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Construction of a precise supervision mechanism for medical insurance dual-channel drugs based on collaborative filtering algorithm in the era of intelligent medical insurance

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ABSTRACT

In recent years, China's health insurance drug negotiation has become increasingly improved, and the speed of access to the health insurance catalog has increased dramatically. Under the implementation of health insurance negotiated drugs and dual-channel policy, this study investigates the application of negotiated drugs in a certain region to explore their accessibility and affordability. On this basis, it links the health insurance department, designated pharmacies and medical institutions to explore the precise regulatory mechanism of dual-channel drugs in health insurance. For the drug safety supervision therein, collaborative filtering algorithms, attention mechanisms and multi-task learning are utilized to construct an adverse drug reaction prediction model. It is found that under the influence of the health insurance dual-channel policy, the accessibility and affordability models of medicines are enhanced, the types of negotiated medicines, the number and total amount of purchases are increased year by year, and the total amount of purchases by medical institutions and retail pharmacies are enhanced by 3.42 times and 2.36 times, respectively. The proposed prediction model has good accuracy and applicability in predicting adverse drug reactions, with AUC and AUPR values of 0.93 and 0.83 on different datasets, which are better than the comparison methods. It is recommended to continuously promote the construction of the "dual-channel" management mechanism of designated medical institutions and retail pharmacies to enhance the convenience and sense of access to medical care of the insured.

Keywords: collaborative filtering algorithm, attention mechanism, multi-task learning, prediction model, dual-channel medical insurance

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1. Introduction

In today's era, with the rapid development of science and technology, China has entered the Internet era, advanced science and technology is widely used in all walks of life, providing more assistance for the development of the industry [1-2]. Under the background of the Internet, health insurance has gained a brand new development and gradually developed in the direction of intelligence. With the close integration of information technology and medical treatment, the resulting intelligent health insurance helps the rational allocation of medical and health resources, meets the medical needs of the general public, and realizes the optimization and innovation of the health insurance industry [3-6]. However, it must still be noted that in the process of building smart medical insurance, due to the influence of many factors, there are still problems such as the proliferation of drug trading, which affects the improvement of the level of medical insurance services [7-8]. Therefore, in order to implement the requirements of the state on the establishment and improvement of the negotiated drugs “dual-channel” management mechanism, to ensure the smooth landing of the national health insurance drugs, to better meet the needs of the majority of insured patients, and with the rapid development of information technology, the construction of the accurate supervision mechanism of drugs is imperative [9-12].

“Dual-channel” refers to the mechanism of meeting the reasonable demand for negotiated drugs in terms of supply guarantee and clinical use through two channels of designated medical institutions and designated retail pharmacies, and synchronized with health insurance payment [13-14]. Collaborative filtering algorithm, as a classic information recommendation technology, has been widely used in many fields such as e-commerce, social networks, music recommendation and so on, by virtue of its high efficiency and accuracy [15-16]. Applying it to build a precise regulation mechanism for medicines can realize the prediction of patients' preference for items based on the use of patients' behavioral data and medicines' attribute information, and recommending medicines to them that they may need [17-19].

This study collects the types, quantities and amounts of purchases, as well as the number of reimbursements of medicare-accessed medicines in a certain region from 2018 to 2023, explores the accessibility and affordability of negotiated medicines, and examines the current status of the application of medicare dual-channel medicines. Subsequently, a tripartite mechanism for precise supervision of health insurance dual-channel medicines is proposed, in which the health insurance department, retail pharmacies and medical institutions are linked together, and information technology is fully utilized to intelligently monitor all aspects of the flow of prescriptions. Based on the needs of drug safety supervision, a patient-feature attention module, a patient-adverse drug reaction attention module, and a causal multicore multi-task learning model are designed using coordinated filtering algorithms and attention mechanisms to propose an adverse drug reaction prediction model. Through model comparison experiments, ablation experiments and specific case studies under multiple datasets, the adverse drug reaction prediction effect of the proposed model is explored to provide technical support for further rational allocation of pharmaceutical resources.

2. Status of application of dual-channel medicines for health insurance

2.1. Two-channel policy

“Dual-channel” refers to a mechanism for meeting the reasonable demand for negotiated medicines in terms of supply assurance and clinical use through both designated medical institutions and designated retail pharmacies, and synchronizing them with the payment of medical insurance. The State has put forward a number of opinions on the establishment and improvement of the “dual-channel” management mechanism for negotiated medicines, including the implementation of categorized management of negotiated medicines, taking into account factors such as clinical value

and patients' reasonable needs for medication. The advantages of retail pharmacies will be utilized, and the selection procedures for pharmacies will be clarified and dynamically adjusted. Establishing a mechanism for full supervision and traceability of drug quality and safety to ensure drug quality and safety. Improve drug payment policies, and explore the establishment of a separate drug protection mechanism. Adhere to the principle of facilitating the people and optimizing the administration and management services. Deploy prescription flow centers to ensure the smooth flow of electronic prescriptions. Strengthen supervision and leadership, and solidly promote the work related to the "dual-channel" policy.

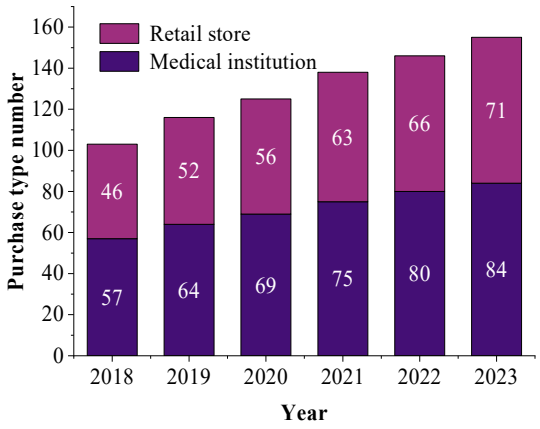
2.2. Data sources

This paper collects data and information related to the price negotiation of medicare access drugs carried out in a certain place from 2018 to 2023. It includes (1) the procurement information of negotiated drugs in public medical institutions in a certain place, and the sales records of some drug suppliers; and (2) the policy documents, implementation situation and summary reports related to the negotiated drugs in a certain place's health insurance.

