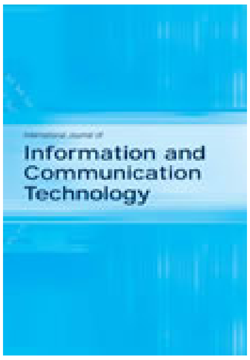


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Hybrid collaborative recommendation of cross-border e-commerce products based on multidimensional evaluation

Liyun Pan

Article History:

Received:	27 October 2024
Last revised:	25 November 2024
Accepted:	25 November 2024
Published online:	20 January 2025

Hybrid collaborative recommendation of cross-border e-commerce products based on multidimensional evaluation

Liyun Pan

Business and Tourism Institute,
Hangzhou Vocational and Technical College,
Hangzhou, 310018, China
Email: 13738191219@163.com

Abstract: With the rapid development of globalisation and e-commerce, cross-border e-commerce platforms are facing the challenge of improving user experience and recommendation system efficiency while meeting the diverse needs of consumers. Traditional recommendation systems rely heavily on users' historical behaviour and simple rating data. However, these methods often face problems such as data sparsity and single recommendation results in practical applications. Therefore, this article proposes a hybrid collaborative recommendation method for cross-border e-commerce products based on multidimensional evaluation, which fully utilises users' multidimensional evaluation information of products to address the complexity of cross-border e-commerce. Then, the system framework and algorithm flow were presented. Finally, the improved algorithm proposed in this paper was experimentally analysed using a cross-border e-commerce enterprise order dataset. Compared with traditional collaborative filtering recommendation algorithms, it reduced the impact of data sparsity in collaborative filtering recommendation algorithms and verified that the improved algorithm has better recommendation performance.

Keywords: recommendation system; cross border e-commerce; collaborative filtering; multidimensional evaluation.

Reference to this paper should be made as follows: Pan, L. (2025) 'Hybrid collaborative recommendation of cross-border e-commerce products based on multidimensional evaluation', *Int. J. Information and Communication Technology*, Vol. 26, No. 1, pp.102–116.

Biographical notes: Liyun Pan obtained her Master's degree from Zhongnan University of Economics and Law in 2010, Lincoln University College, Malaysia Doctor is studying. She is currently an Associate Professor in Hangzhou Vocational and Technical College. Her research interests include innovation, entrepreneurship, and cross-border e-commerce.

1 Introduction

With the continuous growth of consumers' demand for product diversification and personalisation, traditional recommendation systems are no longer able to meet the complex needs of users. Therefore, a hybrid collaborative recommendation model for cross-border e-commerce products based on multidimensional evaluation has emerged. This model not only focuses on users' historical purchasing behaviour, but also comprehensively considers multiple dimensions such as product characteristics, user evaluations, and social network influence, in order to provide more accurate recommendation results.

Firstly, multidimensional evaluation can fully tap into users' potential needs (Carr, 2007). Traditional recommendation systems are often limited to analysing the behaviour of similar users, while ignoring the diverse preferences of users in different contexts.

Secondly, the application of hybrid recommendation methods can effectively overcome their respective limitations. By combining the two, it is possible to better balance new users and cold start issues, improving the adaptability and flexibility of the system.

In addition, in the cross-border e-commerce environment, user behaviour is deeply influenced by cultural, regional, and social factors. Consumers in different regions may be influenced by different external factors in their purchasing decision-making process. Therefore, building a recommendation system that can consider these diverse influences will provide a more competitive advantage for cross-border e-commerce platforms.

In practical applications, cross-border e-commerce platforms can enhance user experience, increase user stickiness, and promote sales growth through this multi-dimensional evaluation recommendation system.

Although traditional recommendation algorithms have become increasingly mature, their accuracy will be quite low if directly applied to Chinese cross-border e-commerce platforms. Especially in terms of imported goods:

1 The types of cross-border goods that domestic users can purchase are limited. According to actual enterprise surveys, they can be roughly divided into six categories: beauty and personal care, clothing and shoe bags, furniture and daily life, food and healthcare, maternal and child products, and automotive spare parts.

2 The amount that domestic users can purchase is limited. According to the new regulations in 2019, the purchase amount for a single order for domestic users cannot exceed 5,000 yuan (previously 2,000 yuan), and the annual purchase amount cannot exceed 26,000 yuan (previously 20,000 yuan).

3 The tax rates for various types of cross-border goods vary, and different tax rates affect users' demand for various types of goods.

Due to significant differences between cross-border e-commerce and general e-commerce (Gomez-Herrera et al., 2014), in order to ensure recommendation effectiveness, the application of recommendation systems in cross-border e-commerce will not be the same as in general e-commerce.

