Personalized Music Recommendation Based on Interest and Emotion: A Comparison of Multiple Algorithms

Xiuli Yan
College of Music and Dance, Fuyang Normal University, Fuyang, Anhui 236041, China

***Abstract*—Recommendation algorithms can greatly improve the efficiency of information retrieval for users. This article briefly introduced recommendation algorithms based on association rules and algorithms based on interest and emotion analysis. After crawling music and comment data from the NetEase Cloud platform, a simulation experiment was conducted. Firstly, the performance of the Back-Propagation Neural Network (BPNN) in the interest and emotion-based algorithm for recommending music was tested, and then the impact of the proportion of emotion weight between comments and music on the emotion analysis-based algorithm was tested. Finally, the three recommendation algorithms based on association rules, user ratings, and interest and emotion analysis were compared. The results showed that when the BPNN used the dominant interest and emotion and secondary interest and emotion as judgment criteria, the accuracy of interest and emotion recognition for music and comments was higher. When the proportion of interest and emotion weight between comments and music was 6:4, the interest and emotion analysis-based recommendation algorithm had the highest accuracy. The interest and emotion-based recommendation algorithm had higher recommendation accuracy than the association rule-based and user rating-based algorithms, and could provide users with more personalized and emotional music recommendations.**

***Keywords*—Interest and emotion; recommendation algorithm; music; personalization**

I. Introduction

With the prevalence of Internet technology and mobile devices, the amount of data and information that users can receive on the network has increased. However, low-quality or invalid information has also increased, making it difficult for Internet users to retrieve effective information. Information recommendation algorithms are a tool to assist in effective information retrieval [1]. When users are not clear about the information they want to retrieve, or only have a vague range, they can use information recommendation algorithms to initially screen information, and search for effective information from the information recommended by the algorithm [2]. Recommendation algorithms can be applied to music platforms for music recommendation. Music platforms can explore users' preferences based on their attributes, historical information, and other information, and provide personalized recommendation services to improve users' efficiency in finding music that fits their preferences [3]. In music recommendation algorithms, the traditional method is to construct a feature of music recommendation [4], such as click-through rate, and recommend music with high click-through rates within a certain period to users. The principle of this type of music recommendation algorithm is relatively simple, and the basis for recommendation is usually a statistical feature. However, this type of recommendation is highly homogeneous for individual users, and the recommended lists for different users are basically the same. Moreover, statistical features reflect the overall preference trend of users. If the user base is large, there will always be many users whose music preferences do not conform to the mainstream [5]. Personalized recommendation algorithms delve into individual users' effective information to provide recommended music that is closer to individual preferences in terms of trend, although there may be some overlap with mainstream recommended music. It can provide different users with different recommended lists and avoid homogeneous recommended music [6]. In order to improve the accuracy and the degree of personalization of music recommendation algorithms, this paper conducted a study on a personalized music recommendation algorithm, where the personalized recommendation was based on the user's interest and emotion. The significance of this paper is to improve the accuracy of the music recommendation algorithm by recommending music to users through their interest tendencies for different music. The contribution of this paper is to provide a personalized recommendation list for users based on their interest tendency toward music, which provides an effective reference for personalized recommendation algorithms.

II. Literature Review

Relevant works are reviewed below. Shi [7] proposed a personalized music recommendation method and verified its feasibility. Wu et al. [8] designed a mixed music recommendation model using personalized measurement and game theory. They found that the model had higher accuracy in recommending new music, good dynamic personalized recommendation ability, and real-time recommendation ability. Gong et al. [9] constructed a deep music recommendation algorithm using dance motion analysis and evaluated it through quantification measures. They verified the validity of the algorithm.

III. Music Recommendation Algorithm

A. Music Recommendation Algorithm Based on Association Rules

Registered users on music platforms not only leave a history of the music they listen to in their corresponding accounts, but they also add music they are interested in to their playlists while listening to music. Both the user's history and the records in their playlist can reflect the user's individual interests and preferences towards music [10]. Personalized recommendation algorithms usually mine user browsing records to construct personalized preference patterns for music, and then recommend music to users based on these patterns. The association rule method is a way to mine user preference patterns and can be used for personalized music recommendations [11].