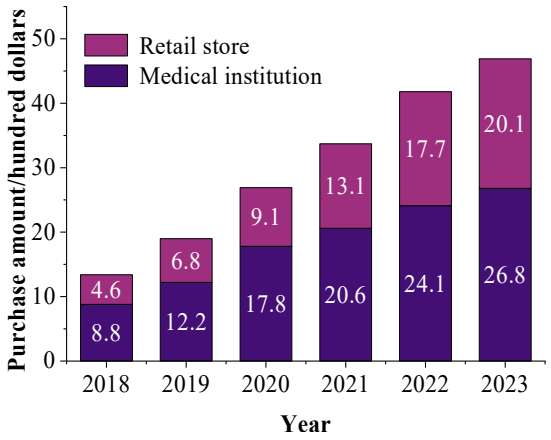
2.3. Analysis of findings

2.3.1. Accessibility of medicines. Drug accessibility analysis of the procurement of dual-channel negotiated drugs, total procurement amount, and total procurement amount in the sample area. The landing of negotiated drugs in the sample area during the study period is shown in Figure 1, and (a) to (c) are the results of the survey on the types of drugs procured, the total amount of drugs procured, and the total amount of drugs procured, respectively.

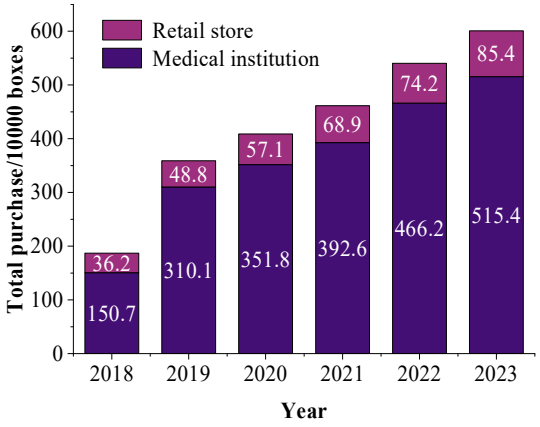
Statistics show that the types of negotiated medicines for health insurance have been on the rise year by year, with an increase of 47.37% in public medical institutions and 54.35% in retail pharmacies. With the increase in the types of procurement, the accessibility of negotiated drugs to patients has been effectively enhanced. The total amount of negotiated drugs purchased is also on the rise, with a significant increase in the retail pharmacy channel. With the implementation of the national negotiation policy, the purchasing motivation of public medical institutions and retail pharmacies has been effectively enhanced. In addition, the "dual-channel" medication guarantee mechanism for nationally negotiated medicines has facilitated an increase in the total volume of purchases by public hospitals and retail pharmacies. From 2018-2023, the total procurement volume of negotiated drugs in the sample area shows a rising trend year by year, increasing from 1.869 million boxes to 6.008 million boxes, or 221.46%. Compared with 2018, the total procurement volume of public medical institutions increased by 3.42 times, and the total procurement volume of retail pharmacies increased by 2.36 times.



(a)Purchase type number



(b)Purchase amount/hundred dollars



(c)Total purchase/10000 boxes

Fig. 1. The situation of negotiating drugs

2.3.2. Affordability of medicines. Analyzing the basic health insurance reimbursement data in the four quarters of 2023, the use and reimbursement of 17 anti-cancer drugs are shown in Table 1, the number of reimbursement visits and the number of reimbursement amount of the 17 negotiated cancer drugs have been gradually improved, the reimbursement ratio is relatively stable, and the total reimbursement amount is 514 million yuan, accounting for 62.91% of the total cost of the drugs, and the sub-average reduction of the burden of patients' visits to the doctor is 4,779 yuan, and the patient's affordability is gradually increased.

Table 1. The use and reimbursement of 17 kinds of cancer drugs

	First quarter	Second quarter	Third quarter	Fourth quarter	Total
Reimburse number	16060	2105	2294	2485	22944
Total drug cost/ Hundred dollars	0.89	1.46	1.89	3.93	8.17
Total expenses incurred/ Hundred dollars	0.61	1.05	1.41	3.16	6.23
Medical insurance reimbursement cost/ Hundred dollars	0.52	0.87	1.11	2.64	5.14
Secondary drug service/yuan	5487	6043	7995	8479	7001
Secondary reimburse service/yuan	3422	4501	5306	5887	4779
Actual reimbursement ratio	58.43%	59.59%	58.73%	67.18%	62.91%
Overall reimbursement ratio	68.54%	71.92%	74.60%	80.41%	76.25%

3. Dual-channel pharmaceutical precision control mechanism for health insurance

Since the implementation of the dual-channel policy for nationally negotiated medicines and health insurance, the accessibility and affordability of negotiated medicines has gradually increased. However, the implementation of the negotiated drug policy under the health insurance program still involves difficulties in the operation of the limited scope of payment for medicines in the health insurance catalog, insufficient improvement in the supporting policies formulated by governmental departments, the prevalence of the phenomenon of "difficulty in entering hospitals" for negotiated medicines in designated healthcare institutions, challenges in the implementation of the dual-channel management policy by designated retail pharmacies, and problems in the policy environment affecting the use of the negotiated medicines. The use of negotiated medicines is also affected by the policy environment. Therefore, in the context of the development of intelligent technology, it is important to explore the precise supervision mechanism of dual-channel medicines under medical insurance. The tripartite linkage and precise supervision mechanism of the "dual-channel" policy for negotiated medicines under the medical insurance is shown in Figure 2.