There have been many achievements in the current research on recommendation systems. In recent years, significant progress has been made in the field of recommendation systems, especially in e-commerce. Conventional recommendation systems mostly depend on collaborative filtering (CF) technology, which forecasts preferences by means of user interaction with objects. These techniques do, however, frequently suffer from cold start and scalability problems (Herlocker et al., 2004). Adomavicius and Tuzhilin (2005) polled the most advanced technology in great detail, emphasising the limitations of traditional methods and the need to integrate multiple data sources for scalability.

Researchers have started looking at hybrid recommendation systems combining several information sources in order to handle these difficulties. Burke's (2002) study, for example, emphasises the advantages of combining content-based recommendations with CF, hence increasing suggestion variation and precision. This hybrid approach is particularly beneficial in cross-border e-commerce, as user preferences may be influenced by various factors, including cultural background and regional trends. Combining these two kinds of data, Thorat et al. (2015) put out a novel hybrid method to raise suggestion accuracy. Rendle (2012) also developed a factorisation machine, which generates more tailored recommendations by essentially simulating the interaction between people and objects.

To handle the changing character of user preferences, we also investigated context aware recommendation systems. Reviewing several situational awareness techniques, Verbert et al. (2012) underlined their applicability in modifying recommendations depending on situational elements, which is especially crucial in cross-border e-commerce contexts.

Deep learning technology has transformed the industry even more by enabling the documentation of intricate user project interactions. Advanced neural network architectures greatly raised the quality of recommendations according to a 2022 survey on deep learning based recommendation systems. Applying deep learning to music recommendation, Mao et al. (2022) shown the possibilities of these approaches in many spheres.

Furthermore well known is the effect on recommendation systems using user produced content including ratings and comments. Koren (2009) investigated factorisation methods including this knowledge to improve user preferences and item attributes. Research by Zangerle and Bauer (2022) indicates that user reviews offer extensive insights into product attributes, which can be efficiently applied to enhance recommendation systems. In cross-border settings especially, this is crucial since different markets could see things differently.

Furthermore encouraged in current research are the incorporation of multidimensional assessment. Weng et al. (2009) conducted research suggesting a multidimensional recommendation system combining social network impact, user feedback, and product attributes. Their study results show that incorporating several aspects greatly increases user happiness and helps to greatly customise recommendations. Using multidimensional tensor decomposition, Taneja and Arora (2018) presented a technique for cross-domain recommendation. While users' interests and behaviours in recommendation systems may cover several domains (including movies, books, and music), conventional recommendation systems are usually limited to one domain and cannot efficiently leverage knowledge from other domains. Multidimensional tensor decomposition lets one simultaneously model data from several domains and capture user preferences in several domains.

Additionally recent attention in research has been on the application of machine learning methods in recommendation systems. One very significant example is the study of Zhang et al. (2023), who use the latest neural network models to dynamically capture complex information for better recommendations. Their study results show a notable increase in suggestion performance, implying the feasibility of implementing cutting-edge techniques in cross-border e-commerce uses.

All things considered, the combination of hybrid recommendation strategies and multidimensional evaluation offers a potential method to enhance recommendation systems. Future studies should concentrate on improving these approaches to fit the special difficulties presented by various consumer behaviour and preferences in the worldwide market.

2 Relevant technologies

2.1 Multi dimensional evaluation model

Multidimensional evaluation models are fundamental component in recommendation systems. This model seeks to fully take into account several elements in order to more faithfully depict consumers' demands and preferences. To offer more customised recommendations, this approach takes into account several factors including product attributes, user reviews, and social network impact.

Usually including the following dimensions, multi-dimensional evaluation models reflect: Behavioural data are the most fundamental recommendation sources; so, by use of past activity analysis, one can forecast future preferences of users. Product characteristics' dimension consists in the description, category, brand, price, and other aspects of the product. These pieces of information help to understand the attributes of the product and match it with the needs of the user.

1 User evaluation dimension: User evaluations of products (such as reviews and ratings) can provide profound insights into product quality and user experience. Analysing user feedback can reveal potential preferences and pain points.

2 Social network dimension: The influence of social media is becoming increasingly significant. The behaviour, recommendations, and evaluations of a user's friends and followers can influence an individual's purchasing decisions. Through social network analysis, richer user interest information can be obtained.

To achieve a comprehensive evaluation of multiple dimensions, we can define a comprehensive scoring function that combines information from different dimensions. Assuming there are D dimensions, each with varying degrees of influence, we can express them as:

$$S_{u,i} = \sum_{d=1}^{D} \omega_d \cdot f_d(u,i) \tag{1}$$

where $S_{u,i}$ represents the comprehensive rating of user u on item i. ω_d is the weight of the d-th dimension, indicating its importance to the final score. $f_d(u, i)$ is the rating function of user u for item i in the d^{th} dimension.