Before using the music recommendation algorithm based on association rules for personalized music recommendations, the user's historical data for association rules should be mined. In music recommendation algorithms, association rules refer to the directional connections between different types of music. The mining steps can be summarized as searching for frequent item sets in the database and strong rules within the frequent item sets. The specific steps are as follows.

1) The user database s scanned, and each piece of music is treated as an item. It is assumed, there are a total of five pieces of music in the database, the candidate item sets obtained from scanning will contain five items. Moreover, the support of each item is computed [12]:

$$SUP = \frac{n}{N} \tag{1}$$

where SUP represents the support of the item, N represents the total number of historical records in the user database (the number of historical records equals the number of users), and n represents the number of historical records that contain the item.

2) The candidate item sets are pruned by removing items with support lower than a set threshold. The remaining set of items form the frequent item sets, which are recorded.

3) The items in the frequent item sets are combined pairwise to obtain new candidate item sets, and the support of each item in the new candidate item sets is computed.

4) Return to step 2 to obtain new frequent item sets, and record them.

5) Steps 2, 3, and 4 are repeated until a new set of candidate items cannot be generated. Then, the confidence level of all association item sets in the recorded frequent item sets is computed. Association item sets are non-empty proper subsets and the remaining element sets of each item set in the frequent item sets that may produce strong associations. The formula to calculate the confidence level of strong rule $X \Rightarrow Y$ [13] is:

$$CON = \frac{|X \cap Y|}{|X|} \tag{2}$$

where CON stands for the confidence level of the strong rule, $|X|$ indicates the number of records that contain the item, and $|X \cap Y|$ stands for the number of records that contain both items. When the confidence is over the set threshold, the association rule is regarded as strong. The recommendation algorithm recommends music based on the music items in the user's music record and the strong rules.

B. Sentiment Analysis-based Music Recommendation Algorithm

The recommendation algorithm based on association rules described earlier, mines data from the overall user history to obtain the association rules between music pieces. The music association rules obtained through data mining of user history indicate a connection between music pieces with the same "traits" [14]. The music pieces in the user's history reflect their interest in the "traits" of the music, and the music found through association rules will also contain the "traits" that the user is interested in. In most cases, this type of recommendation algorithm is sufficient to meet the needs of most users. However, users' moods can change during the process of listening to music [15]. Changes in mood can affect subjective feelings about music, making it difficult to satisfy user needs by recommending music based on rigid association rules.

Fig. 1. Basic flow of the sentiment analysis-based music recommendation algorithm.

To enable music recommendation algorithms to adapt to users' changing emotional needs, this article incorporates sentiment analysis into music recommendation algorithms. Fig. 1 illustrates the basic process of the sentiment analysis-based music recommendation algorithm, and its detailed steps are as follows.

1) The music listening history of registered users on the music platform is collected, which includes the music data that the user listened to and the textual comments that the user made about the music.

2) The Back-Propagation Neural Network (BPNN) [16] is used to quantify the sentiment of music and each user's comment on the music, that is, to classify the sentiment of both. When training the BPNN to recognize the sentiment of music and comments separately, the result labels of the training samples are numerical values of the emotional categories. This article adopts the Hevner emotional circle model, which has eight emotional types. When recognizing the sentiment of music, the Mel Frequency Cepstral Coefficent (MFCC) features [17] of the music are input into the BPNN, which is calculated layer by layer in the hidden layer, and finally the numerical values of the primary and secondary emotions of the music are output in the output layer. When recognizing the sentiment of user comments, the comment text is preprocessed, including word segmentation and removal of redundant auxiliary words. Next, the Wordvec method [18] is used to obtain the text vector of the comment, which is then input into the BPNN and calculated layer by layer in the hidden layer, and finally the numerical values of the primary and secondary emotions of the comment are output in the output layer.

3) The sentiment quantification values of the music are combined with the sentiment quantification values of the user's comment on the music according to a certain weight ratio to obtain the sentiment quantification value of the user for the music.

