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Deep learning model based e-tendering strategy and corporate sustainability

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ABSTRACT

Under the background of the current information age, the electronic and intelligent transformation of the bidding industry has become an inevitable trend, and the e-bidding model stands out and greatly improves people's understanding of bidding. Aiming at the traditional e-bidding system, in order to solve the problem of the lack of the traditional e-bidding system that provides the bidding body with referable opinions, this study firstly constructs the e-bidding risk assessment indexes and realizes the optimization of the evaluation module of the system. Then the recommendation algorithm based on deep learning implements the optimization design of the e-header bidding system. This study constructs an optimized recommendation model by fusing knowledge graphs on the basis of deep learning. Then the e-tendering optimization system is designed according to the actual needs of e-tendering, combined with the recommendation model of this paper. The accuracy index ACC of this paper's recommendation model is improved by about 3% on average compared with other best-performing recommendation models on each dataset, which verifies the excellent performance of this paper's recommendation algorithm. This study constructs an optimized e-tendering system and proposes suggestions for the development and operation strategy of corporate e-tendering, contributing to the development of e-tendering transactions and the participation of social capital.

Keywords: deep learning; knowledge graph; recommendation model; e-tendering; e-tendering system

1. Introduction

With the continuous development of bidding and procurement, electronic bidding has gradually deepened its attention and application due to its advantages of improving bidding efficiency, saving costs, standardizing processes, and improving transparency, and various regions and fields have begun to explore the use of electronic bidding to carry out bidding and procurement work [1-4]. For bidding enterprises, promoting the construction of electronic bidding system and realizing the integration of network

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technology and traditional industry will be the key work of the management and bidding industry in the future [5-6].

The purpose of implementing an e-tendering system is to create a fair and equitable market environment and to optimize the allocation of resources through fair competition. Publishing the bidding announcement on the designated website enables all bidders to obtain equal bidding opportunities, bidders can register online to participate in the voting, and inquire about the bidding matters online, bidders can answer the bidder's query online, while bidders can be informed of the content of the answer at the same time [7-9]. Electronic bid evaluation, on the other hand, is to present the required data of the bid evaluation process in a quantitative form and take a digital mode of evaluation, which is essentially to analyze the reasonableness of the bidder's offer, provide a scientific basis for the bid evaluator's scoring, reduce the factors of human interference, and avoid the malicious manipulation of the evaluation of bids, so as to improve the fairness of the evaluation of bids and avoid unfair competition [10-12]. The implementation of electronic bidding, intermediaries only need to upload the relevant bidding documents to the network platform through the network platform, the competent authorities can be timely review on the network platform, thus improving work efficiency, shortening the work cycle, and the work cost can also be effectively reduced. Electronic bidding is a new mode of engineering transactions, greatly saving the high cost of traditional paper bids, reduce the transaction costs of the bidding party [13-15].

The data information of traditional bidding is only managed by manual registration and re-entry, which is a cumbersome and repetitive working method and consumes a lot of labor costs, and the data update can not be synchronized with the poor correlation, which is easy to make the management and business disconnect [16-18]. And through the electronic network platform to collect relevant data information directly, can improve the relevance of the data, and achieve a better linkage effect. Electronic bidding process is rigorous, the data information is real and reliable, after a certain accumulation can form a large number of effective data information, realize the information management, is conducive to the bidding parties to summarize and analyze the data in a timely manner, to promote the improvement of the business level, and can enable the government regulatory departments to grasp the current situation of the bidding and the development trend, so that the government's macroscopic decision-making to provide accurate data [19-21].

Through the deep analysis of the traditional e-tendering system, this study finds that the traditional e-tendering system lacks the recommendation function for the bidding subject. In order to improve the use experience of the bidding subject, this paper combines deep learning and knowledge graph fusion to construct a recommendation model for e-tendering, and optimizes the e-tendering system based on risk identification and recommendation model. In order to ensure the effectiveness of the recommendation function of the e-tendering system in this paper, the performance of the recommendation model was tested, and its performance was compared with that of other recommendation models. After experimentally verifying the performance of the recommendation model in this paper, the construction of the e-bidding optimization system is finally completed, and strategies and suggestions are put forward for the development of enterprise bidding.

2. Deep learning based e-tendering system

2.1. Electronic bidding system

E-tendering means that through computer, network and other information technologies, the bidding business is reorganized, the workflow is optimized and reorganized, and a series of amateur operations such as online bidding, tendering, bid opening, bid evaluation and supervision and monitoring are carried out on the network, which ultimately realizes the bidding management with high efficiency, professionalism, standardization, safety and low cost.

E-tendering system is a brand-new bidding method established on network information platform, which breaks the regional and time limitations of traditional bidding and saves a lot of time and capital costs of both sides of the bidding and at the same time increases the transparency of the bidding process so that both sides of the bidding and the bidding can have more full and timely communication and improve the efficiency of bidding and tendering activities. Electronic bidding also uses electronic information technology to solidify the bidding process, standardize the operation process, so as to eliminate the implementation of deviation. The biggest difference between electronic bidding and traditional bidding is that the electronic bidding system uses a computerized bid evaluation system, which greatly improves the efficiency of bid evaluation, reduces the interference of human factors, reduces the workload of the evaluation committee experts, and improves the quality of bid evaluation.

The basic framework of the electronic bidding system is shown in Figure 1. The electronic bidding system is generally composed of three parts: electronic bidding and tendering transaction platform, electronic bidding and tendering public service platform, and electronic bidding and tendering administrative supervision platform.

The electronic bidding and tendering transaction platform is an Internet information platform for realizing bidding and tendering transaction activities. The transaction platform is constructed and operated by the enterprise legal person, adopting the safe market-oriented operation mode, and the transaction platform needs to reflect the whole transaction process of electronic bidding.

The public service platform is a service platform that provides all kinds of information for the main body of the transaction, the supervisory and management departments and the general public. The public service platform gathers all the information submitted by the transaction platform, meets the exchange of information between the transaction platforms, as well as the latest news of the government supervisory departments, and realizes the sharing of the resources of all parties. The public service platform gathers all the electronic bidding information, and bidders save the trouble of browsing multiple trading platforms to find information.

The administrative supervision platform is an information platform that realizes online real-time supervision of electronic bidding and tendering activities by administrative supervision and management departments and supervisory authorities. The administrative supervision platform is operated and managed by government departments to supervise and control the e-tendering process, and also accepts complaints and reports.