The determination of weight ω_d is crucial and can be achieved through various methods, such as using questionnaires or interviews to understand how users value different dimensions. Using models such as linear regression and random forest, automatically learn weights of different dimensions based on users' historical data. Alternatively, adjust the weights through multiple experiments and select the weight combination that maximises the recommendation accuracy.

The rating function $f_d(u, i)$ varies depending on the characteristics of each dimension. The rating function designed based on user behaviour is as follows:

$$f_{behavior}(u,i) = \frac{\sum_{j \in R_u} r_{uj}}{\left|\{j \in R_u\}\right|} \tag{2}$$

where R_u is the collection of items evaluated by user u, and r_{uj} is the user's rating of item j.

The function designed for rating based on product characteristics is as follows:

$$f_{content}(u,i) = sim(\vec{v}_u, \vec{v}_i) \tag{3}$$

The function designed based on user evaluation ratings is as follows:

$$f_{review}(u,i) = \frac{1}{n}\sum_{k=1}^{n} r_k \tag{4}$$

where r_k is the score of the k^{th} evaluation of item i by the user.

The function designed based on social network ratings is as follows:

$$f_{social}(u,i) = \frac{1}{m}\sum_{v \in F_u} sim(v,i) \tag{5}$$

where F_u is the friend set of user u, and $sim(v, i)$ is the similarity in rating of item i by friend v.

The multidimensional evaluation model provides a comprehensive approach for cross-border e-commerce recommendation systems, which can significantly improve the accuracy and user satisfaction of recommendations by considering multiple dimensions such as user behaviour, product characteristics, user evaluations, and social networks.

2.2 CF algorithm

CF algorithms often need to process user item matrices, where M and N represent the total number of items and users, respectively. The implicit feedback of user usage data can be represented as $Y \in R^{M \times N}$, where:

$$y_{ui} = \begin{cases} 1, \text{The interaction between user } u \text{ and item } i \text{ is observed} \\ 0, other \end{cases} \tag{6}$$

The user item matrix is a type of user's historical information that can reflect their preferences and tendencies. There are two perspectives on this similarity, namely the similarity between sets or the similarity between vectors. There are many different options for similarity standards, and the selection of similarity standards needs to be determined based on specific application scenarios and requirements.

For example, Euclidean similarity calculates linear correlation based on Euclidean distance.

$$sim_{u,v} = \frac{1}{1 + \sqrt{\sum_{i=1}^{N} (u_i - v_i)^2}} \tag{7}$$

where u and v represent two different vectors, and the index i represents the i^{th} element in the vector. The range of Euclidean similarity values is [0, 1], with closer values to 1 indicating stronger similarity.

$$sim_{u,v} = \frac{\sum u_i v_i - n\overline{uv}}{(n-1)s_u s_v} \tag{8}$$

where $\bar{u}$ represents the mean of the vector, and s_u represents the variance of the vector. Pearson correlation coefficient looks at similarity from the perspective of vectors and calculates the degree of linear correlation between two vectors. The larger the absolute value, the stronger the correlation.

Cosine similarity is used to evaluate the degree of similarity by calculating the difference in direction between two vectors:

$$sim_{u,v} = \frac{\vec{u} \cdot \vec{v}}{\|u\| \cdot \|v\|} \tag{9}$$

where · represents dot product, || || Represents the magnitude of a vector.

The Jaccard similarity coefficient is based on set theory and measures the similarity between two sets:

$$sim_{u,v} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|} \tag{10}$$

where $N(u)$ and $N(v)$ are collections of items that users u and v interact with, || || represents the number of elements in a collection. The range of the Jaccard coefficient is [0, 1], and the closer it is to 1, the more similar the two sets are.

Calculate the user's preference for a certain item based on the preferences of similar users:

$$p(u,i) = \sum_{v \in S(u,K) \cap N(i)} sim_{u,v} r_{vi} \tag{11}$$

Calculate the degree of preference of user u for item i in the formula, where set $S(u, K)$ represents the top K users in terms of similarity ranking among users. R_{vi} represents the level of preference of user v towards item i. Based on this equation, further considering factors such as the different number of items that different users come into contact with and their different rating habits, in order to balance these differences, a normalised calculation method can be proposed:

$$p(u,i) = \bar{r}_u + \frac{\sum_{v \in S(u,K) \cap N(i)} sim_{u,v}\left(r_{vi} - \bar{r}_v\right)}{\sum_{v \in S(u,K) \cap N(i)} sim_{u,v}} \tag{12}$$

where $\bar{r}_u$ and $\bar{r}_v$ represent the average ratings of user u and user v for other items, respectively.