4) The sentiment quantification value of the user for the music obtained in the previous step is used to construct a user-music sentiment rating matrix, as displayed in Fig. 2. The size of the matrix is $m \times n$, each row indicates a user's sentiment rating for different music, each column indicates different users' sentiment rating for the same music, and element e_{ij} in the matrix represent the user's sentiment rating for the music.

$$\begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1j} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2j} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ e_{i1} & e_{i2} & \cdots & e_{ij} & \cdots & e_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mj} & \cdots & e_{mn} \end{bmatrix}$$

Fig. 2. User-music sentiment rating matrix.

5) An item-based collaborative filtering algorithm [19] is used to recommend music, and the associated formula is:

$$\begin{cases} P(a,c) = sim(b,c) \times s(a,b) \\ sim(b,c) = \dfrac{\vec{b} \cdot \vec{c}}{\|\vec{b}\| \cdot \|\vec{c}\|} \end{cases} \tag{3}$$

where music b is the music that user a has listened to, $sim(b,c)$ indicates the cosine similarity between music and music, $\vec{b}$ and $\vec{c}$ are the sentiment rating vector of musics b and c, respectively (the dimension depends on the number of users), $s(a,b)$ is the sentiment rating of user a to music b, which can be checked from the sentiment rating matrix, $P(a,c)$ is the interest level of user a to music c. The top k musics in the nearest neighboring set that is most interesting to the target user are recommended to the target user.

IV. SIMULATION EXPERIMENT

A. Experimental Data and Settings

In this paper, a simulation experiment was conducted in MATLAB software [20] to evaluate a music recommendation algorithm based on sentiment analysis. The simulation experiment used data obtained through web crawlers on the NetEase Cloud Music platform. The data collected by the crawler includes music and comments from different users below the music interface. After initial data cleaning, a total of 200 pieces of music and 200 user comments for each music were collected and analyzed, with some comments shown in Table I. The music codes in the table consist of letters and numbers, where the letters represent the main emotional tendency of the music and the numbers represent the music number. 60% of the data was used as a training set to train the BPNN in the music recommendation algorithm, and the remaining 40% was used for testing. In the recommendation algorithm, after the orthogonal experiment, the number of nearest neighbors was set to 30 when using collaborative filtering to generate the recommendation list, and the number of recommended music in the final recommendation list was set to 10 for each user.

TABLE I. SELECTED COMMENTS OF DIFFERENT USERS ON DIFFERENT MUSIC

	User 1	User 2
Music A1	This song makes me so sad to hear	Feeling sad
Music B1	This song has a wonderful sense of nobility	Sounds pretty sacred.
Music C1	Listen to the impulse to move forward	It will give people a sense of yearning
Music D1	There is a sense of quiet	There is a sense of calmness
Music E1	It's fun to listen to	Very cheerful
Music F1	A sense of relief	Feels very light and fast
Music G1	Can feel the enthusiasm	A sense of power
Music H1	Very life-giving	Vibrant feeling

B. Experimental Design

1) Testing the BPNN in the recommendation algorithm: After training two BPNNs using the testing set, the testing set was used for evaluation. There are two evaluation criteria for the testing plan. Evaluation criteria 1): only when the dominant emotion of the calculated sample is consistent with the dominant emotion in the test sample label, can it be considered a correct prediction; evaluation criteria 2): when either the dominant or secondary emotion of the calculated sample is consistent with the dominant or secondary emotion in the test sample label, it is considered a correct prediction.

2) The influence of the weight ratio of sentiment quantification values between music and comments on the performance of the recommendation algorithm: The weight ratios of sentiment quantification values between comments and music were set to 1:9, 2:8, 3:7, 4:6, 5:5, 6:4, 7:3, 8:2, 9:1. The accuracy of the recommendation algorithm under different weight ratios was tested. The weight ratios were set according to the size of the comment weight ratio.

3) Comparison of three recommendation algorithms: Association rules, user ratings, and sentiment analysis-based: To further prove the performance of the music recommendation algorithm proposed in this paper, it was compared with the association rules-based algorithm and the user ratings-based algorithm. The association rules-based music recommendation algorithm has been described above, while the user ratings-based music recommendation algorithm was the same as the sentiment analysis-based music recommendation algorithm in the basic steps, except that the elements in the rating matrix were no longer sentiment quantification values but rather the number of clicks by the user on the music.