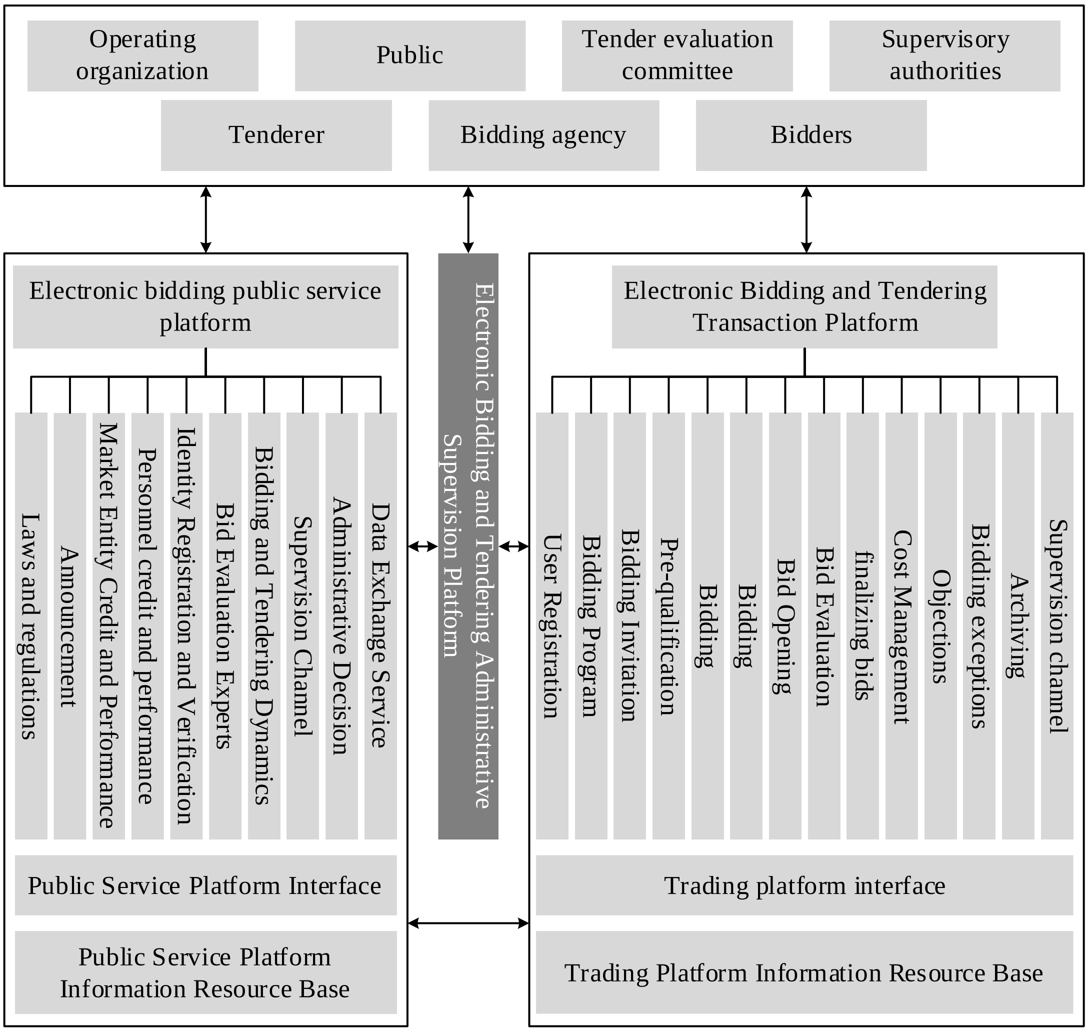


Fig. 1. The basic framework of the electronic bidding system

2.2. Risk assessment system for e-tendering

Risk management starts with identifying and assessing risks, quantifying the degree of uncertainty and the degree of loss caused by the risk, and then controlling the risk in a positive and reasonable way (e.g., risk transfer, risk avoidance, etc.), with the goal of increasing the probability of the occurrence of a positive event and the scope of the positive impact, and minimizing the extent of the loss and the adverse consequences, and finally, to ensure the achievement of the overall goal at a cost acceptable to the subject of the risk. Management process.

Risk identification is the first step of risk management, and by measuring, mastering and applying risk identification methods, we can comprehensively and accurately discover and identify risks and prevent risky accidents from occurring. This study is based on text mining to identify the risk factors of e-tendering, establish a text mining model through text recognition collection, identify the risk of e-tendering after data preprocessing, and establish a risk identification model for the e-tendering system.

2.2.1. Risk identification indicators for e-tendering. After streamlining and categorizing the key points of risk to derive the first and second level indicators of risk, the next step is to quantitatively analyze each factor of e-tendering, and firstly, use the hierarchical analysis method to construct the e-tendering risk assessment

The next step is to quantitatively analyze each factor of e-tendering, firstly, using hierarchical analysis to construct a risk assessment system for e-tendering, which mainly includes 6 risk level 1 indicators and

20 risk level 2 indicators. The first-level indicators include system risk (A), information risk (B), management risk (C), environmental risk (D), technology risk (E), technical risk and credit risk (F).

Level 2 indicators for system risk (A) include system failure (A1), network operating environment (A2), facility service risk (A3), computer virus (A4) and system compatibility (A5).

The secondary indicators of information risk (B) include information leakage (B1), storage risk (B2), transmission risk (B3) and extraction risk (B4).

The secondary indicators of management risk (C) include management level (C1), extraction risk (C2), review risk (C3) and supervision and management (C4).

The secondary indicators of environmental risk (D) include natural environment (D1), social environment (D2) and emergencies (D3).

Technology risk (E) secondary indicators include participant technology level risk (E1), failure contingency (E2) and demand risk (E3).

Credit Risk (F) Level 2 indicators include security risk (F1), contract risk (F2), and malicious competition risk (F3).

The weights of the second-level indicators are shown in Table 1, and it can be seen that the top-ranked weights of the second-level indicators are information leakage (0.1045), contingency (0.0895), transmission risk (0.0798), contract risk (0.0752) and system compatibility (0.0751).

