FFN(S) \tag{2}$$

S is the input of the multi-head self-attention layer, and this mode adopts the Dropout method, which sets a certain threshold between the multi-head self-attention layer and the feed-forward network layer. This can effectively control overfitting and increase the generalization of the model. To evaluate the performance of the matrix factorization algorithm, metrics such as cross-validation, accuracy, recall, F1 score, etc., can be used for evaluation. Based on the evaluation results, the matrix factorization algorithm can be fine-tuned and improved. Additionally, the effectiveness and recommendation performance of the matrix factorization algorithm can be validated through user feedback and experimental data. By adopting the multi-head self-attention mechanism, we can embed the user's historical behavior into multiple subspaces, combining the results using scaled dot-product attention to achieve linear transformation, thus obtaining more accurate results. Applying this multi-head self-attention allows us to extract meaningful information from multiple subspaces and enhances the model's ability for multi-dimensional learning. Below are the detailed computational formulas:

$$\mathrm{A} = \mathrm{I} + \alpha A_{seq} + \beta A_{sem} \tag{3}$$

I is a set of matrices related to the project, and the sequential adjacency matrix *seqA* or the semantic adjacency matrix *semA* can determine their weights. Each set of matrices covers a series of key elements, enabling each set to meet specific requirements. For example, when dealing with campus situations, the matrix's ID, the hotel's name, and the location of the dormitory can be considered as a set of key elements. The project collects multiple users' past interaction activities, forming a complete set.

In summary, the matrix factorization algorithm design for the personalized recommendation-based college student secure education system needs to include steps such as data collection and preprocessing, feature extraction and representation, matrix factorization algorithm selection, personalized recommendation strategies, and model evaluation and optimization. Using the matrix factorization algorithm, secure education resources can be effectively classified and personalized recommendations can be made according to students' needs, greatly enhancing college students' secure awareness.

4. Experimental Design and Analysis

To evaluate the effectiveness of the personalized recommendation-based college student secure education system, experiments need to be designed and data analyzed accordingly. This section will introduce the steps of experimental design and analysis. First, the objectives of the experiments need to be clarified, such as evaluating the accuracy of the system's recommendations, user satisfaction, learning effectiveness, etc. Based on the experimental objectives, appropriate evaluation metrics, such as recommendation accuracy, recall rate, user ratings, etc., are determined. To evaluate the effectiveness of the personalized recommendation system, experimental and control groups can be set up. The experimental group uses the personalized recommendation system for learning content recommendations, while the control group uses traditional secure education methods for learning. By comparing the experimental results of the experimental and control groups, the advantages and disadvantages of the personalized recommendation system can be evaluated. Collecting experimental data is an important step in evaluating system effectiveness. Experimental data can include user personal information, learning behavior data, recommendation results, user feedback, etc. Data can be collected through questionnaire surveys, learning behavior logs, experimental records, etc.The future behavior extraction layer of the FMIST algorithm will carefully select from up to K historical records, which will determine which users' interests most closely match the FMIST algorithm, thus making more accurate judgments about future trends. By adjusting the *K* value to 1 and comparing it with different datasets such as AmazonBooks and Taobao, the relevance of the *K* value to the FMIST algorithm can be checked, and by adjusting the K value to 0, the accuracy of the *K* value can be ensured. The conclusions are presented in Figure 1.

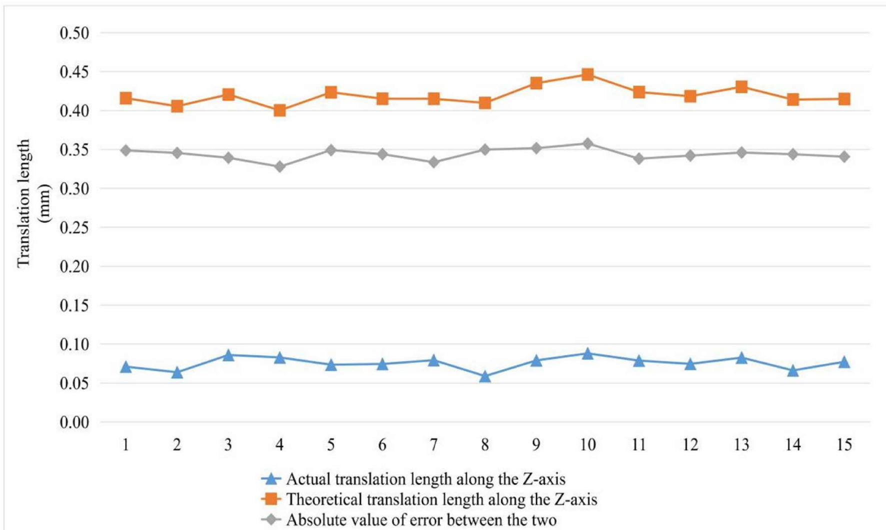

Figure 1. The Influence of Parameter *K* on Personalized Recommendation System Dataset