4) The performance test of three recommendation algorithms in a real music platform: In addition to the above simulation experiments, this paper also tested the performance of the three recommendation algorithms in a real music platform. Ten users of the NetEase cloud platform were randomly invited, and the three recommendation algorithms were used to recommend music to them. Each recommendation algorithm recommended music to each user ten times, and the users selected the music they were interested in from the results of each recommendation. The accuracy of each recommendation algorithm in recommending music of interest to the users was calculated.

C. Experimental Results

Fig. 3 illustrates the emotion recognition accuracy of the two BPNN algorithms in the recommendation algorithm based on emotion analysis under different evaluation criteria. The BPNN algorithm used for music emotion recognition had an identification accuracy of 42.6% under evaluation criteria (1) and 82.9% under evaluation criteria (2). The BPNN algorithm used for comment text emotion recognition had an identification accuracy of 44.3% under evaluation criteria (1) and 83.4% under evaluation criteria (2). Compared with evaluation criteria (1), evaluation criteria (2) had relatively loose requirements for the emotion recognition results. If evaluation criteria (1) was used, the algorithm's performance was weakened due to the low accuracy. Therefore, in the subsequent experiments, evaluation criteria (2) was used to construct the rating matrix, where the dominant emotion and secondary emotion coexist.

Fig. 4 shows the impact of the weight proportion of sentiment quantification values of comments and music on the performance of the music recommendation algorithm based on sentiment analysis. As the weight proportion of the sentiment quantification values of comments gradually increased, the recommendation accuracy first rose and then declined, as can be seen from Fig. 4. When the weight proportion of sentiment between comments and music was 6:4, the recommendation accuracy of the algorithm was the highest, at 89.6%.

Due to space limitations, only partial results were shown here, as shown in Table II. First, the recommendation results of the three algorithms for the same user were compared, and it was found that there were differences in the recommendation results of the three algorithms for the same user. The association rule recommendation results had a variety of emotional categories for the recommended music, while the emotional categories of only one or two songs differed in the user rating recommendation results, and the emotional categories of the recommended music in the sentiment analysis recommendation results were basically the same. It was found from the comparison of the recommendation results obtained by different users under the same recommendation algorithm that the association rule recommendation results had various emotional categories for the recommended music. In the user rating recommendation results, there was some overlap in emotional categories of recommended music among different users, and the emotional categories of recommended music in the sentiment analysis recommendation results were different among different users, but the emotional categories of recommended music for individual users were the same.

From Fig. 5, it was visually clear that the algorithm based on sentiment analysis had the highest recommendation accuracy, followed by the algorithm based on user ratings, and the lowest was the algorithm based on association rules.

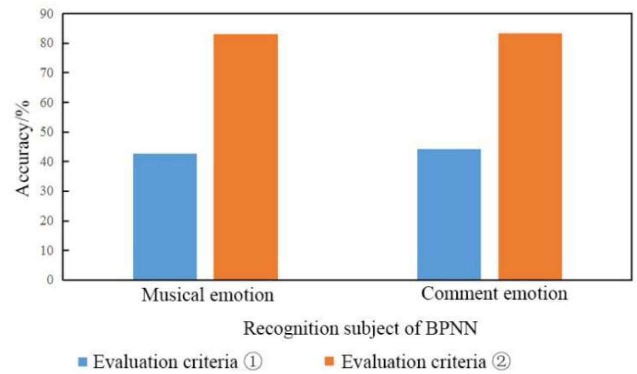

Fig. 3. Test results of the BPNN algorithm.

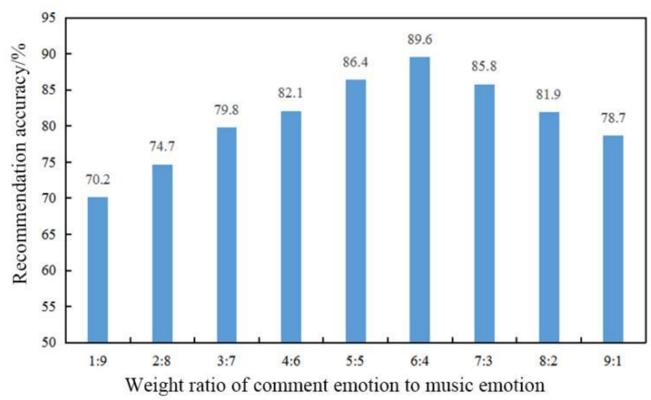

Fig. 4. Impact of the weight ratio of sentiment quantification values between music and comments on the performance of the recommendation algorithm.