Table 1. Secondary index weight

Primary indicator	Secondary indicator	Secondary index weight
A	A1	0.0248
	A2	0.0254
	A3	0.0751
	A4	0.0235
	A5	0.0311
B	B1	0.0812
	B2	0.0145
	B3	0.0798
	B4	0.0321
C	C1	0.0298
	C2	0.0642
	C3	0.0135
	C4	0.0123
D	D1	0.0123
	D2	0.0485
	D3	0.0895
E	E1	0.0354
	E2	0.0489
	E3	0.0450
F	F1	0.0395
	F2	0.0752
	F3	0.0157

2.2.2. Risk analysis of e-tendering. In this paper, through the e-tendering risk analysis module on the risk study according to the actual situation of SX company's e-tendering, the risk level is divided into five levels, high risk, higher risk, general risk, lower risk and low risk, corresponding to the score of 5, 4, 3, 2, 1. The results of the risk analysis of e-tendering are shown in Figure 2.

It can be seen that system risk (A) and technology risk (E) have the greatest impact on SX Company's e-tendering and the highest degree of risk, which are 2.423 and 2.541 respectively, so it is necessary to take more effective and targeted measures to control it as soon as possible, to avoid serious consequences affecting the company's development, and at the same time, deeply cultivate the technological level and optimize the development of e-tendering technology. Management risk (C) and environmental risk (D) are of average level, and only reasonable measures should be proposed for their key risk factors. Information risk (B) is relatively low, below 2 points, but it cannot be ignored and reasonable and effective measures should be taken to protect it.

According to the systematic calculation and the index level division score formulated in the comment set, SX Company's e-tendering risk is 2.2369, and according to the risk index level, 2.2369 belongs to the range between lower risk and general risk, which tends to be lower risk. In summary, the risk level of SX Company's e-tendering is low.

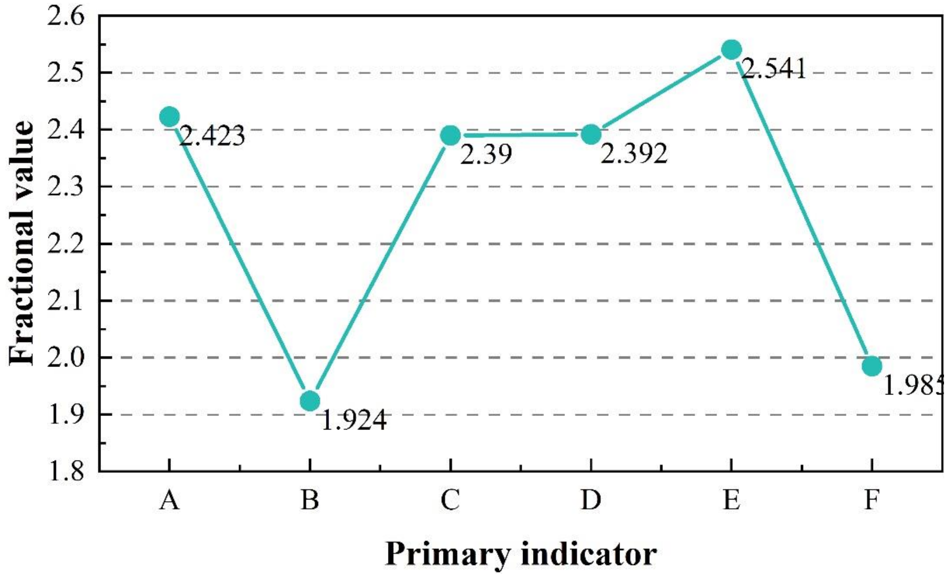


Fig. 2. Results of the risk analysis of electronic tendering

2.3. Deep learning based bidding recommendation

2.3.1. Deep learning based recommendation algorithms. Traditional recommendation algorithms mainly include collaborative filtering-based recommendation, content-based recommendation, and hybrid recommendation, etc. These traditional algorithms play an important role in coping with information overload and realizing personalized recommendation. However, with the increase of data size and the continuous change of user needs, the traditional algorithms gradually expose some defects.

Deep learning is an approach based on the structure of multilevel neural networks, which solves complex pattern recognition and prediction tasks by learning a multilevel representation of data. Deep neural networks have attracted the attention of researchers with their powerful representational ability, which is very favorable for learning from complex big data, which naturally brings new opportunities for the development of recommendation technology. The deep learning recommendation model framework is shown in Figure 3. The deep learning recommendation framework enables rapid evolution and continuous optimization to adapt to the development and changes in the recommendation system. The main improvement directions of the algorithm are model complexity, combining models, and combining attention mechanisms. Compared to traditional recommendation algorithms, deep learning models are able to better capture the complex relationships between data, thus providing more accurate recommendation results.

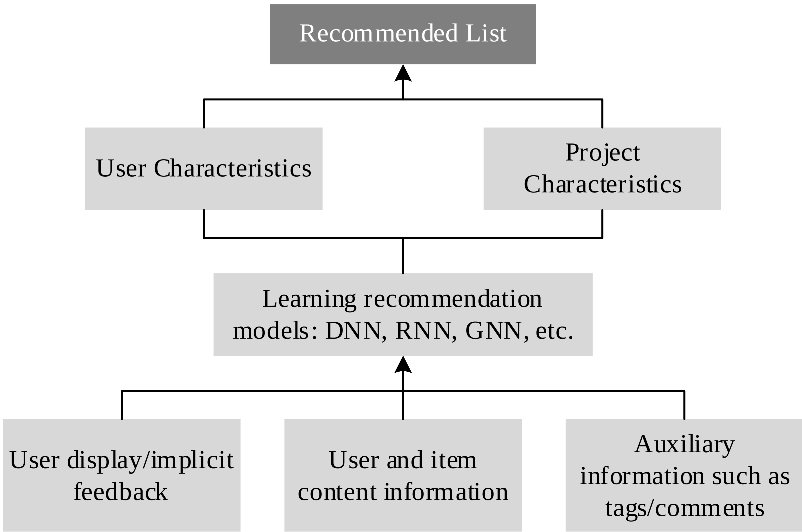


Fig. 3. Recommendation model framework for deep learning

The classical deep learning recommendation algorithms are Wide&Deep, DeepFM, NeuralCF, and DIN algorithms. Among them, DIN is a deep interest network model. since most of the traditional models lack the capture of the two key points of diversity and local activation, DIN introduces an attention-like network structure to locally activate the relevant interests, which can better capture the specific structure of the behavioral data and at the same time bring about an improvement in the performance of the model.DIN follows two data structures by replacing the embedding vectors of the user U with a function of the embedding vectors of the item in question A embedding vectors as a function of Eq. (1). Where V_i is the embedding variable for behavior id, V_u is the weight sum of all behaviors id, and w_i is the attention score for the overall user interest embedding vector for candidate item A at behavior $id = i$, the output of the activation attention mechanism module:

$$V_u = f\left(V_a\right) = \sum_{i=1}^{N} w_i * V_i = \sum_{i=1}^{N} g\left(V_i, V_a\right) * V_i \tag{1}$$