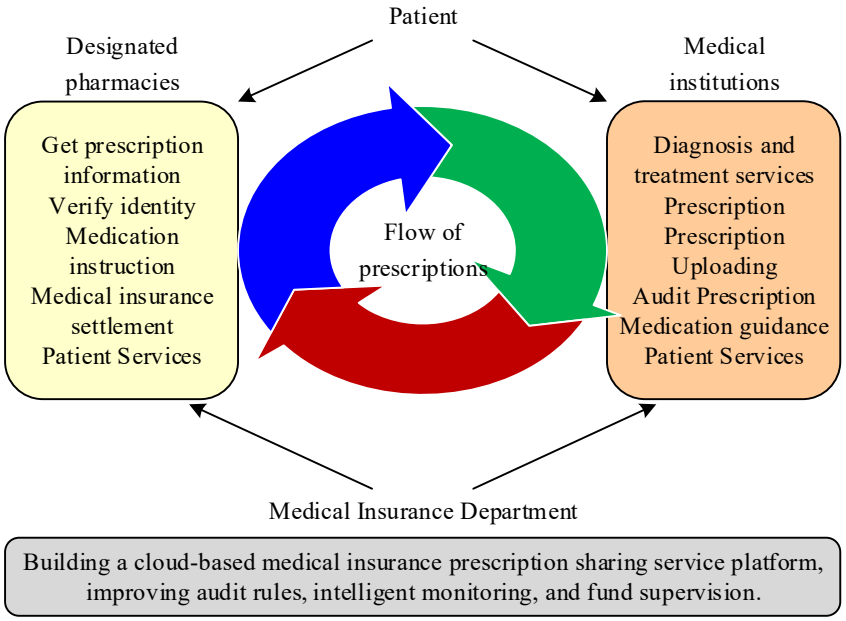


Fig. 2. The precise supervision mechanism of the three-way linkage

3.1. Health insurance sector

The establishment of a sound "dual-channel" precise supervision mechanism for drugs negotiated by the national health insurance is a systematic project involving prescription flow, fund supervision, optimization of the handling process and the construction of intelligent cloud services. Medical insurance and health departments at all levels need to strengthen organizational leadership, carefully deploy and refine measures.

Stimulating the enthusiasm of medical institutions, designated retail pharmacies and physicians to promote the implementation of nationally negotiated medicines, and facilitating the implementation of the "dual-channel" management of medicines negotiated under the medical insurance scheme. The system for reviewing the use of medicines under the medical insurance scheme has been continuously improved, and intelligent control has been strengthened to ensure that the "dual-channel" management is traceable throughout the entire process of medication use, so as to achieve the goal of full control. In order to safeguard the security of the fund, it has improved the statistics and analysis of drug costs and fund expenditures under "dual-channel" management, introduced measures for monitoring, inspecting, evaluating and assessing designated retail pharmacies under "dual-channel" management, and cracked down on fraudulent use of the medical insurance fund. At the same time, a health insurance prescription cloud sharing service platform has been established to simplify the handling procedures, connect the platform with designated medical institutions and designated retail pharmacies, remove obstacles to doctor's prescription, prescription flow, online health insurance settlement, dispensing of medicines, and door-to-door delivery, and improve the transparency of the information, so that the insured can independently choose to buy medicines from the nearest pharmacy or settle the bill online, and further improve the policies benefiting people's livelihoods. Clarifying the scope of urban medical services, utilizing the development of the "Internet + medical insurance" platform, breaking down the information barriers to medical insurance in other places, upgrading the capacity of medical insurance cooperation in various regions, improving the coordinated protection mechanism, implementing cross-location settlement of medicines negotiated under cross-regional medical insurance, and promoting the cross-regional construction of medical associations.

3.2. Targeted pharmacies

For designated retail pharmacies, they should be more standardized in terms of informatization, drug management, medication safety, and review of health insurance information.

Designated retail pharmacies should be connected to health insurance information platforms and electronic prescription flow platforms to ensure that information on medicines and health insurance payments is comprehensive and accurate, and that communication is timely and smooth. Some negotiated medicines require special storage conditions, and designated retail pharmacies should create appropriate warehousing and distribution rules and regulations to ensure the quality and safety of medicines. In addition, designated retail pharmacies need to improve their own systems, enhance the business capacity of licensed pharmacists, guide patients in the rational use of medicines, ensure the safe use of medicines, and improve the quality of pharmacy management services. Designated retail pharmacies are required to strictly examine the identity of patients to prevent the emergence of adverse events of "medical insurance fraud" and to ensure the safety of the fund. Designated retail pharmacies that have obtained "dual-channel" status and payment under the health insurance scheme can give full play to their geographical spread, high degree of marketization, flexible services and other characteristics, and promote each other and form synergies with designated medical institutions, so as to ensure the supply of medicines negotiated by the national health insurance scheme, and effectively improve the accessibility of medicines negotiated by the health insurance scheme.

3.3. Medical institutions

The "dual-channel" medical insurance prescription flow mechanism focuses on connecting medical institutions and designated retail pharmacies. With the rapid development and gradual improvement of Internet hospitals, medical institutions should give full play to the advantages of their own Internet hospital system construction and expand the application of the "dual-channel" system. Medical institutions should give full play to their advantages in the construction of the Internet hospital system, expand the application of "dual-channel", form a synergy with the designated retail pharmacies around them, and strive to create a convenient and comfortable medical service. At the same time, medical institutions should optimize the handling process and take into account the issues of health insurance payment and drug cost control, do a good job of transforming the relevant information interface, improve the internal management system, find a balance between the health insurance fund, hospitals and patients, and promote the rational use of the health insurance fund. Medical institutions must face up to the reality of the cost burden while adhering to the public interest.

4. Collaborative filtering-based prediction of adverse drug reactions

Accurate regulation of dual-channel drugs in health insurance requires the establishment of a drug protection mechanism to realize the whole process of drug quality and safety regulation. Therefore, this chapter designs a multi-frequency adverse drug reaction prediction model based on multi-task collaborative filtering attention, i.e., Collaborative Filtering Attention Model Based on Causal Multi-Kernel Multi-Task Learning (CFA-CMKMT).The CFA-CMKMT model combines the Collaborative Filtering Attention Module (CFA) with the Causal Multi-Kernel Multi-Task Learning (CMKMT) framework, aiming to dig deeper into the deeper associations between adverse drug reactions and patient characteristics, and to provide methods for monitoring patient medication safety in retail pharmacies and healthcare organizations.

4.1. Collaborative Filtering Algorithm

Collaborative filtering algorithm is one of the earliest used recommendation algorithms, which mainly uses the user's behavioral information about the item to get the user's score for the item he/she has interacted with, and constructs the corresponding interaction matrix, and finally carries out the similarity computation method, so that similar items or users can be found easily. The adverse drug reaction prediction algorithm studied in this chapter is based on collaborative filtering techniques.

4.1.1. UserCF. The User-based Collaborative Filtering (UserCF) algorithm first calculates the similarity between users, and when these two users have a lot of data about the items they interact with in common, they are considered to be similar. The user group is segmented by this method, after which the items liked by users with common interests are recommended to the target users, the algorithm is based on the fact that people in the same category are more likely to like the same kind of things.

The basic process of the algorithm:

1) Prepare user vectors. Generally use the vectors formed by the interaction between users and items.

2) Based on the user vectors, calculate the similarity between users.

3) Generate recommendation results for each user, recommending the items that are similar to his user interactions to the target user.