TABLE II. SOME RECOMMENDATION RESULTS OF THE MUSIC RECOMMENDATION ALGORITHMS

User	Association Rules Recommendation Results	User Rating Recommendation Results	Emotional Analysis Recommendation Results
User 1	D2;F23;E24;A1;B25	D2;D23;D24;E21;H1	D23;D24;D23;D9;D8
User 2	F5;D9;G20;F12;G14	F5;D14;D23;D24;F12	G3;G5;G14;G11;G12
User 3	D1;H4;C3;B12;H1	A4;C3;D14;D23;D2	C1;C4;C3;C2;C6

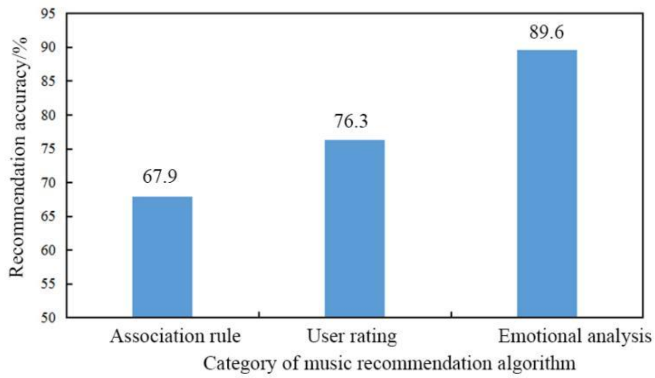

Fig. 5. Recommendation accuracy of three music recommendation algorithms.

In the actual NetEase cloud platform, the above three recommendation algorithms were used to make ten recommendations to each of the ten users, and the number of music items that users were interested in in the recommendation results is shown in Table III. The average number of music items that users were interested in was 66.8 for the association rule-based algorithm, 75.6 for the user rating-based algorithm, and 88.7 for the emotional analysis-based algorithm. It was seen from the comparison in Table III that the recommendation algorithm based on interest and emotional analysis recommended more music that users were interested in. At the same time, the ratio of the average number of songs to the total number of recommendations was very close to the accuracy of the recommendations calculated in the simulation experiment.

TABLE III. PERFORMANCE OF THREE RECOMMENDATION ALGORITHMS IN RECOMMENDING MUSIC OF INTEREST IN THE REAL MUSIC PLATFORMS

	The Number of Music of Interest in the Association Rule-based Recommendation Results/n	**The Number of Music of Interest in user rating-based Recommendation Results/n**	**The Number of Music of Interest under Emotional Analysis-based Recommendation Results/n**
User 1	67	76	89
User 2	66	75	88
User 3	65	75	88
User 4	66	76	87
User 5	67	77	88
User 6	67	77	89
User 7	66	75	89
User 8	67	75	89
User 9	68	76	90
User 10	69	74	90
Average	66.8	75.6	88.7

V. DISCUSSION

With the development of the Internet, people have access to more and more information. Recommendation algorithms can help people find the information they need faster. This paper targeted a music platform and used recommendation algorithms to recommend music that may be of interest to platform users. This paper first introduced the association rule-based recommendation algorithm and the user-rating-based collaborative filtering recommendation algorithm and then introduced the BPNN, which can measure the user's interest and emotion, into the user-rating-based collaborative filtering algorithm in order to make the recommendation results more personalized, so that the algorithm can give the recommendation results based on the user's interest and emotion.