In order to further improve the convergence speed and performance of the model, DIN also designed a new activation function Dice based on PReLU. PReLU was proposed by HeK et al. It is a is a parameter-corrected linear unit, which efficiently improves the performance of the model with almost zero extra computation and a small risk of overfitting.

In order to further improve the convergence speed and performance of the model, DIN also designed a new activation function Dice based on PReLU. PReLU was proposed by HeK et al. It is a is a parameter-corrected linear unit, which effectively improves the model's fitting ability with almost zero extra computation and a small risk of overfitting, i.e., it degenerates into a ReLU function when a_i is 0, and degrades into a ReLU function when a_i is a very small fixed value, then it degenerates to LReLU. PreLU is calculated as:

$$f\left(y_i\right) = \begin{cases} y_i & if y_i > 0 \\ a_i y_i & if y_i \le 0 \end{cases} \tag{2}$$

The Dice activation function is given by:

$$y_i = a_i\left(1 - p_i\right) y_i + p_i y_i \tag{3}$$

$$p_i = \frac{1}{1 + e^{-\frac{y_i - \varepsilon_0}{\sqrt{Var[y_i] + \varepsilon}}}} \tag{4}$$

And for the problem of overfitting generated during the training process, an adaptive regularization method is introduced in DIN, which applies different regularization strengths to the feature ids according to their frequency of occurrence, which is given by Eq:

$$I_i = \begin{cases} 1, & \exists\left(x_j, y_j\right) \in B, s.t.\left[x_j\right]_i \neq 0 \\ 0, & otherwises \end{cases} \tag{5}$$

The update method controls the gradient update variance by penalizing low-frequency features and relaxing high-frequency features:

$$w_i \leftarrow w_i - \eta\left[\frac{1}{b}\sum_{\left(x_i, y_j\right)\in B}\frac{\partial L\left(f\left(x_j\right), y_j\right)}{\partial w_i} + \lambda\frac{1}{n_i}w_i I_i\right] \tag{6}$$

Where B is a small batch of samples of size b, n_i is the frequency of feature i, and λ is the regularization parameter.

The multi-head attention mechanism is a method of integrating the results of multiple attention modules by linking them together through a linear transformation. The multi-head attention mechanism considers multiple perspectives, assigns different weights to the feature vectors, and ultimately integrates the results of the multiple weight assignments obtained.

The multi-head attention mechanism allows the model to jointly focus on different representational subspace information from different locations:

$$Multi\ Head\left(Q, K, V\right) = Concat\left(head_1, \cdots, head_h\right)W^0 \tag{7}$$

$$where\ head\ i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{8}$$

In addition, for the problem of too deep network difficult to train, the residual network structure is introduced to the features over the training directly into the full connector, improve the model structure at the same time, to ensure the integrity of the feature training.

2.3.2. Optimization of Recommendation Algorithms Fusing Knowledge Graphs. To address the data sparsity and cold-start problems of traditional recommendation algorithms, the above two problems can be improved by adding relevant auxiliary information to the recommendation model. Common auxiliary information includes user attribute information, item attribute information, user/item knowledge graph, contextual information and social networks. Among them, knowledge graph is the most effective in alleviating the data sparsity problem. Knowledge graph is a kind of huge network structure composed of ternary form, through the connection between nodes and nodes, it covers the data information of users and items in the recommender system to a great extent. Through the connection in the form of ternary groups, not only the potential interests and higher-order relationships of users can be obtained, but also the connection between users and items can be enriched, so as to better alleviate the data sparsity and cold-start problems, and further improve the recommendation performance. In addition, due to the connections between nodes in the knowledge graph, it can also make the recommendation results more persuasive while covering a wider range. Among them, according to the way of combining knowledge graph and recommendation model, it can be categorized into path-based recommendation, embedding-based recommendation and recommendation combining the two.

The recommendation model for e-tendering in this study is designed on the basis of the traditional recommendation model by combining knowledge graph and convolutional attention network. The acquired bidding dataset is first constructed into a knowledge graph and embedded into the recommendation module of convolutional attention network. Through the improved TransR method, the high-dimensional triples in the knowledge graph are processed into low-dimensional continuous embedding vectors, which are then fed into the subsequent convolutional attention network recommendation model. Next, the embedded knowledge graph triples are processed for dimensionality reduction using the convolutional attention network in deep learning. Meanwhile, in order to capture the user's short-term dynamic interest changes, the attention mechanism module containing dynamic factors is introduced to judge the user's short-term dynamic interest changes by only referring to the bidding items that the user has recently interacted with for more efficient recommendation. In order to further alleviate the noise problem caused by missing data and formatting errors, etc., a denoising autoencoder is used in the data embedding stage to appropriately mitigate the impact of noise on the entire recommendation model.

Considering the noise problems caused by missing data and formatting errors etc. in the acquired dataset, the model introduces a denoising autoencoder (DAE) for noise reduction before embedding the knowledge graph.

The error of DAE is calculated as:

$$\min L(I,J) = \|I - J\|^2 \tag{9}$$

where $L(I,J)$ denotes the error calculation expression of the denoising autoencoder, I denotes the input original knowledge graph triad data, I_1 denotes the knowledge graph triad data after the simulated addition of noise, and J denotes the output data of the knowledge graph triad after DAE processing.

When a user has a N -fold relationship with a bidding item, assume that the k nd-fold relationship is R_k, and also map all relationships between that user and that bidding item into a vector space denoted as M_{R_k}. The corresponding relationship vector $R_{(ht)}$ of the improved TransR method is then denoted as:

$$R_{(k)} = R_k M_{R_k}, k = 1, 2, \ldots, n \tag{10}$$

In this case, the requirements of the knowledge graph triad must be satisfied between the head node and the tail node, i.e., head entity (h) + relation $\approx$ (r) tail entity (t).

