Hierarchical Analysis and Graph Attention Network for University Students' Innovation and Entrepreneurship Learning Platform

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As the boost of the transformation of economy, innovation and entrepreneurship programs have become increasingly important in colleges and universities. Aiming at solving the problem that college students cannot obtain high-quality learning materials and related competition questions when they participate in innovation and entrepreneurship programs. The study firstly constructs the overall framework of the innovation and entrepreneurship platform for college students, and then constructs the cluster KAI model and the competition question model based on hierarchical analysis to portray the core disciplinary competence of college students and recommend the competition questions. Finally, a fusion gated graph-attention group competition topic recommendation model is proposed to complete the recommendation of competition topics and information such as materials by capturing the higher-order features of groups and competition topics. The results show that the research model starts to converge after 462 iterations and the convergence is stable. Meanwhile, when the recommendation list is 12, the model recommendation accuracy reaches 98.2%, the normalized discounted cumulative gain is 0.598, the average inverse ranking is 0.331 and the AUC-ROC detection index is 0.865. It shows that the model constructed by the research has high accuracy and stability. The integration of the research model into the innovation and entrepreneurship learning platform for college students can greatly reduce the corresponding time of the platform, and the comprehensive satisfaction of college student users with the platform is above 85%. Through the platform constructed by the research, students can obtain relevant competition questions and learning resources more accurately, and the outcomes could also offer a theoretical basis for the construction of other platforms of the same type.

Povzetek: Prispevek predstavi platformo za učenje inovativnosti in podjetništva pri študentih s hierarhično analizo in modelom priporočanja tekmovanj s pomočjo grafov. Model izboljšuje priporočanja virov in tekmovanj ter s tem povečuje uspeh študentov pri učenju.

1 Introduction

Innovation and entrepreneurship (IAE) education is an essential section of the teaching reform of higher education and the need to cope with economic transformation and development. College students' (CS) IAE project learning is the key content of IAE education, and the completion of practical projects can enhance students' innovation ability and entrepreneurial spirit [1, 2]. However, under the traditional teaching method, students could only passively accept the knowledge, and it is difficult to apply the learned knowledge for addressing the practical issues [3]. In IAE activities, students need to have self-learning ability, practical ability and resource acquisition ability, etc. However, there are subjective factors in the current way of team formation, which can not be organized scientifically and reasonably. In addition, students with different abilities are unable to participate in competitions matching their abilities, which leads to students' intimidation. These problems have an essential influence on enhancing students' core disciplinary ability and innovation ability. When constructing the learning platform for CS' IAE projects, existing platforms may not accurately match students' personalized learning needs, resulting in a disconnect between the resources provided and the actual needs of students. The cluster model and the competition model can solve the above problems well, but the attributes involved in the construction of these two models are more complicated, so the hierarchical analysis method (AHP) is used to model these two models [4-5]. The AHP method can decompose complex decision-making problems into different constituent factors, and determine the relative importance of each factor through pairwise comparisons, building more scientific and reasonable cluster and competition models. In order to connect the two sets of models effectively, this study designed a graph attention group recommendation model (GGAGR) based on fusion gating. The GGAGR model can accurately capture the mutual influence among members within the group and the correlation features between the group and competition questions, thereby providing more accurate recommendation services. The research and design plan is expected to accurately provide high-quality innovative and entrepreneurial learning resources and scientific team formation for CS. The study is divided into six parts, the second part mainly explains the current research status of experts around the world on learning platforms and group recommendation models in general sense; the third part mainly talks about the overall construction framework of IAE platform for CS, the construction of KAI model, the construction of AHP-based competition model, and the construction of GGAGR recommendation model. The forth part mainly designs experiments to analyze the effectiveness of the research model and the specific utilization effect. The fifth part discusses the results of the paper. The sixth part mainly summarizes the experimental results and puts forward the deficiencies in the research method.

2 Literature review

In order to better promote IAE education for CS, schools and related organizations have established a large number of IAE learning platforms. However, the current platform for CS' IAE programs mainly focuses on project information management, and the platform has a single function that cannot satisfy the requirements. For this reason, many experts and scholars have performed research on the construction of platforms in the general sense. Qian Z and other Jen have studied the insufficiency of intelligent function design in the network teaching platform of colleges and universities, and constructed a personalized learning platform on the grounds of reinforcement learning and data mining (DM) intelligent algorithms. The relevant outcomes demonstrate that when the number of visitors reaches less than 3000, the CPU utilization rate achieves 70% and the performance reduces, but normal operation can still be guaranteed [6].Guan X et al. for the process of scientific and technological achievements into productivity accompanied by a variety of influencing factors, constructed on the grounds of the combination of deep learning and DM technology to establish a platform for science and technology transfer and transformation. The results show that the platform can greatly remove the influence of unfavorable factors on the transformation of technology into productivity [7]. Li H scholars constructed a distance learning platform on the grounds of mobile communication technology for the purpose of realizing the exchange of information between the teaching platform and the traditional campus network. The results show that the distance learning platform can transmit more learning resources to learners faster [8]. Cui Y et al. constructed an intelligent home care service platform on the grounds of machine learning and wireless sensor network around the home living condition, disease stage, physical condition and intellectual status of the elderly. The results show that through the processing and analysis of intelligent algorithms, the platform can provide functions such as health management, emergency rescue, life assistance and social interaction for the elderly, which can effectively enhance the quality of life [9].

Group recommendation can categorize platform users in terms of their interests, expertise and skills and recommend relevant groups for users to participate in. A UDA model was proposed by Zan S et al. as they felt that existing methods were not sufficient for determining the significance of a user in a group. The model compares each user with all other users and then performs a nonlinear transformation using a multilayer perceptron. Experiments on three public datasets show that UDA markedly outperforms other state-of-the-art competing methods [10]. Zhao et al. proposed a point-of-interest group recommendation method on the grounds of Extreme Learning Machines (ELMs) in response to the problem that traditional point-of-interest group recommendation methods only consider aggregating individual preferences into group preferences. It was experimentally demonstrated that the method has high recommendation accuracy and efficiency [11].

Yaln E et al. proposed a personality-aware aggregation technique called Personality Weighted Average (PwAvg) for the problem that the influence of individuals in group algorithms may depend on the user's personality traits, which utilizes the five basic personality traits (openness, pleasantness, emotional stability.) for determining the level of influence of each member of the cluster. The results show that the PwAvg method is able to improve the accuracy and personalization of group recommendations [12]. Yang Q et al. proposed an entropy-based method to address the problem of not being able to balance the requirements of multiple users in a group recommendation system. The method extracts the implicit features of users on the grounds of their historical ratings to obtain the weights of group members. The relevant outcomes showcase that this method achieves essential enhancement in group recommendation performance compared to the baseline method [13]. The summary of several methods for group recommendation is shown in Table 1.