Equation (1) is the output formula of this algorithm:

$$P_{u,j} = \frac{\sum_{j}^{n} \left(sim_{u,j} \cdot R_{j,i} \right)}{\sum_{j}^{n} sim_{u,j}} \tag{1}$$

where u and j are users, i is the item, n is the total number of users, definition $P_{u,i}$ is the predicted user u rating of item i, R_{ji} is the user j rating of item i, and $sim_{u,j}$ is the similarity of user u to user j.

4.1.2. ItemCF. Item-based collaborative filtering algorithm (ItemCF), by calculating the similarity of historical behavioral information of all items, and then recommending similar items for that target user based on the items that the user has consumed. In general, the number of recommended items in the same period is often less than the number of users, so calculating the similarity between items will not be a bottleneck in the performance of the recommender system. Secondly, the similarity between items will not change easily, which can solve the problem of user interest migration to a certain extent, and the number of consumers corresponding to the items has a larger base, so the calculated similarity between items is more reliable and effective than the similarity between users.

The key to ItemCF lies in the calculation of similar items, when the number of common users who like two items is more, it means that the similarity of the two items is higher, and the recommended items obtained are more likely to be liked by users, and the recommendation effect is better.

Algorithm process:

1) Construct the user-project relationship matrix. The elements in the matrix can be the user's evaluation information, user browsing information and so on.

2) Calculate the similarity between items through the similarity formula, and construct the similarity matrix according to the similarity.

3) Recommend items with higher user similarity according to different scenarios.

Equation (2) is the output formula of this algorithm:

$$P_{u,j} = \frac{\sum_{j}^{m} \left(sim_{i,j} \cdot R_{u,j} \right)}{\sum_{j}^{m} sim_{i,j}} \tag{2}$$

where u is the target user, i and j are different items, m is the total number of items, define $P_{u,i}$ as the recommended rating of item i by user u, $R_{u,j}$ is the true rating of item j by user u, and $sim_{i,j}$ is the similarity between item i and item j.

4.2. Attention mechanisms

The basic principle of the attention mechanism is that when processing sequential data, the model can learn to dynamically assign attention weights to be able to focus more on different time steps or locations. This enables the model to pay more attention to specific parts of the input sequence, thus improving the processing of important information. Three important components are usually included in an attention mechanism: query vectors, key vectors, and value vectors.

The basic process of the attention mechanism can usually be divided into the following steps. First, given a Query and a set of Keys, the correlation between them is first computed by the $F(\square)$ function. There are many ways to compute it, such as dot product, additive attention or scaling dot product attention mechanism and other methods. Next, the weights of the attention mechanism are computed by transforming the results of the correlation between the two obtained in the first step to obtain a distribution of the attention weights, which is generally implemented using the Softmax function to

ensure that the sum of the attention weights is 1, which indicates the proportion of the model's weights in focusing on the different parts of the model. Next, the attention weights obtained in the previous step are multiplied and summed with the corresponding Values to obtain the final representation, where the attention weights determine the contribution of each value. The final weighted summation obtained is the output representation of the attention mechanism, which captures the part of the model's focus on the input data.

The process of attention mechanism computation can be seen that the computation process is clearly divided into three phases, which are the weight computation phase, the normalization processing phase, and the computation of the ATTENTION value phase.

1) Calculation of weights. The first stage of the attention mechanism is the weight calculation stage, which is performed by selecting a suitable similarity function. The dot product attention mechanism calculates the attention scores by calculating the dot product between Query and Key and then normalizes these scores using Softmax function to get the final attention weights. The formula is as follows:

$$Attention\left(Q,K,V\right)=soft\max\left(\frac{QK^{T}}{\sqrt{d_{k}}}\right)V \tag{3}$$

where: Q--Query, K--Key, V--Value, $\sqrt{d_k}$ --Dimension of Key.

2) Normalization. Normalize the weight values obtained above:

$$a_{i}=soft\max\left(f\left(Q,K_{i}\right)\right)=\frac{\exp\left(f\left(Q,K_{i}\right)\right)}{\sum_{j}\exp\left(f\left(Q,K_{j}\right)\right)} \tag{4}$$

3) Calculate the ATTENTION value. The weighted sum of the weight values and VALUE obtained from normalization is weighted to obtain the ATTENTION value:

$$attention\left(Q,K,V\right)=\sum_{i}a_{i}X_{i} \tag{5}$$

4.3. The CFA-CMKMT model

4.3.1. Patient-characterized attention module. Feature-layer Attention aims to better capture the impact of individual patient characteristics on adverse drug reactions of different frequencies. By assigning weights to different patient features with different degrees of adverse reaction preference, Feature-layer Attention will focus on patient features that are consistent with adverse reaction preference, thereby improving the understanding and prediction of adverse reactions. Specifically, the Feature Attention module will calculate the attention weights for each feature based on the set of patient i features $\left\{x_{i^{*}}\right\}$ suffering from adverse reactions, and then construct a content representation of the patient using a weighted sum. The calculation formula is as follows:

$$a\left(n,i,t\right)=w_{1}^{T}\delta\left(W_{1n}u_{n}+W_{1x}x_{it}+b_{1}\right)+c_{i} \tag{6}$$

where weight matrix W_1 and offset b_1 denote the parameters of the first layer of Feature-layerAttention, w_1 and offset c_1 denote the parameters of the second layer of Feature-layer Attention, $x_{t^{*}}$ denotes the set of features of a patient i with a history of an adverse reaction, and x_{it} denotes the t th feature of a patient i, and u_n denotes the latent vector of patients suffering from an adverse reaction n denotes, and $\delta(\cdot)$ denotes the ReLU activation function.

Normalization of $a(n,i,t)$ using softmax function yields $\alpha(n,i,t)$ i.e., the attention weight of each feature. As shown in Equation (7):

$$\alpha(n,i,t) = soft\max(a(n,i,t)) = \frac{\exp(a(n,i,t))}{\sum_{n=1}^{\left|\{x_*\}\right|} \exp(a(n,i,t))} \tag{7}$$

The $\alpha(n,i,t)$ of the patients are weighted and summed to obtain the feature score y_i for each patient as shown in Equation (8):

$$y_i = \sum_{t=1}^{\left|\{x_*\}\right|} \alpha(n,i,t) \cdot x_{it} \tag{8}$$

4.3.2. Patient-Adverse Drug Reaction Attention Module. The Adrs-layer Attention module improves the understanding and prediction of adverse reactions by assigning weights to the degree of preference of different patients for different frequencies of adverse reactions, placing the focus of attention on individual patients with consistent preferences for adverse reactions.The specific formulae used by the Adrs-layer Attention module to calculate the Force Score $CFA(i,j)$ are calculated as shown in equation (9):

$$d(n,i) = w_2^T \delta\left(W_{2u}u_n + W_{2p}p_i + W_{2q}q_i + W_{2y}y_i + b_2\right) + c_2 \tag{9}$$

where S_j denotes the feature vector of patient j, weight matrix W_2 and offset b_2 denote the parameters of the first layer of Adrs-layer Attention, w_2 and offset c_2 denote the parameters of the second layer of Adrs-layer Attention, and $\delta(\cdot)$ denotes the ReLU activation function.