In convolutional neural network, firstly the knowledge graph after noise reduction process is embedded. Secondly, the knowledge graph is passed through a convolutional layer containing multiple filters, where the embedded high-dimensional knowledge graph triples are processed into low-dimensional continuous embedding vectors by using multiple different convolutional kernels for the embedded knowledge graph. Then through the maximum pooling layer, the obtained low-dimensional continuous embedding vectors are turned into long vectors by using the maximum pooling operation. Finally, through the fully connected layer, the features of users and bidding items are obtained and output.

After the convolution operation, the embedded high-dimensional knowledge graph triple data is processed into low-dimensional continuous embedding vectors, and two types of low-dimensional vectors are obtained: the set of similar user low-dimensional vectors and the set of candidate project low-dimensional vectors.

After the convolution operation, the candidate bidding projects in the set of candidate projects are obtained, which is the process of turning the embedded high-dimensional project knowledge graph triad data into low-dimensional embedded vectors after CNN convolution processing, and the specific realization principle is:

$$P_{im} = P_u^k * K_p, Q_{jm} = Q_j^h * K_Q \tag{11}$$

where * denotes the convolution operation, K_p and K_Q denote the convolution kernel, P_u^k denotes the union matrix of the user's historical interaction items, Q_j^h denotes the union matrix of the user's candidate items, P_{im} denotes the representation vector of the user's historical interaction items, and Q_{jm} denotes the representation vector of the user's candidate items.

The attention mechanism, which can be used to assign different attention levels to the items in the set of candidate items when the recommendation model predicts the preferred items of the target user.

The corresponding formula for the attention mechanism is:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{12}$$

where Q denotes a query, which corresponds to this chapter denoting a candidate item. K denotes the key, which corresponds to this chapter denoting the item of interest in the user's historical interactions. V denotes the value, which corresponds to the value owned by the candidate item.

Combined with the KG-NAMR model, the embedded high-dimensional item knowledge graph triples P_u^k and Q_j^k are directly processed into low-dimensional continuous embedding vectors P_{im} and Q_{jm} after the CNN convolution operation, and the obtained low-dimensional continuous embedding vectors are given different attention weights to different candidate items according to the size of the weights through the attention mechanism:

$$A_{us} = \sum_{w \in I_j} S\left(P_{im}, Q_{jm}\right)V_j \tag{13}$$

where P_{im} denotes a low-dimensional continuous embedding vector of historical interaction items of user u, Q_{jm} denotes a low-dimensional continuous embedding vector of candidate items of user u, $S\left(P_{im}, Q_{jm}\right)$ denotes the magnitude of similarity between the candidate item j and the target user's u real sense of interest item i, V_j denotes the value corresponding to the candidate item j, and A_u denotes the attentional weight acquired by the candidate item i that is finally recommended for the target user u.

2.3.3. E-tendering recommendation optimization system construction. This study aims to optimize the traditional e-tendering system based on the previous study of recommendation algorithms for deep learning and knowledge graph. An e-tendering system based on deep learning and knowledge graph recommendation algorithm is developed and designed to improve the utility of the system, enhance the user's viscosity, and then improve the life of the system's life cycle. In this paper, the system is based on the role and business requirements, and on the basis of retaining the functions of retrieving and viewing information in the traditional e-bidding system, based on the knowledge graph of bidding data constructed and the proposed deep learning recommendation algorithm, the construction of the portrait and the visual display of the recommended items are oriented to the bidding subject.

The bidding recommendation system is mainly designed for three roles: visitor, ordinary user and administrator. In the bidding system, users can initialize and log in their accounts on the home page of the system. Among them, the initialization user account can only be set as an ordinary user. Users who already have an account are identified by the system after entering their account number and password, and are given the corresponding administrator or ordinary user system privileges. Ordinary users and administrators will enter the homepage of the system after successfully logging into the bidding system. In the homepage interface, you can search the bidding information, users can enter the keywords they want to query information in the search box, and then click search to jump to the search result interface. Users can also directly click the title of the information displayed on the page to view the information.

The overall design of the e-tendering optimization system is shown in Figure 4. The bidding recommendation system is mainly designed to solve the problem of the lack of existing e-tendering information websites that provide referable opinions for the bidding subject, based on the research of recommendation optimization of deep learning and knowledge graph in this paper, and in the spirit of the purpose of visualization of information and simplicity of operation, we carry out the system framework design on the basis of the demand analysis to make clear that the system each layer implements the Main functions. Among them, the technical architecture of the system is divided into three layers, which are data access layer, recommendation model layer and function display layer. The data source of the system is the public bidding information website, using crawler technology to collect and pre-process the bidding subject and the corresponding bidding project information and store it into the graph database Neo4j, and realize the visual display of the bidding knowledge graph and the calculation of node similarity in Neo4j. In addition, user account information, bidding public information, and bidding subject transaction information are stored in the relational database MySQL. The main function of the recommendation model layer is to train the bidding subject and project features, generate the recommendation list, and output it to the function display layer for display.