Table 1: Several Group Recommendation Methods

Character	Model	Accuracy	Convergence evaluation
Zan S et al [10]	Group recommendation based on UDA model	86.2%	Multilayer perceptron has good convergence
Zhao et al [11]	ELM based interest point group recommendation	92.2%	Has a fast convergence rate
Yaln E et al [12]	Group recommendation based on Personality Weighted Average	89.3%	Relying on the collection and processing of user personality data, the convergence speed is moderate

Yang Q et al. [13]	Group recommendation based on entropy method	90.2%	The calculation of entropy increases the complexity of the model, and the convergence speed is moderate
Research method	Fusion Gated Graph Attention Group Competition Theme Recommendation Model	98.2%	Fast convergence speed

Based on the research conducted by scholars around the world, group recommendation algorithms have been widely applied in various industries and have achieved good results. However, group recommendation algorithms are rarely applied in the construction of CS innovation and entrepreneurship learning platforms, and the recommendation accuracy still needs to be improved. To this end, a fusion gate graph attention network group recommendation model was proposed, which closely links the KAI model with the competition model, and completes the competition recommendation and related materials and other information through capturing the group and competition.

3 AHP-GGAGR based learning platform design for CS' IAE

In this chapter, the general framework of the IAE platform for CS is firstly constructed, and then the cluster KAI model and the AHP-based competition question model are built. Finally, it constructs a group learning generative network, uses fusion gating and graph attention network to obtain group learning features, and gets the final group embedding vector representation and competition question embedding vector representation, and uses the inner product function to get the corresponding predictive scores, so as to complete the recommendation of the competition questions and related materials and other information.

3.1 Overall construction program of IAE platform for CS

At present, IAE has become one of the important ways for CS to pursue career development and realize the value of life. Thus, the study constructs a platform for CS' IAE according to the specific needs of CS' IAE users, and the business process of this platform is shown in Figure 1.

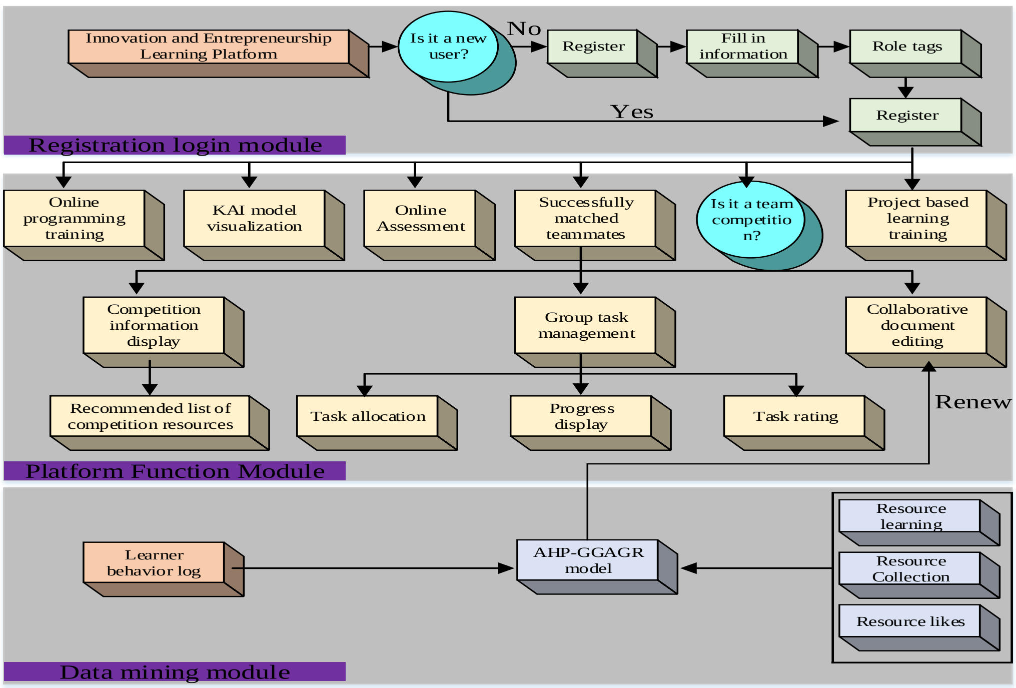


Figure 1: Business flow chart for university students' IAE users.

As shown in Figure 1, the platform business is mainly divided into login and registration module, platform function module, and DM module. CS are required to fill in personal information and select role labels for registration and login. CS can choose to study individually or in teams, evaluate each other after completing the project, and conduct online assessment and programming training. CS can get teammates and competition topic recommendations from the platform, which supports group task management and online collaborative editing, and provides competition-related learning resources. Aiming at realizing the stable operation of the above IAE platform, the study adopts the B/S structure to design the overall architecture of the IAE platform for CS, which is shown in Figure 2 [14].

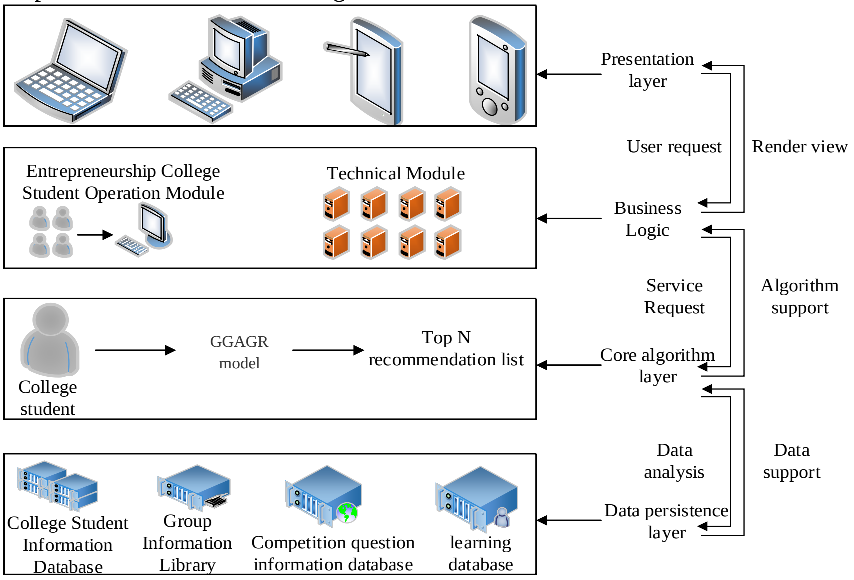


Figure 2: Overall architecture of IAE learning platform for university students.