The attention weights of $\beta(n,i)$, i.e., patient i, are obtained by normalization using softmax function for $d(n,i)$, and the computational formula is shown in (10):

$$\beta(n,i) = soft\max(d(n,i)) = \frac{\exp(d(n,i))}{\sum_{m\in R(n)} d(n,m)} \tag{10}$$

where R denotes the set of historical patients suffering from adverse drug reactions n.

4.3.3. Causal Multicore Multitask Learning Module. The goal of the Causal Multi-Kernel Multi-Task Module (CMKMT) is to calculate the causal effect between a patient and an adverse drug reaction suffered. This module draws on the matching idea in causal inference and the nearest neighbor matching method, firstly, it is assumed that the individual information of patient i, the medication taken and the disease suffered from are the covariates affecting the causal relationship between the patient and the adverse drug reaction suffered from u, and secondly, according to the individual characteristics of a particular patient i, the Euclidean distance matches the most similar to the individual patient $\left(d_{i,j} \le 1\right)$, the calculation formula is as follows:

$$d_{i,j} = \sqrt{\left(age_i - age_j\right)^2 - \left(gender_i - gender_j\right)^2 - \left(weight_i - weight_j\right)^2} \tag{11}$$

where age, gender, and weight denote the age, gender, and weight of the patient, respectively.

After that, the similarity scores of multiple patients with that particular patient are calculated separately by the multicore multitask learning framework with the following formula:

$$K(i,j) = \sum \eta^* \sum_{o=1} \sum_{l=1} w^* sim_*\left(f_o^*, f_i^*\right)_{*\in\{IF,DF,SF,BF\}} \tag{12}$$

where η denotes the weight score of each type of kernel function pool in the overall kernel function, w denotes the percentage of specific features in the overall features, and $sim(\cdot)$ denotes the similarity score calculated by the kernel function.

The similarity scores between all patients and patient i were summed and averaged to obtain the average treatment effect (ATT) between the patient and the adverse reaction, i.e., the causal effect score between patient i and the adverse reaction u of the drug, which was calculated using the following formula:

$$CK(u,i) = \mathrm{ATT}_{u,i} = \frac{1}{N}\sum_{j=1}^{N} \tau \cdot K(i,j) \tag{13}$$

where, N denotes the total number of patients who have been matched by Euclidean distance, τ denotes the correlation coefficient with the adverse drug reaction u, i.e., if the patient with whom the similarity score is calculated for a particular patient i does not suffer from an adverse drug reaction u, then the correlation is recognized as negative, $\tau = -1$ and vice versa $\tau = 1$.

4.3.4. Objective function. The objective function consists of a loss function and a regular function, in which the BPR loss function is improved to obtain a new loss function for the multi-frequency adverse reaction prediction problem, i.e., the frequency-specific Bayesian personalized ranking based loss function (FSBPR), which is calculated, as shown in equation (14):

$$F(\theta) = \arg\min Loss_{FSSPR}(\theta) + \mathrm{Re}\, g\_Loss(\theta) \tag{14}$$

where $Loss_{FSBPR}$ denotes the FSBPR loss function, Reg_Loss denotes the regular loss term in order to reduce the model complexity, and θ denotes the parameters during model training.

1) FSBPR loss function. On the basis of the BPR loss function, three sets of potential vector representations are incorporated, namely, adverse reactions, patients, and auxiliary potential vector representations, which enable the model to more effectively take into account the degree of preference of different frequencies of adverse reactions for patient characteristics and the correlation between them in the calculation process.FSBPR loss function:

$$Loss_{FSBPR} = -\sum_{(i,j,i,k)\in R} \ln\delta\left(\sum_{h=1}^{y} z_{j,h}\left(\begin{array}{c}\left(u_n + \sum_{i\in R(i)} \beta(n,i) q_i\right)^T p_j \\ -\left(u_n + \sum_{i\in R(i)} \beta(n,i) q_i\right)^T p_k + CK(u,i)\end{array}\right)\right) \tag{15}$$

where $\left(u_n + \sum_{i\in R(i)} \beta(n,i) q_i\right)^T p_j$ and $\left(u_n + \sum_{i\in R(i)} \beta(n,i) q_i\right)^T p_k$ denote the preference of different patients i, j, and k for different frequencies of an adverse drug reaction u, $CK(u,i)$ denotes the causal effect between patient i and adverse drug reaction u, R denotes the patient-adverse reaction interaction matrix, y denotes the total number of shared parameters, and $z_{j,h}$ denotes the strength of the association between the tasks, which is designed to promote mutual learning between the tasks to realize the exchange of information and the sharing of knowledge. u, q, p denote and belong to adverse reaction potential vector U, patient potential vector Q, auxiliary potential vector P, $\delta(\cdot)$ denote sigmoid functions, respectively.

2) Regular loss function. The regular loss function reduces the complexity of the model to avoid overfitting, and at the same time ensures the validity of the model parameters, the formula is as follows:

$$\begin{aligned}\mathrm{Re}\,g\_Loss &= \vartheta\left(\|A\|^2+\|U\|^2+\|Q\|^2+\|P\|^2\right)\\ &+\mu_1\sum_{t=1}^{y}\left(w_t w_t^T-1\right)^2+\mu_2\sum_{t=i}^{y}\left(w_t w_t^T\right)^2\end{aligned} \tag{16}$$

The regular loss function consists of three terms, ϑ_1, μ_1, μ_2 are the penalty variables of the three regularization terms, w_t represents the weight vector of the t th feature, w_i represents the feature vector of any feature other than the t th feature, $\vartheta\left(\|A\|^2+\|U\|^2+\|Q\|^2+\|P\|^2\right)$ This term represents the Frobenius norm canonical, with the aim of reducing the complexity of the model, A represents the weight matrix composed of the four types of feature vectors of the patient, U, Q, and P represent the potential vector of adverse reactions, the potential vector of the patient, and the potential vector of the auxiliary one, respectively. $\mu_1\sum_{t=1}^{y}\left(w_t w_t^T-1\right)^2$ denotes the penalty weight vector, w_t the purpose is to make the weight vector w_t regular, $\mu_2\sum_{tai}^{y}\left(w_t w_t^{\tau}\right)^2$ This one forces the different weights w_t to have orthogonal properties, which helps to maintain the diversity of the model and make the different feature weights independent of each other.