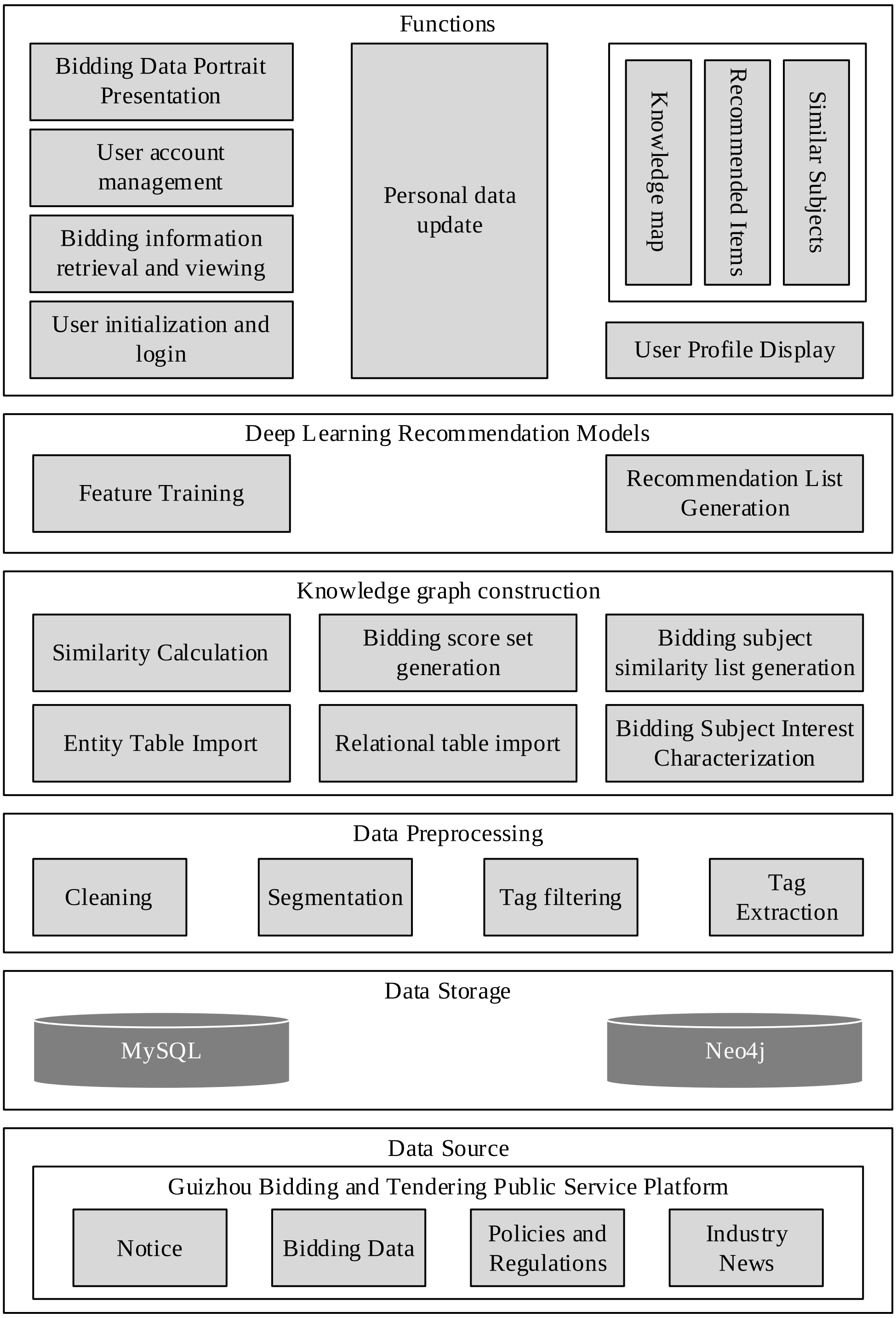
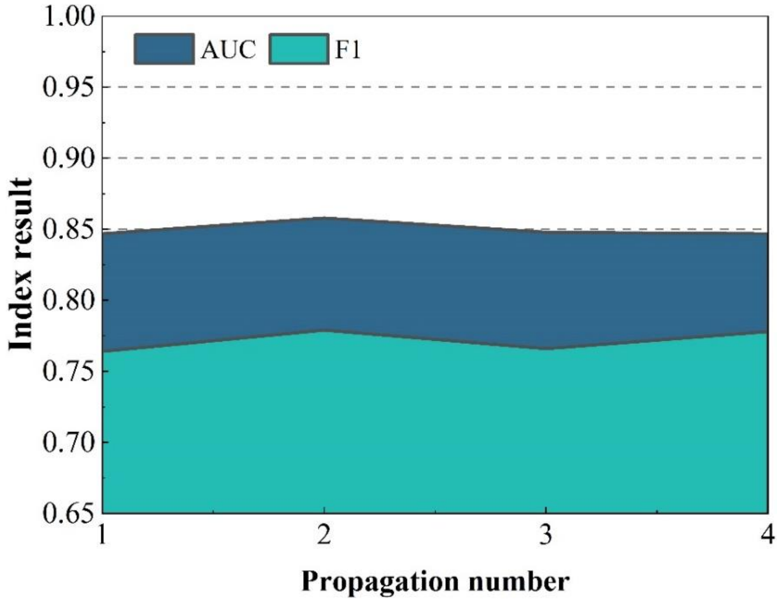


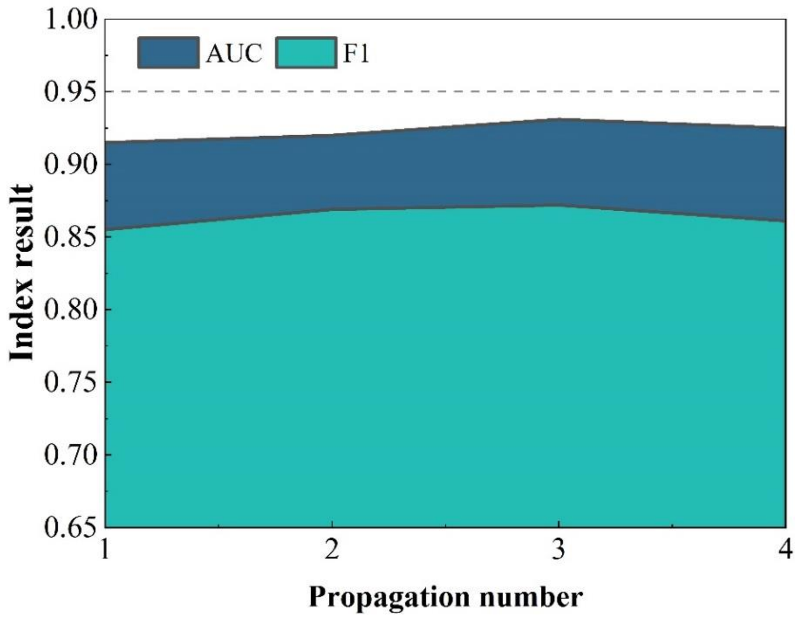
Fig. 4. Overall design of electronic bidding optimization system