Recommendation systems typically need to run on actual datasets and determine the effectiveness of algorithms based on performance metrics. There are various performance metric algorithms available. The TOP-N recommendation method generates a recommendation list of size N, and evaluates the recommendation algorithm based on the recommendation list of the recommendation algorithm and the recommendation list of real data. For example, the standard for expressing the quality of recommended items, recall rate:

$$Recall = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|} \tag{13}$$

where R (u) represents the user recommendation list obtained by the algorithm, and T (u) represents the recommendation list. The recall rate mainly reflects whether the recommendation algorithm can cover the items that users like as much as possible. In addition, there is normalised discount cumulative revenue (NDCG), which takes into account both the correct quantity of recommended items and the order of the recommended list. Firstly, let's introduce the cumulative benefits of discounts. Users who like certain products will receive higher scores before the exam:

$$DCG(b, L) = \sum_{i=1}^{b} r_i + \sum_{i=b+1}^{L} \frac{r_i}{\log_b i} \tag{14}$$

where whether r_i is equal to 1 indicates whether the i^{th} product is a favourite item of the user, On the basis of cumulative discount revenue, normalisation is required to compare different users. Firstly, using the test set to calculate the cumulative discount revenue under the most ideal recommendation list as iDCG, we can then obtain:

$$NDCG_{@K} = \frac{DCG}{iDCG} \tag{15}$$

As a classic recommendation algorithm, CF algorithm has the advantages, online processing, and implicit feedback from users.

3 CF recommendation algorithm based on multidimensional evaluation

3.1 Traditional CF algorithm

The CF algorithm, as the most popular algorithm for building personalised recommendation (PR) systems today, was first proposed by Goldberg et al. (1992). It was utilised to news information filtering in 1994 and has since become the most popular recommendation algorithm in the business world. The CF method assumes that the behaviour of the intended audience can be inferred by examining the perspectives of other users who share common experiences and similar interests. In CF based recommendation systems, the recommendation of target users is based on their historical ratings on the project set and the similarity of neighbouring users. Therefore, collecting user behaviour information and nearest neighbour search are the two major foundations for implementing CF.

This article mainly focuses on the CF algorithm based on user similarity, which is the most direct embodiment of the CF idea. The general process is as follows:

1 Calculate user product rating matrix

In certain application scenarios, PR systems have known user preference ratings for products, such as rating videos on video websites or books on book review websites. However, in more e-commerce application scenarios, users' ratings of items are unknown and need to be calculated by PR systems based on users' online behaviour records. For example, shopping websites can calculate users' ratings of products based on users' clicks, searches, collections, adding to shopping carts, etc., and news websites can calculate users' evaluations of products based on users' textual comments on news. These explicit or implicit user rating data can form a user product rating matrix A (m, n), as shown in Table 1.

Table 1 Collection of regular user product ratings

	$Item_1$	...	$Item_i$	...	$Item_n$
$User_1$	$R_{1,1}$	...	$R_{1,i}$	...	$R_{1,n}$
...	...	...	...	...	...
$User_u$	$R_{u,1}$	...	$R_{u,i}$	...	$R_{u,n}$
...	...	....	...	...	...
$User_m$	$R_{m,1}$	...	$R_{m,i}$	...	$R_{m,n}$

2 Calculate user similarity

Similarity statistics can be employed to determine the similarity between users based on the user-product rating matrix. In this matrix, each row represents a rating vector for a single user across n items. By comparing the rating vectors of two users, their degree of similarity can be assessed. Common techniques for calculating similarity between rating vectors include cosine similarity and the Pearson correlation coefficient.

3 Nearest neighbour search

After obtaining user similarity, neighbours with similar behaviours or preferences to the intended audience can be searched based on user resemblance, usually using K-nearest neighbours (KNN) and threshold methods.

KNN method: Regardless of the similarity between neighbouring users and the intended audience. In this method, setting the K value too high may result in the inclusion of neighbouring users with low similarity as the nearest neighbours, leading to a decrease in the final PR effect. Setting the K value too low may result in a small preference item set for the nearest neighbours and a low diversity of recommendation results.

Threshold method: Set a similarity threshold δ, where all neighbouring users with similarity exceeding δ will be included in the nearest neighbour set, while the rest will not be selected. Due to the varying levels of similarity among different user groups, a single threshold may result in some target users only being able to search for a very small number of nearest neighbours, leading to unsatisfactory recommendation results. On the other hand, some target users may find too many nearest neighbours, resulting in a long time to generate recommendation results.