4.4. Experimental results and analysis

In order to verify the effectiveness of the CFA-CMKMT algorithm, it was trained and validated on multiple datasets in this paper, and the experiments mainly consisted of the following parts: (1) Comparison experiments: the adverse drug reaction prediction effects of the CFA-CMKMT algorithm and other algorithms were mainly compared. (2) Ablation experiments: various mechanisms used in the model were ablated and experimented on the Pauwels dataset to verify the effectiveness of the mechanisms in the model. (3) Conducting specific case studies.

4.4.1. Data sources. In order to validate the performance of the adverse drug reaction prediction methods and to facilitate comparisons with other methods using the same dataset, three open source datasets are used in this paper. They are Pauwels dataset, Mizutani dataset, and Liu dataset.

The Pauwels dataset contains drug and adverse reaction information and chemical structure information of drugs, drug and adverse reaction information from the SIDER database, from which 888 drugs and 1,385 adverse reactions were extracted, and chemical structure coding of drugs from the PubChem database.

The Mizutani dataset contains drug and adverse reaction information, chemical structure information of drugs, drug-target protein interaction information, drug and adverse reaction information from the SIDER database from which 658 drugs and 1339 adverse reactions information were extracted. The chemical structure coding information of drugs came from PubChem database, the target protein information of drugs came from DrugBank database and Matador database, 658 drugs selected in SIDER database corresponded to 1,368 kinds of protein information, and the target proteins of the drugs that need to be annotated came from KEGG database.

The Liu dataset contains information on drugs and adverse reactions, information on chemical structures of drugs, biological properties (target proteins of drugs, transporter proteins, enzymes, pathways of target proteins) and some other known adverse reactions, information on drugs and adverse reactions was obtained from SIDER, information on 832 drugs and information on 1385 side effects were collected from the species. The chemical structures of the drugs were coded from the PubChem database, and the biological properties were obtained from the DrugBank database and the KEGG database.

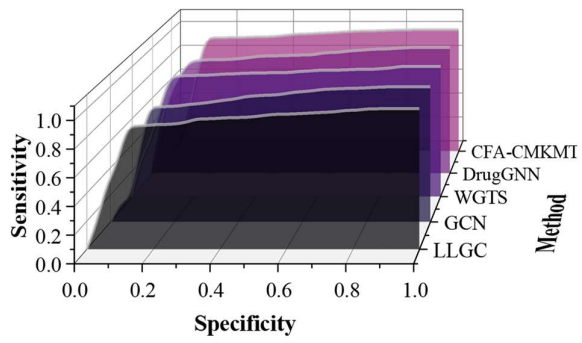
4.4.2. Comparative Experimental Results. Subject Characterization Curve (ROC) and Precision-Recall Curve (PR) are used in order to evaluate the proposed method.AUC is the area under the ROC curve and AUROC takes the value from 0 to 1, where a larger value indicates a better performance of the model. LLGC, GCN, WGTS, and DrugGNN are selected as comparison methods.

The AUC and AUPR values of the models are shown in Table 2. The ROC and PR curves of the different methods are shown in Fig. 3, where (a) to (f) correspond to the results of the ROC and PR curves of the three selected datasets.

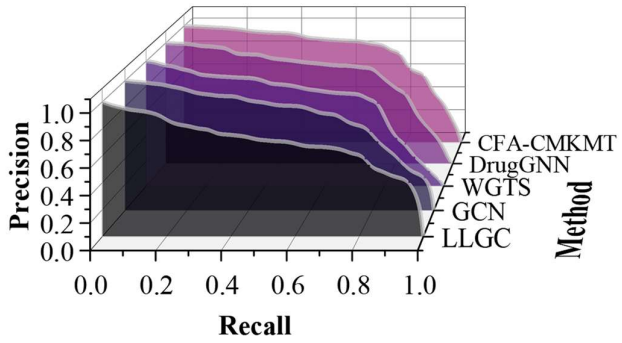
In the three datasets, the AUC and AUPR values of the CFA-CMKMT model in this paper are significantly improved relative to the other four methods, both of which are around 0.93 and 0.83, respectively, while most of the AUC and AUPR values of the comparison methods are below 0.9 and 0.8. Meanwhile, from the curves in the figure, it can be seen that the ROC curves of CFA-CMKMT experiments are closer to the upper left of the axes, while the PR curves obtained from CFA-CMKMT model experiments almost completely cover the curves obtained from the experiments of the other methods, so it further proves that the CFA-CMKMT model can better predict the adverse reactions of the drugs compared with the other methods.

Table 2. The AUC and AUPR values of the model

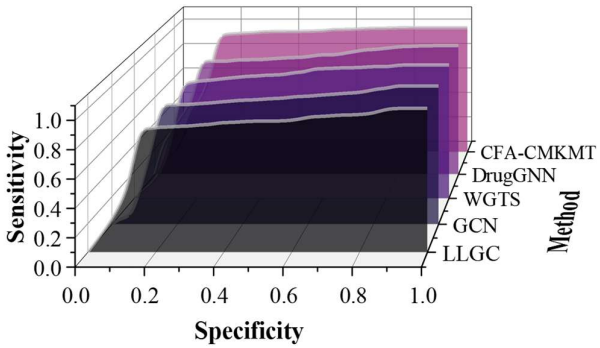
Method	Pauwels		Liu		Mizutani	
	AUC	AUPR	AUC	AUPR	AUC	AUPR
LLGC	0.873	0.658	0.851	0.652	0.863	0.675
GCN	0.848	0.678	0.862	0.696	0.891	0.682
WGTS	0.912	0.735	0.854	0.733	0.848	0.737
DrugGNN	0.879	0.795	0.877	0.765	0.873	0.771
CFA-CMKMT	0.932	0.837	0.931	0.836	0.927	0.835