2.4. Performance testing of deep learning based recommendation models

2.4.1. Analysis of the optimization effect of knowledge mapping, In this study, experiments were conducted on two publicly available datasets, Ck1 and SM for two bidding projects.Ck1 includes 17,850 users, 14,500 entries, and 139,856 interactions between users.SM is for 4,522 bidding projects, which provides about 7.5 million valid messages. The development environment utilized for the model implementation is the JetBrains Pycharm software, which uses the Python language and utilizes the Pytorch deep learning framework to implement the model. During the experimentation, for the dataset 60% is randomly selected as the training set, 20% as the validation set and the remaining 20% as the test set. The effect of the number of knowledge graph propagation layers is first analyzed. The experiment was conducted by adjusting the number of layers of knowledge graph propagation in order to determine the optimal layer settings, and the evaluation metrics were AUC and F1-score, and the impact of the number of layers of knowledge graph propagation on the results is shown in Fig. 5, and (a) and (b) are the results on the Ck1 and SM datasets, respectively. From the experimental data, it can be seen that the SM dataset has the best test results at the third layer, with AUC and F1 of 0.931 and 0.872, respectively, while the Ck1 dataset has the best results at the second layer, with AUC and F1 of 0.858 and 0.779, respectively.It can be seen that when the number of knowledge graph propagation layers is low, the semantic information of the knowledge graph is not complete enough to be acquired. When the number of propagation layers increases too much, too much irrelevant noise information is introduced, which leads to lower results.



(a) Results from the Ck1 data set



(b) Results from the SM data set

Fig. 5. The influence of the layer of knowledge mapping on the results

The accuracy comparison results before and after model optimization are shown in Fig. 6, which shows that before optimization, the convergence speed of the model is faster, and the accuracy of the model after convergence is stable at about 0.735. After the optimization of this paper's method, the convergence speed of the model is relatively slower, but the accuracy of the model after convergence has been significantly improved, and the accuracy is stable at about 0.912, which is improved by 0.177 compared with the previous one.In a comprehensive view, the recommendation algorithm proposed in this paper combines knowledge graph propagation technology and deep learning technology, which is used to make up for the sparsity of the data and to enhance the representation ability of the items. In terms of processing knowledge graph, the propagation mechanism based on sampling is used to obtain higher-order information of items and reduce the complexity of the model. Experiments prove that the method in this paper is effective in optimizing the recommendation model and exhibits better performance under fusion, proving that it is effective for knowledge graph and user information extraction, helping to alleviate the data sparsity problem and improve recommendation performance.

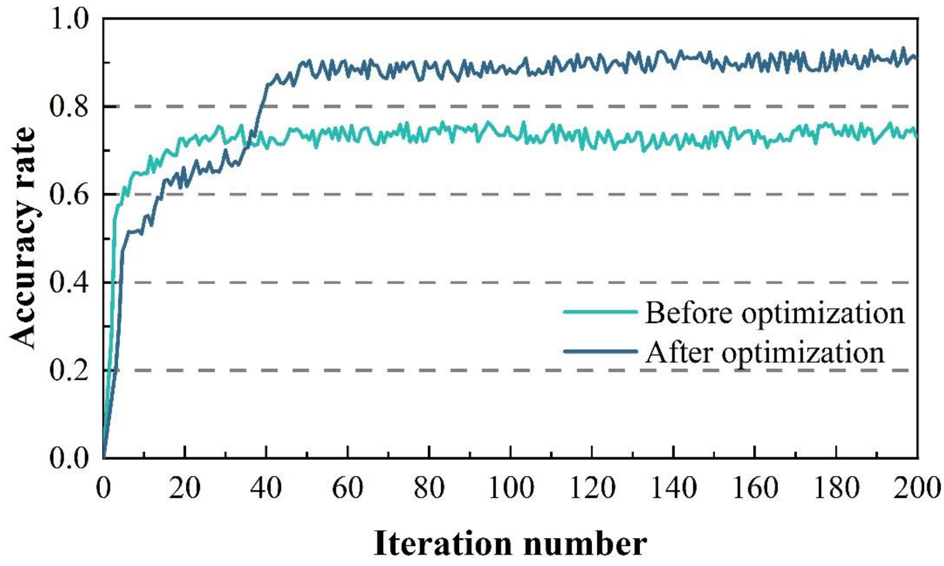
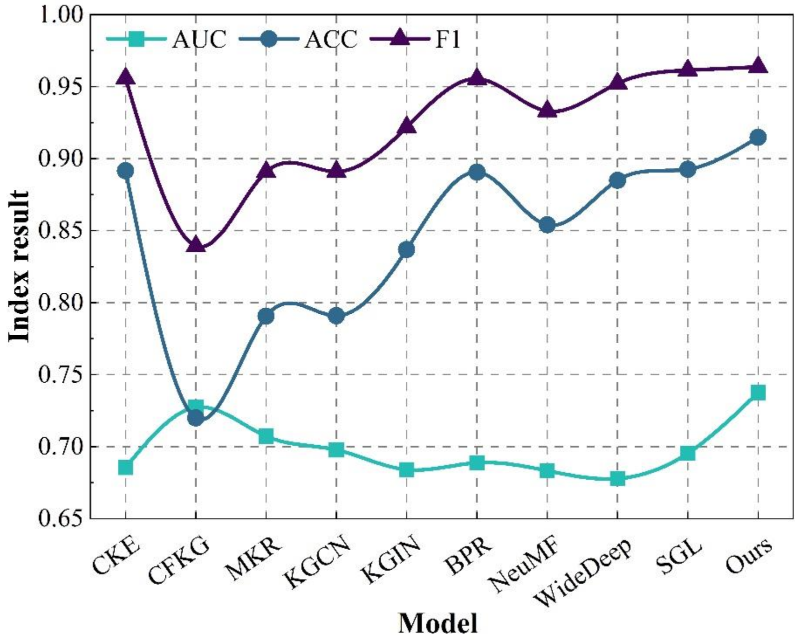