4 Recommendation results generated

Two weighted average calculation methods are mainly used, namely the weighted average of neighbourhood and product scores and the weighted average of neighbouring product score increments. Let *N* represent the nearest neighbour set of user *u*, and the two calculation methods are as follows:

$$\tilde{r}_{ui} = \frac{\sum_{v\in N} sim(u,v)\times r_{vi}}{\sum_{v\in N} |sim(u,v)|} \tag{16}$$

$$\tilde{r}_{ui} = \bar{r}_u + \frac{\sum_{v\in N} sim(u,v)\times\left(r_{vi} - \bar{r}_v\right)}{\sum_{v\in N} |sim(u,v)|} \tag{17}$$

3.2 CF algorithm based on multidimensional evaluation

This simple processing method does not distinguish the preferences of the target user on a certain product from their preferences on a certain type of product, ignoring the specific details of the product preferences of target users with special preferences, resulting in poor recommendation performance. For example, for the same pair of basketball shoes, some users may purchase them because they prefer its brand, some users may prefer its colour, some users may prefer its cushion, and some users may prefer its endorsed celebrity. But these users have all purchased this pair of basketball shoes and given high ratings. In this case, traditional CF recommendation algorithms will consider these users with different special preferences as “users who like a certain basketball shoe”. Therefore, in order to highlight the special preferences of users, it is necessary to assign different weights to the specific attributes of each product.

It is necessary to establish a user product attribute preference matrix. In practical applications, a product generally has multiple attributes, and each attribute has multiple attribute values. For example, for a pair of basketball shoes, it has multiple attributes such as brand, endorsed stars, style, colour, etc., while brand attributes have multiple attribute values such as Adidas, Nike, JORDAN, etc. In the recommendation system, there are *m* users involved in s-class product attributes.

Table 2 User product attribute rating table

	$Attr_1$			$Attr_2$			…	$Attr_s$		
	$Attr_{1,1}$	$Attr_{1,2}$	…	$Attr_{2,1}$	$Attr_{2,2}$	…	…	$Attr_{s,1}$	$Attr_{s,2}$	…
$User_1$	$P_{1,1,1}$	$P_{1,1,2}$	…	$P_{1,2,1}$	$P_{1,2,2}$	…	…	$P_{1,s,1}$	$P_{1,s,1}$	…
…	…	…	…	…	…	…	…	…	…	…
$User_u$	$P_{u,1,1}$	$P_{u,1,2}$	…	$P_{u,2,1}$	$P_{u,2,2}$	…	…	$P_{u,s,1}$	$P_{u,s,2}$	…
…	…	…	…	…	…	…	…	…	…	…
$User_m$	$P_{m,1,1}$	$P_{m,1,2}$	…	$P_{m,2,1}$	$P_{m,2,2}$	…	…	$P_{m,s,1}$	$P_{m,s,2}$	…

The attributes in Table 2 represent the degree of preference of the user for a certain attribute of an item. By analysing the table data, the cosine similarity formula can be used to calculate attribute preference similarity:

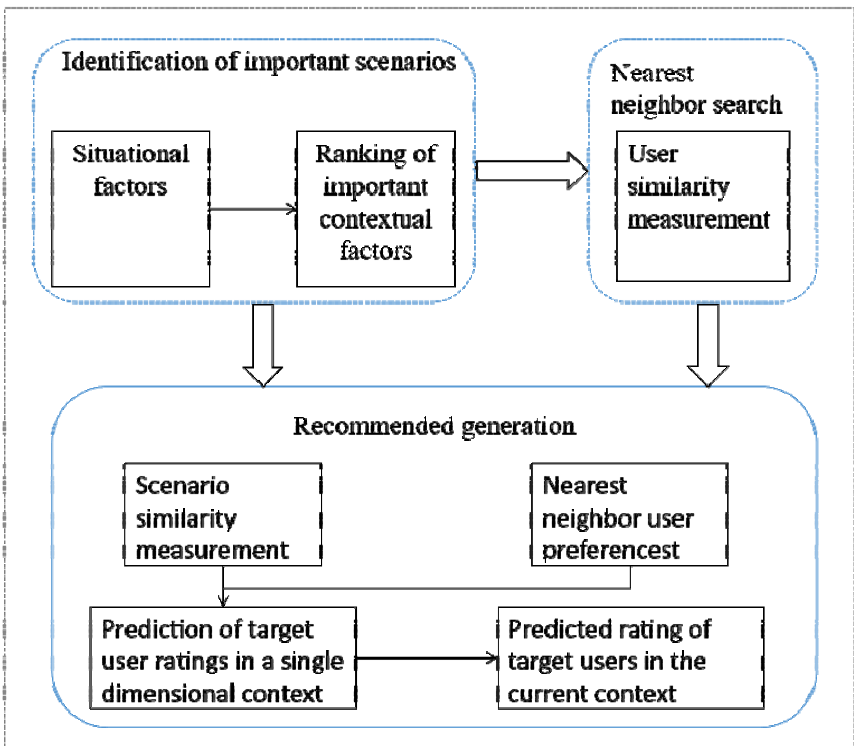
$$sim_{Attr}(u,v)=\frac{\sum_{b=1}^{|Attr_a|}\sum_{a=1}^{s}p_{u,a,b}\cdot p_{v,a,b}}{\sqrt{\sum_{b=1}^{|Attr_a|}\sum_{a=1}^{s}p_{u,a,b}^{2}}\cdot\sqrt{\sum_{b=1}^{|Attr_a|}\sum_{a=1}^{s}p_{v,a,b}^{2}}} \tag{18}$$