As can be seen from Figure 2, the whole platform architecture is divided into four layers: data persistence layer, core algorithm layer, business logic layer and representation layer. The data persistence layer is responsible for storing information into the MySQL database and performing data operations through the MyBatis-Plus framework. The core algorithm layer generates the Top-N recommendation list by constructing the cluster learning generation network and updating the learning generation network using graph convolutional network, and finally generating the Top-N recommendation list through the GGAGR model. The business logic layer is the bridge between the representation layer and the data persistence layer and is developed using Java language and SpringBoot framework. The representation layer displays a variety of Web dynamic web pages. The representation layer integrates HTML, CSS, and JavaScript languages and is developed using the Vue framework to provide project learning training, group task management, and other pages.

3.2 Cluster KAI model construction

The IAE learning platform has constructed the cluster KAI model according to the different knowledge, ability and innovation of the CS in order to recommend suitable competition questions for the participating CS, which is shown in Figure 3.

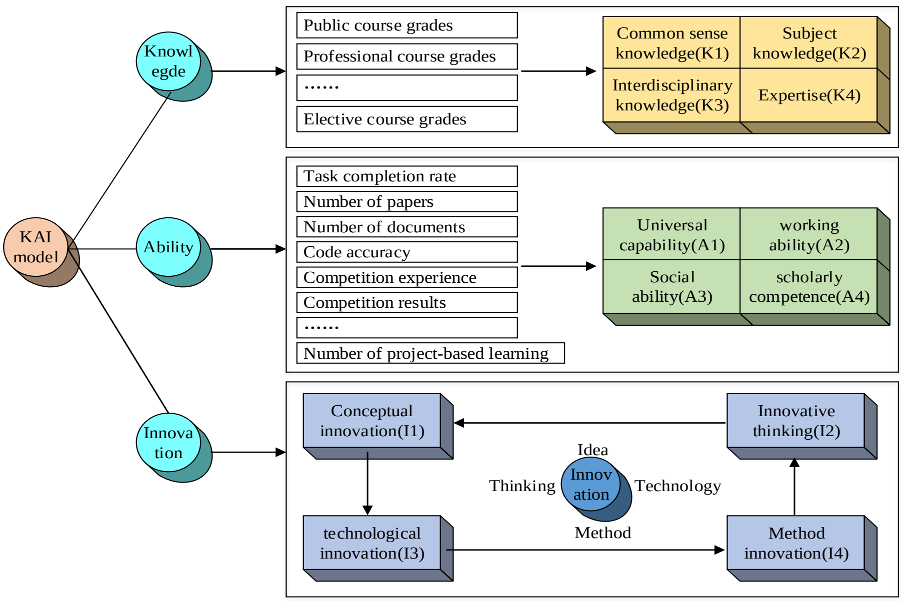


Figure 3: Cluster KAI model architecture.

As shown in Figure 3, the constructed KAI model is divided into three dimensions: knowledge, ability and innovation. For the knowledge dimension, it is divided into four indicators of general knowledge, subject knowledge, specialized knowledge and interdisciplinary knowledge, with the corresponding weights of $w_K\left(K=1,2,3,4\right)$. The KAI model is divided into three levels of $\text{Difficulty}\in\left[0.1,0.3\right]$, $\text{Medium}\in\left[0.4,0.7\right]$ and $\text{Aasily}\in\left[0.8,1\right]$ for the purpose of speculating the difficulty of CS' knowledge of a certain knowledge point k_i in the competition question t_i. Then the statistics of the questions in each difficulty level are showcased in equation (1).

$$\begin{cases} r_i=\left(x,y,z\right) \\ x,y,z\in\left\{0,1\right\} \end{cases} \quad (1)$$

Eq. (1) in r_i is the statistical result; 0 means wrong; 1 means right. The degree of CS' comprehension of the knowledge of the contest questions is shown in equation (2).

$$\begin{cases} f_i=\dfrac{r_i*v_i}{n*v_i},n=3 \\ \begin{cases} rank_1=\dfrac{\sum_{i=1}^{n}\text{Easily}_i}{n} \\ rank_2=\dfrac{\sum_{i=1}^{n}\text{Medium}_i}{n} \\ rank_3=\dfrac{\sum_{i=1}^{n}\text{Difficulty}_i}{n} \end{cases} \end{cases} \quad (2)$$

If the CS' comprehension of the knowledge of the tournament topic belongs to $rangk_1$, it is memorized; belongs to $rangk_2$, it is comprehended; belongs to $rangk_1$, it is applied. So the knowledge dimension of the cluster KAI model is quantified as equation (3).

$$GK=\sum_{i=1,j=1}^{i=n,j=4}f_{ij}W_iw_j \quad (3)$$

Eq. (3) in which f_{ij} is the degree of familiarity of CS i with the knowledge j; W_i is the weight of CS i in the whole cluster; $i=\left\{1,2,3...,n\right\}$ the set of CS in the cluster.

For the ability dimension, it is divided into four indicators: general ability, social ability, academic ability, and engineering ability. These abilities can be measured by the certificates, number of awards, and task completion rate of the cluster members, so the ability attributes of the KAI cluster model are quantified as equation (4).

$$GA=\sum_{i=1,j=1}^{i=n,j=4}A_{ij}W_iw_j^{'} \quad (4)$$

In Eq. (4), A_{ij} serves as the score of CS i on competency j; $w_j^{'}$ serves as the weight of each of the four indicators included in the competency dimension.

For the innovation dimension, it is divided into four indicators: thinking innovation, concept innovation, method innovation, and technology innovation. Because the innovation attributes are jointly determined by the knowledge and ability of CS, the innovation attributes are quantified as equation (5).

$$GI=GK*W_k+GA*W_A \quad (5)$$

In Eq. (5) W_k is the weight of knowledge dimension; W_A is the weight of capability dimension. In summary, the constructed KAI cluster model is shown in

Eq. (6).

$$\begin{cases} G_{KAI}=\left(GK,GA,GI\right) \\ GK=\sum_{i=1,j=1}^{i=n,j=4}f_{ij}W_iw_j \\ GA=\sum_{i=1,j=1}^{i=n,j=4}A_{ij}W_iw_j^{'} \\ GI=GK*W_k+GA*W_A \end{cases} \quad (6)$$