Fig. 6. The accuracy of the model was compared

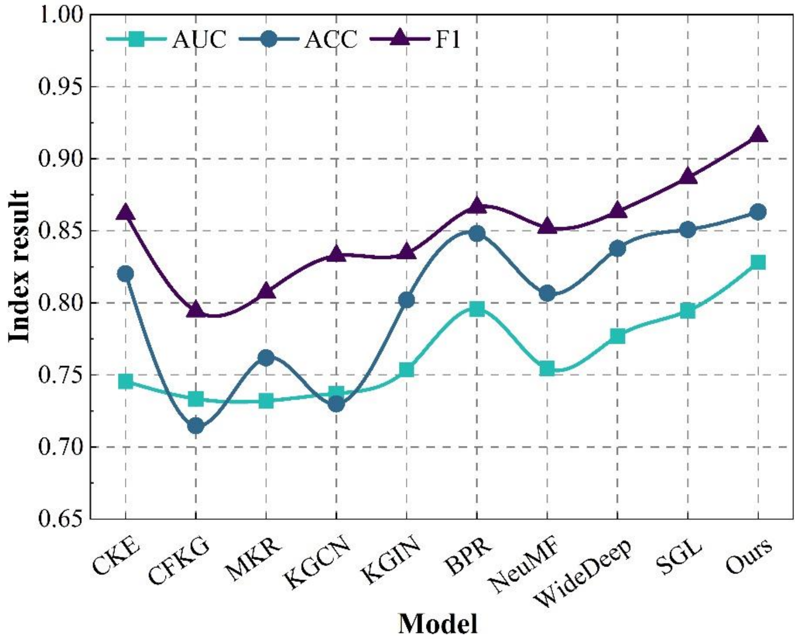
2.4.2. Comparative Performance Analysis of Recommendation Models. To further validate the performance of the recommendation models in this paper, the recommendation models in this paper are compared with the recommendation models of CKE, CFKG, MKR, KGCN, KGIN, BPR, NeuMF, WideDeep and SGL. Among them, CFKE, CFKG, MKR, KGCN and KGIN are knowledge-aware recommendation models, BPR and NeuMF are general type recommendation models, WideDeep is a context-aware recommendation model and SGL is a graph recommendation model. In this experiment, the data were organized in a ratio of 8:1:1 and divided into three parts: training set, validation set and test set, in order to better control and optimize the operation of the models. To evaluate the performance of the model, three metrics, AUC and ACC and F1 scores, were used to help measure the effectiveness of the model.

In order to ensure the generalization of the model while testing its performance, this study was conducted by organizing the self-constructed Cross and Sn bidding project datasets. The performance comparison results of different models are shown in Fig. 7, (a) and (b) are the results on the Cross and Sn datasets, respectively. according to the data of the comparison experimental results, the model of this paper achieves better results on the AUC, ACC and F1 metrics, which are 0.7375, 0.9147, and 0.9637 on the Cross dataset, and 0.8280, 0.867, and 0.8637 on the SM dataset, respectively. 0.8280, 0.8630 and 0.9157. From the results, it is concluded that this paper improves the accuracy metric ACC by about 3% on average for the other best performing models on each dataset. Looking at the results for the Cross dataset, it is found that the model in this paper improves the most on smaller and sparser datasets, while it works best on larger and denser datasets. This is due to the fact that the sparse dataset has fewer interactions on average, and passing relational messages can help the model uncover more hidden information in the limited information. Whereas on the dense dataset, the average number of interactions of items is more, the model can get more relevant information between items and predict more accurate relationships.

However, since the dense graph can better aggregate neighborhood information, it somewhat undermines the advantage of delivering neighborhood messages, narrowing the performance gap between the model in this paper and other models. Observing the results of each model on the Sn dataset, compared to the Cross dataset the AUC score is higher by 0.0905 but the ACC score is lower by 0.0517. This is due to the fact that the SM dataset, although denser, has fewer relational categories, and therefore the proportion of positive and negative samples in the dataset is more unbalanced compared to the other datasets, and the model prefers predicting the categories that are dominant, which reduces the ACC score. On the other hand, the AUC scores have less effect on the category proportions, so even if there is a category imbalance, the AUC may still perform better. The experimental results demonstrate that this paper's recommendation model based on the fusion of deep learning and knowledge graph has certain advantages over other benchmark models, and the advantages for the accuracy of prediction results are more obvious on the sparse graph.



(a)Cross data set



(b)Sn data set

Fig. 7. Performance comparison results of different models

3. E-Tendering Strategies and Suggestions

Electronic bidding is an important practice of market economy system reform, the state has introduced government procurement law, bidding law, bidding implementation regulations to regulate and guide the bidding market, to protect the healthy development of the national economy. In this environment should be adapted as soon as possible to the changes in the procurement market, and actively respond to the impact of the development of the bidding market to the enterprise and the new situation caused by the active exploration, to modernize the means of operation to improve the enterprise's winning rate, to promote the development of the enterprise, and to enhance the level of business management.

With the development of digital law enterprises should first learn to use modern means to optimize the bidding organizational structure, clear bidding workflow, countermeasures bidding strategy and risk control is to improve the enterprise bidding rate indispensable four elements. Secondly, enterprises need to bid according to the bidding project owner credit risk, market competition risk, technology risk, other risks, should be a comprehensive assessment of the overall risk coefficient of the bidding project, to assist in bidding decisions. At the same time, it is also necessary to directly find the most appropriate bidding strategy according to the current market environment in which the enterprise survives, and formulate the bidding program, so as to realize the sustainable development of the enterprise.

4. Conclusion

The purpose of this paper is to construct a knowledge graph of the bidding data, fused to establish a recommendation model for e-bidding, and supplemented with a risk assessment module applied to the e-bidding system to achieve the optimization and improvement of the traditional e-bidding system.

The risk analysis of e-tendering in this paper shows that the system risk (A) and technology risk (E) of SX company's e-tendering have the highest degree of risk, which are 2.423 and 2.541, respectively, and the degree of information risk (B) is relatively low, which is 1.924. SX company's e-tendering comprehensive risk score is 2.2369, which means that the company's e-tendering has a relatively low degree of risk, but there is still room for further improvement. The risk level of the company's e-tendering is low, but there is still room for further improvement.

The AUC, ACC and F1 indexes of this paper's recommendation model are 0.7375, 0.9147 and 0.9637 respectively on the Cross dataset, and the three indexes on the Sn dataset are 0.8280, 0.8630 and 0.9157 respectively, and the ACC value is improved by about 3% on average compared with other best-performing recommendation models, which indicates that the recommendation model proposed in this paper is relatively low risk compared with other recommendation models, and the risk level of the company's e-tendering is 2.2369, but there is still room for further improvement. This shows that the recommendation model proposed in this paper has better performance than other models, and it is suitable for the construction of e-tendering optimization system.

This paper puts forward strategies and suggestions for e-tendering in order to provide reference for the modernization and sustainable development of the e-tendering industry.

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