FPMC has a lower recommendation accuracy because it only focuses on the surface phenomena of behavior sequences without considering the inner needs of college students, resulting in much lower accuracy compared to other control groups. However, as *K* increases, the value of HitRate also gradually rises, reaching 11.236, and the previous accuracy becomes almost negligible. AmazonBooks and Taobao data support the FMIST algorithm, but the former shows superior results. Specifically, as *K* increases from 4, the HitRate value gradually improves, reaching nearly 40.676, and then *K* decreases again, approaching 3. For Taobao, *K* is set to 3, which allows the FMIST algorithm to perform exceptionally well.

By observing Figure 2, we find that as the size of nearest neighbors increases, the mean absolute error for all four calculations significantly decreases. In comparison, the lower MAE values are mainly due to the Jaccard and Pearson similarity calculation methods, which are based on the overall user population but do not consider relevant information about the college. As a result, their MAE values are higher. On the other hand, the similarity calculation methods used in the literature can more accurately reflect the actual situation and estimate similarity more precisely. Despite optimizing the recommendation results through two approximations, they fail to fully consider the timely changes in college students' secure needs. Therefore, adopting a new approach, such as using a time-weighted function, highlights the importance of college students' security and allows for early detection of early data, better reflecting the actual situation of the college and significantly improving the accuracy and timeliness of college student secure education.