3.3 Model construction of IAE competition questions on the grounds of AHP method

Aiming at recommending the IAE topics to the participating CS that are appropriate to their abilities and knowledge, the study is modeled on the grounds of the current main topics. Let the set of IAE topics be $C=\left\{c_1,c_2,...,c_m\right\}$, and each topic is denoted as $c_i=\left\{c_i^{pf},c_i^{cd},c_i^{tk},c_i^{pa}\right\}$, where c_i^{pf} is the topic's field of specialization, c_i^{cd} is the topic's difficulty, c_i^{tk} is the topic's theoretical knowledge, and c_i^{pa} is the topic's practical ability. The professional field, theoretical knowledge and professional field of the competition question can be obtained directly from the information of the competition question, and the textual information obtained contains a lot of unnecessary information such as stop words and punctuation marks, which need to be pre-processed to remove and normalize the textual information. Then the words of these three attributes are classified and summarized by the expert evaluation method, then each word is regarded as an independent semantic unit, which is transformed into one-hot encoding, and then the customized word embedding is realized by using the PyTorch deep learning framework, and finally the obtained text information of the contest questions is transformed into word vectors by word embedding. The difficulty of the race question is a more abstract attribute, which is difficult to be expressed in the model, so the study adopts the AHP method to quantify the difficulty of the race question. The structural level of constructing the difficulty of the race question is shown in Figure 4.

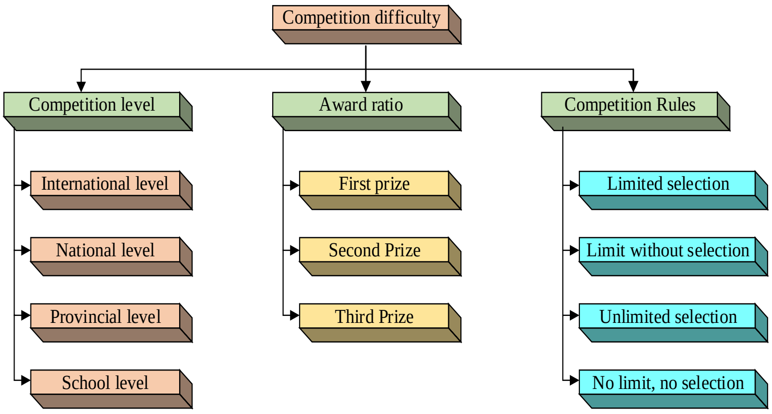


Figure 4: Difficulty level construction of questions.

AHP decomposes complex decision-making problems into different constituent factors and groups these factors according to their dominant relationships to form a hierarchical structure. It quantitatively describes the relative importance of factors in the hierarchy through pairwise comparisons, and then uses mathematical methods to calculate the sub total ranking that reflects the relative order of each element in the hierarchy. It calculates the total ranking of all elements and calculates the total ranking of all elements. As shown in Figure 4, the construction of the competition level includes a number of indicators, and the weights of different indicators are different, so the "1-9 scale method" is utilized for comparing the importance of the indicators in the same layer to determine the weights of the indicators. After comparing all the indicators in the same layer, the judgment matrix of the layer is obtained, see equation (7).

$$M=\begin{bmatrix} 1 & m_{12} & \dots & m_{1n} \\ m_{21} & 1 & \dots & m_{2n} \\ \dots & \dots & \dots & \dots \\ m_{n1} & m_{n2} & \dots & 1 \end{bmatrix} \tag{7}$$

In the matrix, m_{ij} is the element of the j column of the i row, representing the relative importance of the i indicator to the j indicator pair, and $m_{ij}=\frac{1}{m_{ij}}, m_{ij}\geq 0\left(i,j=1,2,\dots,n\right)$. Then according to the judgment matrix of each layer, the maximum eigenvalue of each indicator is calculated $\lambda_{\max}$ and the eigenvector W, and the eigenvector W is normalized to get the weight vector of each layer $\omega=\left(\omega_1,\omega_2,\dots,\omega_n\right)$, see equation (8).

$$\omega_i=\frac{1}{n}\sum_{j=1}^{n}\frac{m_{ij}}{\sum_{i=1}^{n}m_{ij}}\left(i,j=1,2,\dots,n\right) \tag{8}$$

After getting the weight vector, multiply the weights of the layer indicators with their corresponding weight vectors, and then do the normalization in order to get the difficulty of the race C^{cd}, see equation (9).

$$C^{cd}=\delta_{\alpha1}*\omega_{\alpha1}+\delta_{\alpha2}*\omega_{\alpha2}+\delta_{\alpha3}*\omega_{\alpha3} \tag{9}$$

In Eq. (9), $\delta_{\alpha1},\delta_{\alpha2},\delta_{\alpha3}$ is the weight of $\alpha1\sim\alpha3$ in the first-level indicator; $\omega_{\alpha1},\omega_{\alpha2},\omega_{\alpha3}$ is the weight vector of $\alpha1\sim\alpha3$ in the first-level indicator. The constructed competition model C and competition similarity sim are shown in equation (10).

$$\begin{cases} C=\left\{C^{pf},C^{cd},C^{tk},C^{pa}\right\} \\ sim\left(c_i,c_j\right)=1-\sqrt{\left(c_i^{cd}-c_j^{pf}\right)^2+\left(c_i^{cd}-c_j^{cd}\right)^2+\left(c_i^{tk}-c_j^{tk}\right)^2+\left(c_i^{pa}-c_j^{pa}\right)^2} \end{cases} \tag{10}$$

3.4 Construction of IAE competition topic recommendation model on the grounds of GGAGR

In order to link the group owner KAI model and the contest question model, the study constructs a fusion gated graph attention group recommendation model, which is divided into three parts: an embedding layer, a convolutional layer and a prediction layer. First, the initialized vector embedding representation of groups, knowledge and contest questions is performed through the embedding layer [15, 16]. Next, a multilayer convolutional layer is utilized to obtain the higher-order embedding vectors of the clusters and race questions as well as the interaction information between them, and then the final cluster embedding vector representations are updated using a GRU network. Finally, the corresponding predicted scores are obtained by the inner product function of the prediction layer [17], thus accomplishing the recommendation of information such as race questions and related materials. The GGAGR model is a group recommendation model that combines graph attention mechanism and gated loop units, which can improve the accuracy of group recommendations. The structure of the GGAGR model is showcased in Figure 5.