Among them, s represents the total number of attributes of a certain item, and $|Attr_a|$ represents the total number of attribute values of type a.

$$e_{ui}=\overline{r}_u+\frac{\sum_{v\in N}\left(sim_{Attr}(u,v)\cdot\left(r_{vi}-\overline{r}_v\right)\right)}{\sum_{v\in N}sim_{Attr}(u,v)} \tag{19}$$

where $\overline{r}_u$ and $\overline{r}_v$ represent the average rating of the product set that user u and any other user v have already rated. The overall framework of the algorithm is shown in Figure 1.

Figure 1 Algorithm framework (see online version for colours)



4 Experiment

4.1 Data set

To verify the effectiveness of the multi-dimensional evaluation based cross-border e-commerce product hybrid collaborative recommendation model, we used a real dataset from a large cross-border e-commerce platform. This dataset includes information on users, products, ratings, comments, and social network connections.

There are 10,000 active users, each of whom has interacted with at least 20 different projects. Project feature data: This includes product features such as category, brand, price, and other metadata. There are a total of 5000 unique items in different categories, such as electronic products, fashion, and household appliances. User comment data: This dataset contains over 50,000 user comments in text format. Emotion analysis techniques are applied to these comments to derive emotion scores that can be used for multidimensional evaluation. Social network data: including information on users' social relationships, with 15,000 edges (connections) between users. This allows the model to consider social influence during the recommendation process. Geographic and cultural data: This dataset includes user location information, enabling the system to analyse the impact of geography and culture on user preferences.

4.2 Evaluating indicator

Accuracy refers to the ratio of products that meet user preferences or requirements to the recommended products in the recommendation results provided by the recommendation system (Kumar and Thakur, 2018); The recall rate is the ratio of products that meet user needs or preferences to all products that users like in the recommendation results, which reflects the comprehensiveness of the recommendation list. Let *R* (*u*) represent the recommended product set made by the system to user u based on their behaviour on the training set, and *T* (*u*) represent user *u*'s preferred product set for the test set. The calculation method for the accuracy and recall of the predicted results is as follows:

$$Precision = \frac{\sum_{u \in U} \left| R(u) \cap T(u) \right|}{\sum_{u \in U} \left| R(u) \right|} \tag{20}$$

$$Recall = \frac{\sum_{u \in U} \left| R(u) \cap T(u) \right|}{\sum_{u \in U} \left| T(u) \right|} \tag{21}$$

Let *R*(*u*) represent the set of items recommended by the system to user u, and I represent all the products in the system's product library. The calculation of coverage is as follows:

$$Coverage = \frac{\bigcup_{u \in U} R(u)}{|I|} \tag{22}$$

4.3 Experimental results and analysis

The experiment compared the CF recommendation algorithm (MDHCF) proposed in this article with the traditional User CF algorithm. In this experiment, K values were taken as multiples of all 10 values in the range of 10–100. The results were then compared and analysed, and the final results are shown in Figures 2, 3, and 4.

Figure 2 Comparison of accuracy of MDHCF algorithm (see online version for colours)

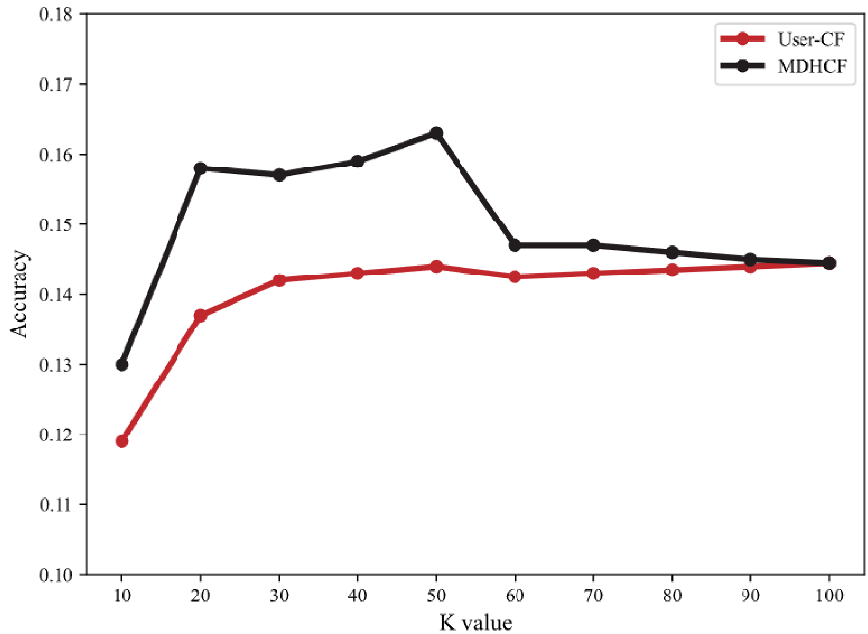


Figure 3 Comparison of recall rates of MDHCF algorithm (see online version for colours)