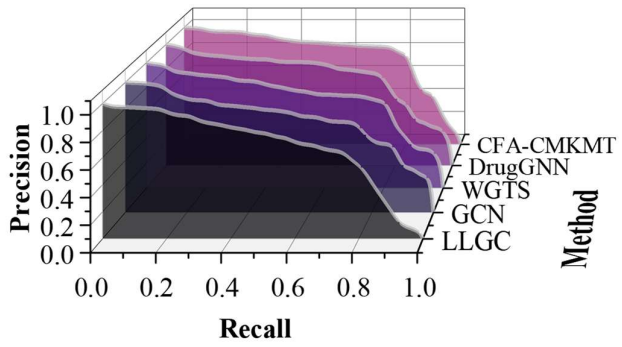


(a)ROC curve of Pauwels



(b)PR curve of Pauwels





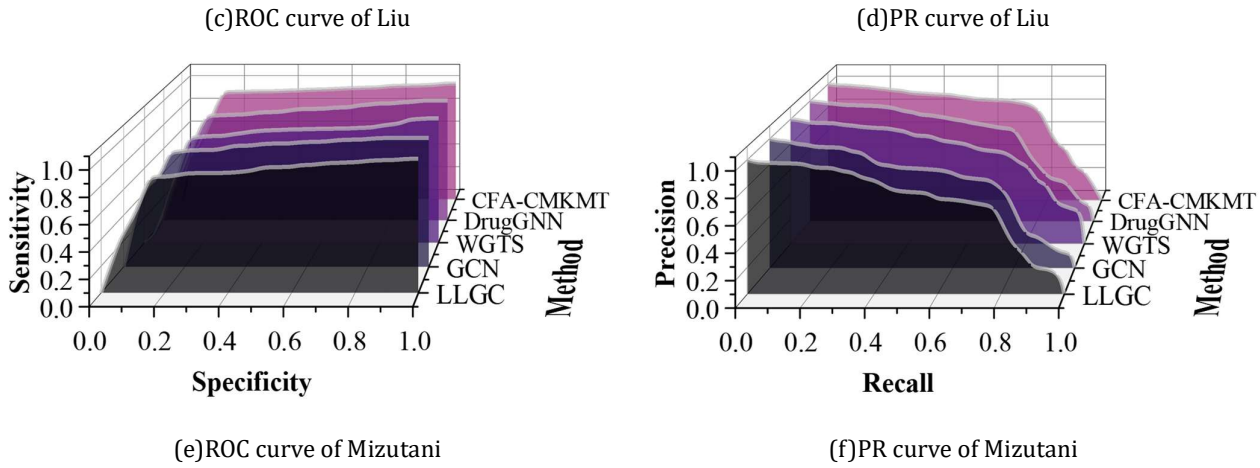


Fig. 3. The ROC and PR curve of the models

4.4.3. Results of ablation experiments. In order to explore the effects of various mechanisms in the CFA-CMKMT model, various ablation experiments were conducted in this paper. The results of the ablation experiments are shown in Figure 4. Among them, CFA-CMKMT-F removes Feature-layer Attention, CFA-CMKMT-A removes Adrs-layer Attention, and CFA-CMKMT-C removes causal multicore multitasking module. The AUC values of the CFA-CMKMT model in the three datasets were 0.925, 0.936, and 0.933, and the PR values were 0.844, 0.838, and 0.841, and the complete CFA-CMKMT model had the best performance in both the AUC and PR metrics, which showed that the model's Patient-Feature Attention Module, Patient-Adverse Drug Reaction Attention Module, and effectiveness of the causal multinuclear multitasking module.

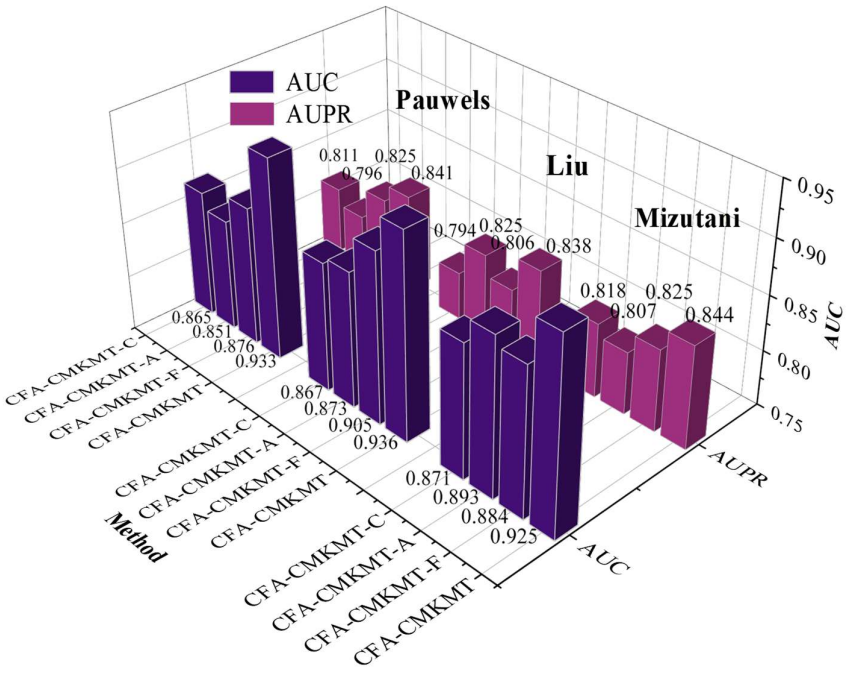


Fig. 4. Ablation experiment results

4.4.4. Case studies. While the experiments in the previous section analyzed the performance of the model from the perspective of statistical indicators, this section analyzes the model from the

perspective of specific cases. Specifically, in this section, a common antibiotic drug “Cefaclor” was selected from the test set, and the top ten predicted adverse reactions with the highest probability were listed. The results of the “Cefaclor” case study are shown in Table 3. From the experimental results, it can be seen that except for "Rash" and "Vomiting", the top 10 adverse reactions in the prediction of other adverse reactions were recorded in the SIDER database, and the three most common adverse reactions (abdominal pain, diarrhea, and headache) models in the dataset could be correctly predicted, indicating that the model had a good prediction effect.