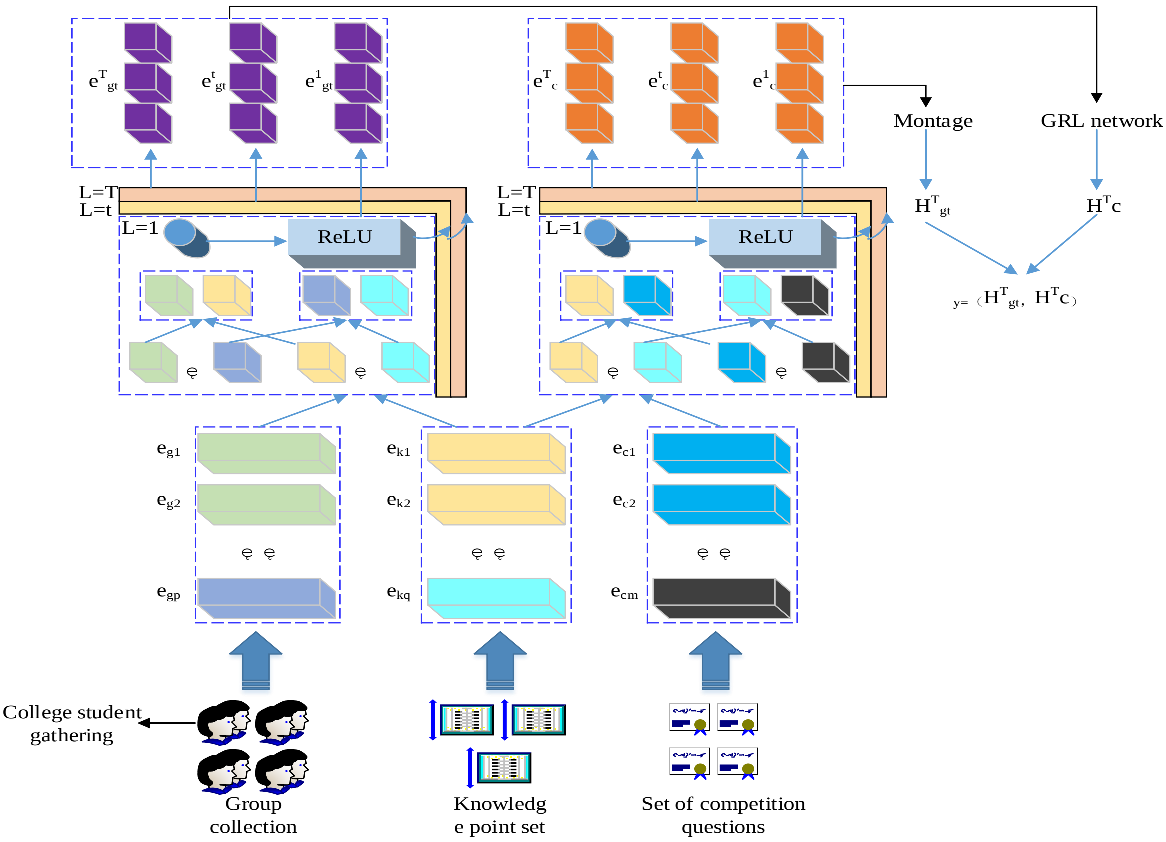


Figure 5: Structure of the GGAGR model.

In Figure 5, let the set of CS be $L=\{l_1,l_2,\ldots,l_k\}$, the set of clusters be $G=\{g_1,g_2,\ldots g_p\}$, and the corresponding embedding of the set of clusters be $e_{g1},e_{g_2},\ldots e_{g_p}$; the target cluster be $g_t=\{l_1,l_2,\ldots l_n\}$; the set of knowledge points be $K=\{k_1,k_2,\ldots k_q\}$, and the corresponding embedding of the set of knowledge points be $e_{k1},e_{k_2},\ldots e_{k_q}$; and the set of race questions be $C=\{c_1,c_2,\ldots c_m\}$, and the corresponding embedding be $e_{c1},e_{c_2},\ldots e_{cm}$. At the time of embedding, *Xavier* is used to initialize the vector representations of college student groups, knowledge of questions and questions. The embedding matrices of "Student Groups - Question Knowledge" $E_{G,K}$ and "Question Knowledge - Question Topics" $E_{K,C}$ are obtained, see Eq.(11).

$$\begin{cases} E_{G,K.}=\left[e_{g1},e_{g2},\ldots,e_{gp},e_{k1},e_{k2},\ldots,e_{kq}\right] \\ E_{K,C.}=\left[e_{k1},e_{k2},\ldots,e_{kq},e_{c1},e_{c2},\ldots,e_{cm}\right] \end{cases} \tag{11}$$

In the convolutional layer, graph convolution is used to capture the information and perform embedding propagation [18]. The information encoding function $f(.)$ is first defined so as to realize the information propagation in the $l=t$ layer in the convolutional layer, see equation (12)

$$m^t_{g_t\leftarrow k_t}=\frac{1}{\sqrt{\left|N_{g_t}\right|\left|N_{k_t}\right|}}\left(W^t_{e_{gt}}+M^t\left(e^{t-1}_{gt}\odot e_{kt}\right)\right) \tag{12}$$

In Eq. (12), $|N_{gt}|$ is the number of students in the college cluster; $|N_{kt}|$ is the number of interactive knowledge points in the college cluster; W^t and M^t are the parameter matrices; e_{gt}^{t-1} is the aggregation function in the $t-1$ layer; $\square$ is the Hadamard product. Then the disseminated information is aggregated to get the enhanced embedding vector of the university clusters or questions, and the aggregation function e_{gt}^t in the t layer is shown in Eq. (13).

$$e_{gt}^t = \sum_{i\in|N_{kt}|} \alpha(g_t, k_t) \cdot Leaky\,\mathrm{Re}\,LU\left(W_1^t e_t^{t-1} + m_{g_t \leftarrow kt}^t\right) \tag{13}$$

In Eq. (13), $\alpha(g_t, k_t)$ is the attention coefficients normalized by the $soft\max$ function; $Leaky\,\mathrm{Re}\,LU$ is the activation function; and W_1^t is the parameter matrix. Then the output of g_t from the convolutional layer is updated by GRU network to get the final embedding vector H_{gt}^T, see Eq. (14).

$$H_{gt}^T = GRU\left(H_{gt}^{T-1}, e_{gt}^T, \theta\right) \tag{14}$$

Similarly, the race title embedding quantity H_c^T ,can be obtained through the convolutional layer, see equation (15).

$$H_c^T = e_c^0 \left\|e_c^1\right\| \ldots \left\|e_c^T\right\| \tag{15}$$

In Eq. (7) θ is a parameter in the GRU network. After obtaining the cluster embedding vectors and the race embedding vectors, the inner product method is used to construct the recommendation function, see equation (16).

$$y\left(H_{gt}^T, H_c^T\right) = \left(H_{gt}^T\right)^T \square H_c^T \tag{16}$$

For this recommendation function model, the loss function is calculated as showcased in equation (17) [19].

$$\begin{cases} L_{gt} = -\sum_{(gt,i,j)\in R} \ln \varepsilon\left(y_{gt,i}, y_{gt,j}\right) + \lambda_{\square} \left\|\otimes\right\|^2 \\ \varepsilon(x) = \dfrac{1}{1+\exp(-x)} \end{cases} \tag{17}$$

Eq. (17) where R is the set of triples of the training set; $\lambda_{\square}$ is the regularization coefficient.