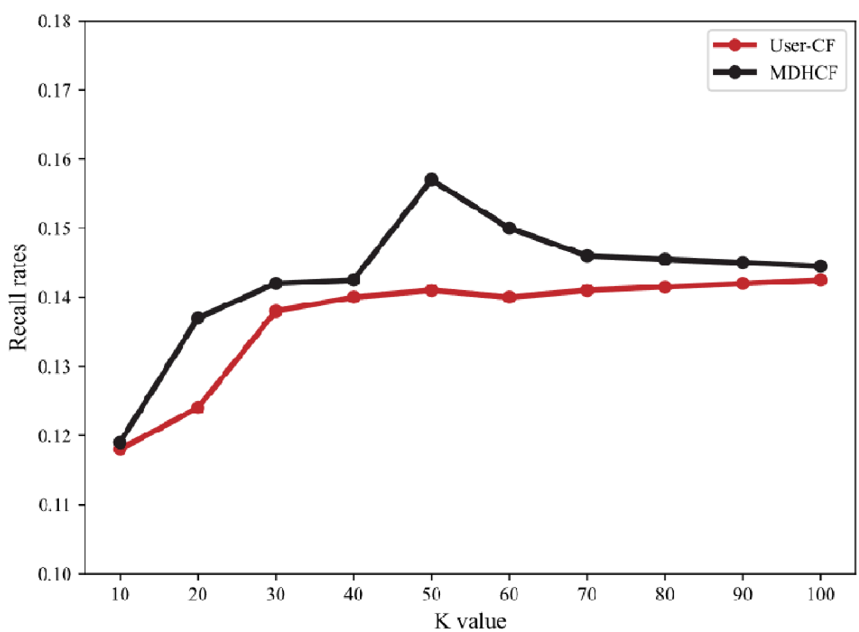
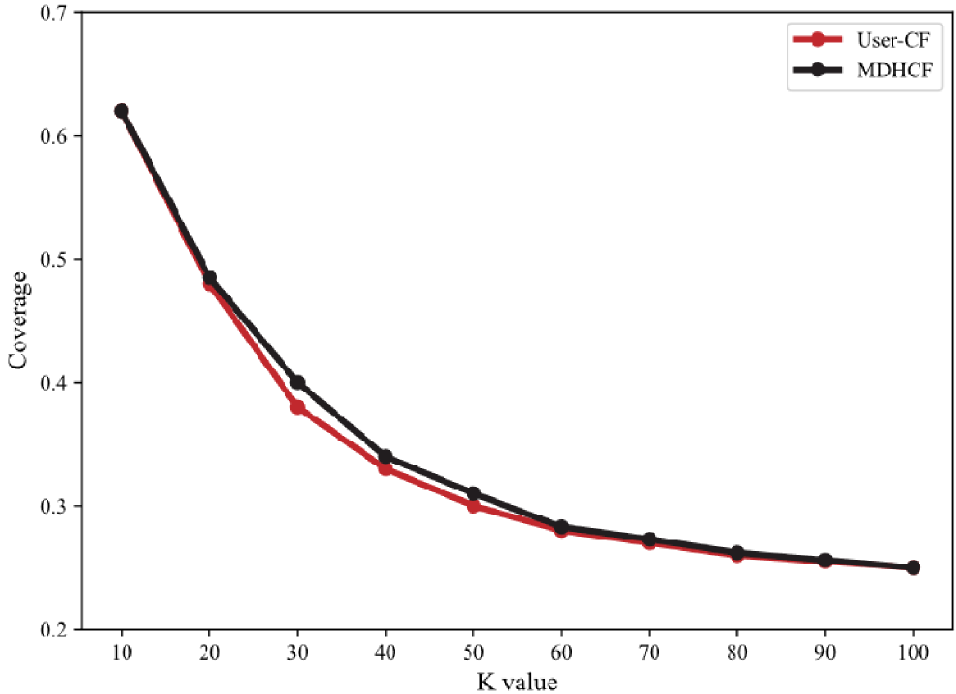


Figure 4 Comparison of coverage of MDHCF algorithm (see online version for colours)



From Figures 2 and 3, it can be seen that under different numbers of nearest neighbour users, Method 1 (MDHCF) has higher overall accuracy and recall compared to Method 2 (User CF); In addition, as shown in Figure 2, When the number of nearest neighbours for the user reaches 50, Method 1 decreases again with the rise in the number of closest neighbours, while Method 2 tends to flatten out overall. Therefore, in this experimental dataset, setting the number of nearest neighbours of the target user to 50 can achieve the best prediction accuracy for both methods, and compared with method 2, method 1 has an accuracy 1.3% higher, with similar conclusions in terms of recall indicators. In terms of coverage indicators, the coverage values of Method 1 having slightly higher overall coverage than Method 2. This is mainly due to the rich dimensionality of contextual information contained in the dataset, which enables the algorithm to be fully trained in multiple dimensions such as user behaviour, product features, and user reviews. It can therefore show superior performance overall in both suggestion comprehensiveness and prediction accuracy, thereby raising the quality of the recommendation system.