Table 3. Case experiment results of “Cefaclor”

Adverse reaction	Whether in the database	Incidence rate/%
Abdominal pain	Yes	3.38% - 4.63%
Diarrhoea	Yes	2.58% - 4.10%
Asthenia	Yes	1.39% - 3.35%
Vertigo	Yes	Post-market monitoring report
Nausea	Yes	2.48%
Anaphylactic	Yes	Post-market monitoring report
Hypotension	Yes	Post-market monitoring report
Rash	No	
Vomiting	No	
Headache	Yes	2.65% - 5.42%

5. Conclusion

The “dual-channel” policy provides a new supply channel for patients to use negotiated drugs, and this study provides statistics on the current implementation status of negotiated drugs in a region from 2018 to 2023 to analyze the accessibility and affordability of negotiated drugs. Combined with the background of the era of intelligent health insurance, the study proposes a three-party linkage mechanism for accurate regulation of dual-channel medicines in health insurance and constructs an adverse drug reaction prediction model based on collaborative filtering algorithms.

In recent years, under the implementation of the “dual-channel” medication protection mechanism for negotiated medicines in the sample areas, the types of negotiated medicines, the total volume of purchases and the amount of purchases have all increased markedly, with the types of negotiated medicines available to medical institutions and retail pharmacies increasing by 47.37 per cent and 54.35 per cent, respectively, and the total volume of purchases increasing by 3.42 and 2.36 times, respectively, and the availability and affordability of negotiated medicines gradually increasing. The accessibility and affordability of negotiated medicines has also gradually increased.

The AUC and AUPR values of the CFA-CMKMT model proposed in this paper centered around 0.93 and 0.83 in different data, which is better than the existing baseline model in terms of prediction accuracy and applicability. The validity of the various modules of the model for the prediction of adverse drug reactions was also validated by ablation experiments. The model can be used to reduce the health hazards caused by adverse reactions to patients and promote the safe use of medicines negotiated by health insurance.

The dual-channel drug precision supervision mechanism of medical insurance requires the medical insurance department to build a cloud medical insurance prescription sharing platform, improve the audit rules and the supervision mechanism of the medical insurance fund, and intelligently monitor the audit system of the medical insurance medication, and the medical institutions and retail pharmacies need to tacitly cooperate and closely collaborate with the medical insurance department, utilize the information technology means, and strengthen the network audit of the relevant expenses as well as supervision, so as to improve the convenience, accuracy, and coordination of the use of

medication for the insured people. Linkage.

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References

[1] Li, J. Q., Yu, F. R., Deng, G., Luo, C., Ming, Z., & Yan, Q. (2017). Industrial internet: A survey on the enabling technologies, applications, and challenges. IEEE Communications Surveys & Tutorials, 19(3), 1504-1526.

[2] Beier, G., Niehoff, S., & Xue, B. (2018). More sustainability in industry through industrial internet of things?. Applied sciences, 8(2), 219.

[3] Xu, B. C., Xu, X. N., Zhao, J. C., & Zhang, M. (2022). Influence of internet use on commercial health insurance of Chinese residents. Frontiers in Public Health, 10, 907124.

[4] Li, Y., Lu, C., & Liu, Y. (2020). Medical insurance information systems in China: mixed methods study. JMIR medical informatics, 8(9), e18780.

[5] Kumar, S., Kalra, G., Bhardwaj, H. K., Rajoria, Y. K., Kumar, D., & Boadh, R. (2022). Internet of Medical Thing and FIS evaluation for selecting and delivering the best health insurance coverage. J. Pharm. Negat. Results, 13(8), 3438-3446.

[6] Liu, Z., Li, W., & Zhang, T. (2022). Internet and private insurance participation. International Journal of Finance & Economics, 27(1), 1495-1509.

[7] Ren, Y., & Yang, Z. (2022). Application of Smart Healthcare in LTCI, Outpatient Mutual-Aid Guarantee Mechanism, and Sustainability of Medical Insurance Fund for Urban Employees. Journal of Healthcare Engineering, 2022(1), 3406977.

[8] Winter, A., Stäubert, S., Ammon, D., Aiche, S., Beyan, O., Bischoff, V., ... & Löffler, M. (2018). Smart medical information technology for healthcare (SMITH). Methods of information in medicine, 57(S 01), e92-e105.

[9] Wen-hua, H. O. U., & Dan-dan, Y. A. N. G. (2019). Competition Strategy of Dual-channel Pharmaceutical Supply Chain Based on Medical Insurance Regulation and Consumer Utility. Operations Research and Management Science, 28(2), 8.

[10] Wang, W., & Yang, W. (2024, February). Research on Drug Supply Chain Channel Strategies Considering Consumer Preferences and Medical Insurance. In ICEMME 2023: Proceedings of the 5th International Conference on Economic Management and Model Engineering, ICEMME 2023, November 17–19, 2023, Beijing, China (p. 469). European Alliance for Innovation.

[11] Wei, H., & Liu, Y. (2025). Research on the selection of OTC drug supply chain sales models: based on medical insurance policy. Frontiers in Public Health, 13, 1484635.

[12] Wang, J. J., Zhang, X., & Shi, J. J. (2023). Hospital dual-channel adoption decisions with telemedicine referral and misdiagnosis. Omega, 119, 102875.

[13] Ma, Y., Li, Z., Liu, K., & Liu, Z. (2022). Price Decision-Making in Dual-Channel Healthcare Services Supply Chain Considering the Channel Acceptance, Price Ceiling, and Public Welfare. International Journal of Environmental Research and Public Health, 19(20), 13028.

[14] Kluver, D., Ekstrand, M. D., & Konstan, J. A. (2018). Rating-based collaborative filtering: algorithms and evaluation. Social information access: Systems and technologies, 344-390

[15] Jalili, M., Ahmadian, S., Izadi, M., Moradi, P., & Salehi, M. (2018). Evaluating collaborative filtering recommender algorithms: a survey. IEEE access, 6, 74003-74024.

[16] Ajaegbu, C. (2021). An optimized item-based collaborative filtering algorithm. Journal of ambient intelligence and humanized computing, 12(12), 10629-10636.

[17] Xiaojun, L. (2017). An improved clustering-based collaborative filtering recommendation algorithm. Cluster computing, 20, 1281-1288.

[18] Li, X., & Li, D. (2019). An improved collaborative filtering recommendation algorithm and recommendation strategy. Mobile Information Systems, 2019(1), 3560968.

[19] Zhang, J., Lin, Y., Lin, M., & Liu, J. (2016). An effective collaborative filtering algorithm based on user preference clustering. Applied Intelligence, 45, 230-240.