4 Performance analysis and application analysis of AHP-GGAGR IAE recommendation model

In this chapter, the corresponding experimental environment and dataset were constructed, and the convergence, accuracy, ROC curve and other metrics of the model were tested. Then the model was integrated into the IAE platform, and the corresponding time, customer satisfaction and other metrics of the platform were tested, and all the results were analyzed and discussed.

4.1 Performance analysis of recommendation models

Aiming at verifying the effectiveness of the recommended model constructed by the research, the basic hardware environment and model parameters of the experiment are set up as showcased in Table 2.

Table 2: Basic hardware environment and model parameters for the experiment

1 Project	2 Parameter
3 Operating system	4 Windows 10
5 System PC side memory	6 16G
7 CUP	8 Intel Core i9
9 Storage	10 256GB SSD
11 Graphics card	12 NVIDIA GGTX 1060
13 Development tool	14 Pycharm 3.6, Anaconda 3
15 Deep learning framework	16 PyTorch 1.2.0
17 Embedding dimensions	18 32
19 Convolutional layer parameter initialization	20 Gaussian distribution
21 Learning rate η	22 0.005

The dataset required for the experiment is selected from the tournaments of students participating in IAE competitions from January 2017 to January 2022 in a university and the background data of IAE learning platform. The dataset contains 87 IAE competition events such as "China "Internet+" CS' IAE Competition", "National CS' Extracurricular Academic and Scientific and Technological Works Competition", "Wireless Motion Sensor Node Design", "Design of Wireless Motion Sensor Nodes", "Measurement of Size and Morphology of Non-Etched Objects", and other 598 competition questions, 653 college student competition groups, with 1254 participants, involving 14653 competition knowledge points, and the number of group-competition question interactions is 25687 times, and the number of group-knowledge point interactions is 86354 times. The dataset was divided into training set, testing set and validation set according to the ratio of 70%:20%:10%.

In order to demonstrate the achievability and excellence of the models constructed in the study, the recommendation model on the grounds of the fusion strategy of Nash equilibrium (Model 1), the group recommendation model on the grounds of the attention factor decomposer (Model 2), and the recommendation model on the grounds of the stochastic wandering strategy (Model 3) are selected to compare with the models constructed in the study. Firstly, the convergence of four models was tested, which can be used to evaluate the stability of the models during long-term operation. The results are shown in Figure 6.

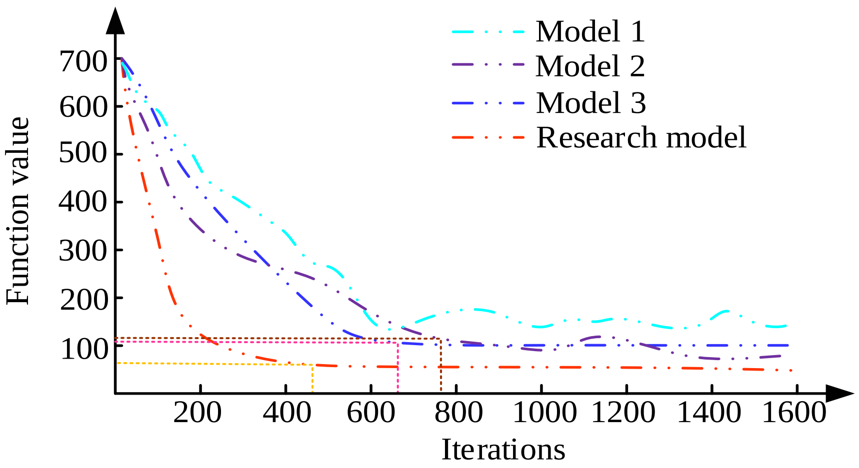
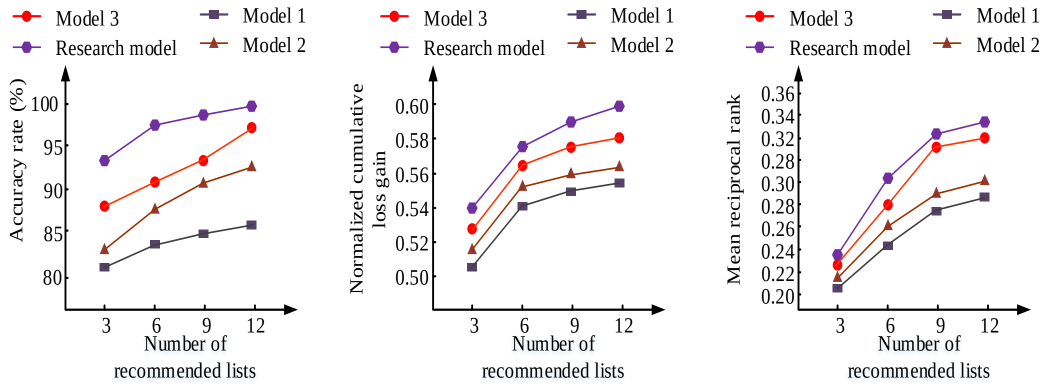


Figure 6: Convergence test results of four models.

Figure 6 demonstrates that when the number of iterations reaches 462, the research model begins to converge, and the convergence performance is stable, with a convergence degree of about 78; when the number of iterations reaches 669, model 3 begins to converge, and the convergence is also more stable, with a convergence degree of about 105. This is because the random walk strategy itself has a certain degree of randomness, which requires more exploration in the process of finding the optimal solution. when the number of iterations reaches 669, model 2 begins to gradually converge, but its convergence performance fluctuates slightly. This is because the convergence process of Model 2 is influenced by the complexity of the attention mechanism. The attention mechanism needs to consider multiple factors when allocating weights, which leads to unstable weight allocation during the iteration process and ultimately affects the convergence performance of Model 2. And the convergence performance of model 1 shows obvious fluctuations and does not have stable convergence. This is because the Nash equilibrium fusion strategy faces high complexity in finding the optimal solution, resulting in unstable convergence of the model. The research model has higher efficiency because the lower the iterations, the lower the training time and computational resource consumption of the model, so the research model has higher efficiency. Next, the number of recommendation lists of the model is set to 3, 6, 9, and 12, and the accuracy of the recommendation results, the cumulative gain of normalized discount, and the average inverse ranking of the model are tested, and the relevant outcomes are showcased in Figure 7. Accuracy is an important indicator for measuring the consistency between the predicted results of a model and the actual results. In recommendation systems, high accuracy means that the model can predict users' preferences more accurately, thereby providing more personalized recommendations. The cumulative gain of normalized discounts is an important indicator for evaluating the quality of ranking results, especially in recommendation systems, where it measures the quality of the entire ranking list by assigning higher weights to the top ranked related results. The closer the NDCG value is to 1, the more the sorting result meets the user's expectations and preferences. The average inverse ranking of the model measures the reciprocal of the average ranking of the items actually selected or clicked by users in the recommendation list. A higher MIR value means that users are more inclined to choose recommended items that rank higher.