5 Conclusions

In this work, we present a hybrid cooperative recommendation model based on multidimensional evaluation for cross-border e-commerce systems. This methodology offers more accurate and customised suggestions by aggregating user behaviour, project features, user comments, and social network influence.

Particularly in the framework of cross-border e-commerce, where cultural, geographical, and social elements have a major influence on purchasing behaviouir, the experimental results underline how well multidimensional approaches reflect users' various preferences. Combining sentiment analysis with social influence in user comments improves suggestions' quality and relevance even more.

Using multidimensional data, the suggested model generally solves the constraints of conventional recommendation systems, hence it is quite appropriate for the dynamic and sophisticated environment of cross-border e-commerce. Future studies can investigate the application of real-time feedback systems to maximise models and mix them with other contextual elements to increase their responsiveness to always shifting market trends.

Acknowledgements

This work is supported by Hangzhou vocational and technical college: Hangzhou hongqi mechanical and electrical Co., Ltd. online operation service (No. 2021hx040), and the '14th Five-Year Plan' Teaching Reform Project of Higher Vocational Education in Zhejiang Province (No. 20230084).

References

Adomavicius, G. and Tuzhilin, A. (2005) 'Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 17, No. 6, pp.734–749.

Burke, R. (2002) 'Hybrid recommender systems: survey and experiments', *User Modeling* and *User-adapted Interaction*, Vol. 12, pp.331–370.

Carr, C.L. (2007) 'The FAIRSERV model: consumer reactions to services based on a multidimensional evaluation of service fairness', *Decision Sciences*, Vol. 38, No. 1, pp.107–130.

Goldberg, D., Nichols, D., Oki, B.M. et al. (1992) 'Using collaborative filtering to weave an information tapestry', *Communications of the ACM*, Vol. 35, No. 12, pp.61–70.

Gomez-Herrera, E., Martens, B. and Turlea, G. (2014) 'The drivers and impediments for cross-border e-commerce in the EU', *Information Economics* and *Policy*, Vol. 28, pp.83–96.

Herlocker, J.L., Konstan, J.A., Terveen, L.G. et al. (2004) 'Evaluating collaborative filtering recommender systems', *ACM Transactions on Information Systems (TOIS)*, Vol. 22, No. 1, pp.5–53.

Koren, Y., Bell, R. and Volinsky, C. (2009) 'Matrix factorization techniques for recommender systems', *Computer*, Vol. 42, No. 8, pp.30–37.

Kumar, P. and Thakur, R.S. (2018) 'Recommendation system techniques and related issues: a survey', *International Journal of Information Technology*, Vol. 10, pp.495–501.

Mao, Y., Zhong, G., Wang, H. et al. (2022) 'Music-CRN: an efficient content-based music classification and recommendation network', *Cognitive Computation*, Vol. 14, No. 6, pp.2306–2316.

Rendle, S. (2012) 'Factorization machines with libfm', *ACM Transactions on Intelligent Systems and Technology (TIST)*, Vol. 3, No. 3, pp.1–22.

Taneja, A. and Arora, A. (2018) 'Cross domain recommendation using multidimensional tensor factorization', *Expert Systems with Applications*, Vol. 92, pp.304–316.

Thorat, P.B., Goudar, R.M. and Barve, S. (2015) 'Survey on collaborative filtering, content-based filtering and hybrid recommendation system', *International Journal of Computer Applications*, Vol. 110, No. 4, pp.31–36.

Verbert, K., Manouselis, N., Ochoa, X. et al. (2012) 'Context-aware recommender systems for learning: a survey and future challenges', *IEEE Transactions on Learning Technologies*, Vol. 5, No. 4, pp.318–335.

Weng, S-S., Lin, B. and Chen, W-T. (2009) 'Using contextual information and multidimensional approach for recommendation', *Expert Systems with Applications*, Vol. 36, No. 2, pp.1268–1279.

Zangerle, E. and Bauer, C. (2022) 'Evaluating recommender systems: survey and framework', *ACM Computing Surveys*, Vol. 55, No. 8, pp.1–38.

Zhang, Z., Patra, B.G., Yaseen, A. et al. (2023) 'Scholarly recommendation systems: a literature survey', *Knowledge and Information Systems*, Vol. 65, No. 11, pp.4433–4478.