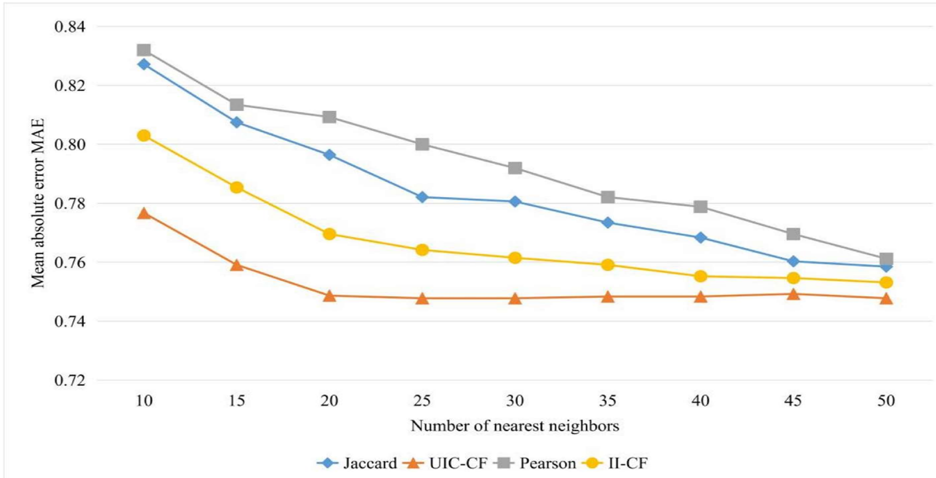

Figure 2. Comparison of Mean Absolute Error (MAE) for Four Algorithms

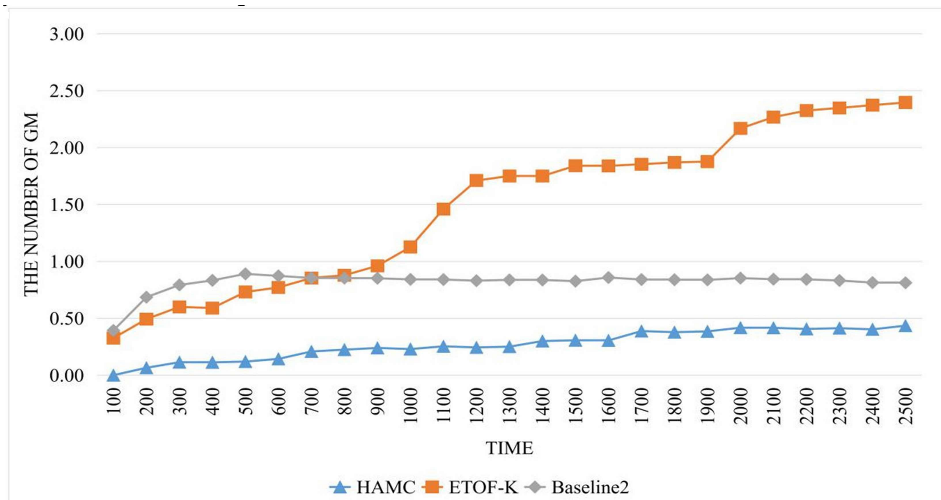

Figure 3. Pareto Front of Users in Dataset Data1

From Figure 3, it can be observed that the same dataset *Data1* shows significant differences under different systems, with ETOF-K showing the most optimal development trend. In the experimental process, according to the experimental design, users in the experimental group and control group are arranged to perform learning tasks separately. University students in the experimental group will use the personalized recommendation system for secure education to receive learning resource recommendations, while university students in the control group will use traditional secure education methods for learning. During the experiment, it is necessary to record users' learning behaviors and evaluations. After data collection is completed, data analysis is performed to evaluate the effectiveness of the personalized recommendation system. Statistical methods and machine learning algorithms can be used to analyze the data, such as calculating recommendation accuracy, recall rate, user satisfaction, and other metrics. Additionally, qualitative and quantitative analyses of users' learning behaviours and evaluations can be conducted to gain a deeper understanding.

Based on the results of data analysis, the experimental results are interpreted, and the system is improved and optimized accordingly. Personalized recommendation algorithms, resource classification, and recommendation strategies can be adjusted based on user feedback and evaluations to enhance the system's performance and user experience. In conclusion, experimental design and analysis are essential in evaluating the effectiveness of the personalized recommendation-based college student secure education system. By defining experimental objectives and indicators, setting up experimental and control groups, collecting experimental data, conducting data analysis, and interpreting results for improvements, the system's teaching effectiveness and student satisfaction can be assessed, guiding the optimization and improvement of the system.

5. Conclusions

The personalized recommendation-based college student secure education system is a promising solution to provide personalized secure education resources to college students and enhance their learning effectiveness and interest. Through design and research, we can conclude that personalized recommendation systems can recommend secure education resources that match users' needs based on their characteristics and interests. This personalized recommendation approach can increase users' attention and interest in learning content, enhancing learning effectiveness. Additionally, the design of matrix factorization algorithms plays a crucial role in the performance of the personalized recommendation system. Proper selection and design of matrix factorization algorithms can effectively classify secure education resources and provide personalized recommendations, improving recommendation accuracy and user satisfaction. Furthermore, in the process of experimental design and analysis, we can evaluate the effectiveness of the personalized recommendation system by comparing the experimental group and the control group. Experimental results and data analysis can help us understand the system's strengths and weaknesses and improve the recommendation strategies and algorithms based on user feedback and evaluations.

Lastly, the personalized recommendation-based college student secure education system has further research and development potential. Continuously collecting user feedback and behavior data and optimizing the recommendation algorithms and personalized recommendation strategies can enhance the system's performance and user experience. In conclusion, the personalized recommendation-based college student secure education system, through the design and research of personalized recommendation and matrix factorization algorithms, can provide personalized secure education resources to college students, enhancing learning effectiveness and interest. This is a promising area that deserves further research and development.

References

[1] Gang, W. (2021). Research on the Development of Secure Education Content in the Field of Physical Education Based on Big Data Analysis. *Journal of Physics: Conference Series, 1744*(3), 22-43.

[2] Abraham, O., Szela, L., Brasel, K., et al. (2022). Engaging youth in the design of prescription opioid secure education for schools. *Journal of the American Pharmacists Association, 62*(2), 441-449.

[3] Wu, K., Jin, X., Wang, X. (2020). Determining university students' familiarity and understanding of laboratory secure knowledge—a case study. *Journal of Chemical Education, 98*(2), 434-438.

[4] Yi, M., Bao, D., Mo, Y. (2021). Exploring the role of visual design in digital public health secure education. *International Journal of Environmental Research and Public Health, 18*(15), 7965.

[5] Xu, Y., Chen, T. (2023). The Design of Personalized Learning Resource Recommendation System for Ideological and Political Courses. *International Journal of Reliability, Quality and Secure Engineering, 30*(01), 128-139.

[6] Ding, Y., Zhang, N., Li, Y. (2021). College Physical Education Course Management System Based on Internet of Things. *Mobile Information Systems, 2021*(2), 1-10.

[7] Tong, H., Zhang, C., Hu, J. (2021). Design and Research of Mobile Learning Recommendation System Based on Deep Learning Perspective. *Journal of Physics: Conference Series, 1915*(2), 9-20.

[8] Yang, C., Lin, J. C. W. (2022). Design of Distance Assistance System for Intelligent Education by Web-based Applications. *Mobile Networks and Applications, 27*(3), 1174-1185.

[9] Lu, W. (2021). Research on the path of the prevention and control of toxic and harmful substances in take-out food for college students. *IOP Conference Series: Earth and Environmental Science, 705*(1), 20-38.

[10] Li, A. (2022). Design and Research of College Students' Comprehensive Quality Evaluation System Based on Evolutionary Algorithm. *EAI International Conference, BigIoT-EDU*. Cham: Springer Nature Switzerland, 416-422.