(a) Hit rate test results

(b) Normalized loss cumulative gain test results

(c) Average reciprocal ranking test results

Figure 7: Model's recommendation result accuracy, normalized discounted cumulative gain, and average inverse rank test results.

Figure 7(a) shows the accuracy test results of the four recommendation models, it can be seen that the recommendation accuracy of the research model is always the highest, and in the recommendation list is 12, the recommendation accuracy of this model can reach 98.2%, while the accuracy of model 1, model 2 and model 3 are 84.6%, 93.2% and 96.4% respectively. Figure 7(a) shows the results of the model's normalized discounted cumulative gain test, which measures the quality of the ranking of recommendation lists. When the number of recommendation lists is 12, the normalized discounted cumulative gains of the research model, model 1, model 2, and model 3 are about 0.598, 0.548, 0.561, and 0.576, which shows that the research model has the best recommendation quality. Figure 7(c) shows the average inverse ranking of the model, which is a metric measure representing the inverse of the ranked position in the recommendation list of the items that CS choose to interact with. Again, when the number of recommendation lists is 12, the average inverse of the research model, model 1, model 2, and model 3 are 0.331, 0.272, 0.293, and 0.294, which is still the research model with the largest value. It showcases that the method used in the research model is more conducive to improving the effectiveness of the cluster recommendation model. This is because Model 1 is not flexible enough to be directly applied in recommendation systems, making it difficult to fully adapt to the dynamic and complex nature of recommendation tasks. Model 2 is highly effective in handling sequential data and complex interactions, but there are shortcomings in effectively integrating the attention weights of different users and achieving group consensus in group recommendation. Model 3 is mainly used for node recommendation in graph data, but its simplicity limits its performance in accurately matching user preferences and group needs. Aiming at validating the effectiveness of the model constructed by the study, the performance of the model was evaluated using the ROC curve and the results are shown in Figure 8. The ROC curve can evaluate the stability and generalization ability of a model.

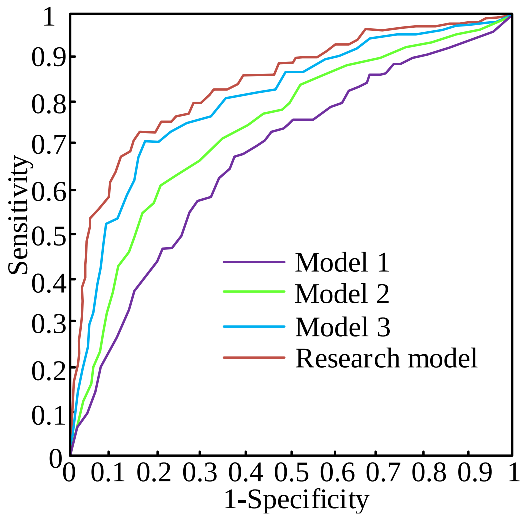
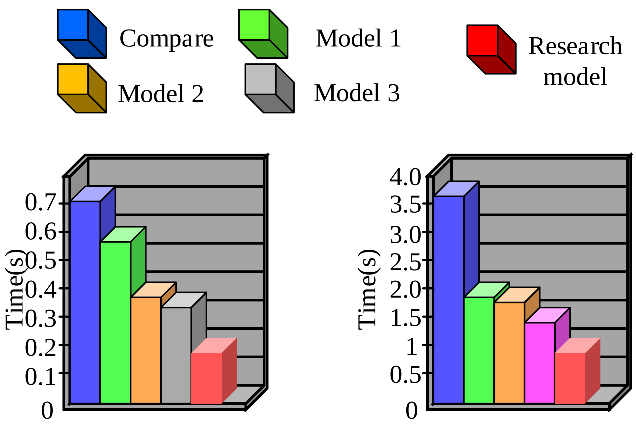


Figure 8: ROC curves for the four recommendation models.

As shown in Figure 8, the four models have different AUC-ROC indicator values. Among them, the research model has the highest AUC-ROC index, which is 0.865; while the recommended model 1 has the lowest AUC-ROC index, which is only 0.621. This indicates that the research model has the strongest performance in predicting whether CS will accept the recommended tournament topics or not, while the predictive ability of model 1 is relatively weak. The used more suggests that the research model is suitable to be applied in the IAE learning platform for CS.

4.2 Application analysis of recommendation modeling

The four models were integrated into the IAE learning platform for CS, and 1,000 CS who had just registered the IAE learning platform for CS were selected as the experimental subjects. Using a controlled experiment, the 1,000 new users were divided into five groups, in which the CS in the four groups used the IAE learning platform integrated by the research model, model 1, model 2 and model 3, while the CS in the control group did not take any action. The background of each student was collected and a questionnaire was administered to each student as a data base to assess the combined effect of the innovative entrepreneurial learning platforms integrated by different models. First, take a provincial "Internet+" IAE competition in 2023 as an example, test the response time of the platform to the competition questions and learning resources, see Figure 9.



(a) Competition questions (b) Resources

Figure 9: Response time of the platform in providing competition questions and learning resources.

Figure 9(a) demonstrates that the response time of the platforms integrated with different models to provide the contest questions is different, and the response time of the platform without integrating the recommendation model is the longest, which is about 0.73 s. And after integrating the recommendation model, the response time of the platforms has a substantial reduction. The response time of the platform integrated with Model 1, Model 2, and Model 3 is 0.57s, 0.37s, and 0.34s, respectively, while the response time of the platform integrated with the research model is the lowest, 0.18s. And from Figure 9(b), the response time of the platform to provide the learning materials is much longer than that of the platform to provide the contest questions. Still the platform without integrated recommendation model has the longest response time, which is about 3.78 s. The response times of the platforms integrated with model 1, model 2, model 3 and the research model are 1.9 s, 1.8 s, 1.4 s, and 0.9 s, respectively. This suggests that integrating the recommendation model improves the efficiency of the platforms and the user experience, so that the users can get the needed competition questions and study materials faster, and the research model has better performance. Next, the background data of each platform is used to observe the number of new user registrations, if the information provided by the platform is accurate and effective, more users are bound to log in, and the results are shown in Figure 10.

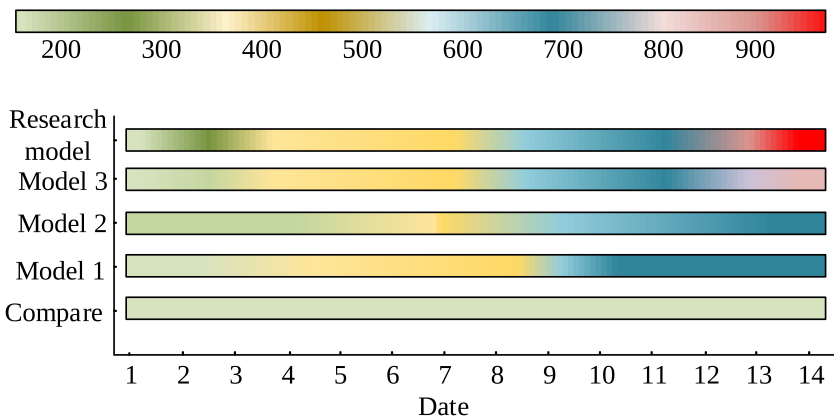


Figure 10: Increase in new users by platform.

As can be seen in Figure 10, the number of new users of each platform changed within two weeks of using the IAE platform. The platform integrated by the research model grew the most from the initial 200 people to nearly 900 people. The number of new users for the platforms integrated with Models 1 and 2 grew to nearly 700, and the number of new users for the platform integrated with Model 3 grew to nearly 800. The number of new users on the traditional platform increased the least, only to about 300. Finally, a questionnaire was used to collect CS' satisfaction with the platform's recommended information for collection, and the results are shown in Figure 11.

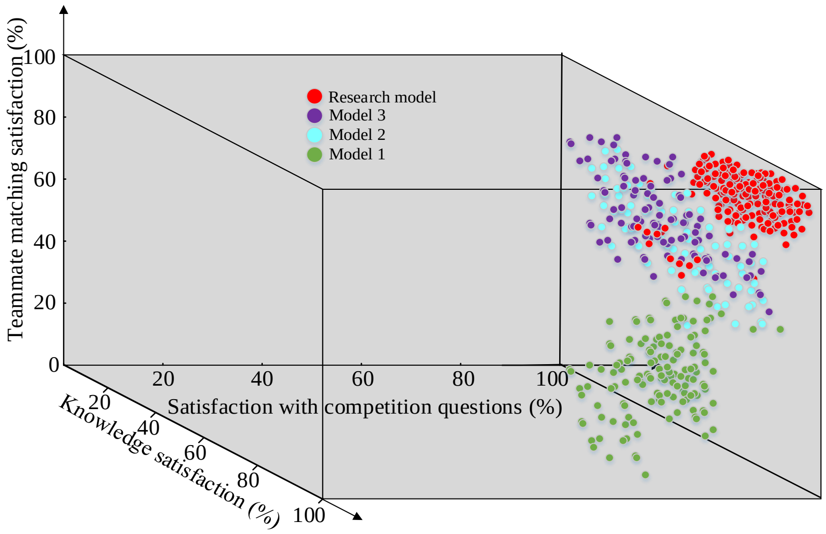


Figure 11: Results of the survey on university students' satisfaction with the platform's recommended information.

Figure 11 shows the results of the survey of CS' satisfaction with the three dimensions of competition question information, question profile information and matching teammates provided by the platform, which shows that the platform integrating the research model achieved satisfactory results in all aspects, with a combined satisfaction rate of almost 85% or more. The platform integrated with Model 2 and Model 3 has the next highest satisfaction level, which is about 60%-70%. The platform integrated with Model 3 has the lowest overall satisfaction level, which is about 50%.

5 Discussion

In terms of improving recommendation accuracy, Zan et al.'s method enhances the model's expressive power by using multi-layer perceptrons for nonlinear transformation. However, the computational complexity is high and not suitable for large-scale datasets, resulting in low recommendation efficiency [10]. The methods mentioned in this article are suitable for scenarios that require high accuracy and personalized recommendations, and have large datasets. Zhao et al.'s method can quickly aggregate individual preferences into group preferences, improving recommendation efficiency. However, this recommendation model is mainly suitable for point of interest recommendation [11]. The method mentioned in this article has generalization ability and is applicable to various recommendation scenarios. Yaln et al.'s method considers the influence of user personality traits on individual influence within a group, and improves the personalization and accuracy of group recommendations through personality weighted averaging. However, it requires additional collection of a large amount of user personality data, which increases the difficulty and cost of data collection, and has poor adaptability [12]. The method mentioned in this article can use historical data as a recommendation basis and has high recommendation accuracy. Yang et al.'s method uses entropy theory to determine member weights, thereby improving the fairness of recommendations. But it cannot fully capture the complex relationships between users [13]. The method mentioned in this article integrates gate graph attention mechanism and group competition topic model to accurately capture the mutual influence among members within the group and the correlation characteristics between the group and competition problems, providing more accurate recommendation services.

6 Conclusion

It is extremely important to provide accurate information to CS involved in IAE, recommending tournament information matching their abilities as well as scientific grouping. To this end, the research designed an IAE platform, and in order to realize the business requirements of the platform, the group KAI model and the AHP competition tournament model were constructed, and then the GGAGR recommendation model was constructed on the grounds of them. The results show that the research model started to converge after 462 iterations and the convergence was stable. Relative to the other three models, the model took less time and resources to train. At the same time, the model's recommendation accuracy is also higher, when the recommendation list is 12, the model recommendation accuracy reaches 98.2%, which is 1.8% higher than the highest among the other three models. At this point, the model also has the highest normalized discounted cumulative gain of about 0.598. indicating that the research model possesses a more superior performance. The ROC curve of the model was evaluated and the research model had the highest AUC-ROC metric of 0.865. indicating that the research model had the strongest performance in predicting whether CS would accept the recommended tournament topics. The model constructed by the research is integrated into the IAE learning platform for CS, and the corresponding time for the platform to provide competition questions and related information is 0.34 s and 0.9 s. The comprehensive satisfaction of college users with the information provided by the platform is 85%. Above. The above data show that the method adopted in the study can provide the corresponding resources for the participating CS accurately. However, there are still about 15% who are dissatisfied, and the follow-up study will further understand the specific reasons and optimize the platform accordingly.

Ethics declaration

This study was performed in line with the principles of the Declaration of Helsinki, and approval from the Ethics Committee is obtained.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Data availability statement

All data generated or analysed during this study are included in this article.

Conflict of interest

The authors declare that they have no competing interests.

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