After that, the BPNN for measuring users' interest and emotion was tested first, and then the recommendation accuracy of the three recommendation algorithms was compared. The recommendation performance was tested in the actual NetEase cloud platform with ten randomly invited users. The final test results verified the accuracy of the BPNN for measuring users' interest and emotion, and the algorithm based on interest and emotional analysis had the highest recommendation accuracy among the three recommendation algorithms. The recommendation performance of this recommendation algorithm was also verified in the actual music platform. The reasons for why the algorithm based on interest and emotional analysis had the highest accuracy are as follows: The association rule-based recommendation algorithm mined the entire history of user records to obtain the association rule between music, assuming that users will select the next song according to the mined association rules after listening to a song, but the association rule mined from the entire data did not take into account the individual interests and hobbies of users. The algorithm based on user ratings used the number of times users clicked on music as an indicator of their interest, integrated users with similar interests, and provided personalized recommendations, resulting in higher recommendation accuracy. The recommendation algorithm based on sentiment analysis was based on the emotional tendencies of users and music, integrated users with similar emotional tendencies, and provided recommendations. Because it took into account the influence of emotions on music selection, it was more personalized, and the recommendation results were more accurate.

VI. CONCLUSION

This article briefly introduced the recommendation algorithms based on association rules and sentiment analysis. Then, through web scraping of music and comment data on the Netease Cloud platform, a simulation experiment was conducted. First, the performance of the BPNN in the sentiment analysis-based recommendation algorithm was tested. Then, the influence of the proportion of sentiment weight between comments and music on the algorithm based on sentiment analysis was tested. Finally, the algorithms based on association rules, user ratings, and sentiment analysis were compared. The results were as follows: 1) The accuracy of sentiment recognition for music and comments was higher when the BPNN used dominant and secondary emotions as judgment criteria. 2) As the proportion of sentiment quantification values between comments and music gradually rose, the recommendation accuracy of the algorithm suggested an increasing trend followed by a decreasing trend. When the proportion of sentiment weight between comments and music was 6:4, the algorithm had the highest recommendation accuracy, at 89.6%. 3) The music recommended by the association rule recommendation algorithm had a diverse range of emotional categories. The emotional categories of the recommended music by the user rating recommendation algorithm were relatively consistent within a single user, and there was some overlap between different users' recommended music emotional categories. The emotional categories of the recommended music by the sentiment analysis recommendation algorithm were consistent within a single user, but different users' recommended music emotional categories were different. 4) The recommendation accuracy of the algorithm based on sentiment analysis was the highest, followed by the user rating-based algorithm, and the association rule-based algorithm had the lowest accuracy. 5) The interest and emotional analysis-based algorithm also had better recommendation performance in the actual music platform.

REFERENCES

[1] J. R. Edwards, S. Borgstedt, and B. Barth, "New Music Recommendation Algorithm Facilitates Audio Branding," Market. Rev. St Gallen, vol. 4, pp. 888-894, January 2019.

[2] S. Wang, M. Gong, Y. Wu, and M. Zhang, "Multi-objective optimization for location-based and preferences-aware recommendation - ScienceDirect," Inform. Sciences, vol. 513, pp. 614-626, November 2020.

[3] A. Ramasuri, A. K. Badhan, B. Pushpa, A. J. Rani, A. S. Dharani, and M. Sindhuja, "Music recommendation system with advanced classification," IJERT, vol. 10, pp. 505-509, August 2021.

[4] C. Wu, S. Liu, Z. Zeng, M. Chen, A. Alhudhaif, X. Tang, F. Alenezi, N. Alnaim, and X. Peng, "Knowledge graph-based multi-context-aware recommendation algorithm," Inform. Sciences, vol. 595, pp. 179-194, March 2022.

[5] H. C. Yan, Z. R. Wang, J. Y. Niu, and T. Xue, "Application of covering rough granular computing model in collaborative filtering recommendation algorithm optimization," Adv. Eng. Inform., vol. 51, pp. 1-10, January 2022.

[6] B. Li, J. Li, and X. Ou, "Hybrid recommendation algorithm of cross-border e-commerce items based on artificial intelligence and multiview collaborative fusion," Neural Comput. Appl., vol. 34, pp. 6753-6762, May 2022.

[7] J. Shi, "Music recommendation algorithm based on multidimensional time-series model analysis," Complexity, vol. 2021, pp. 1-11, April 2021.

[8] Y. Wu, J. Lin, and Y. Ma, "A hybrid music recommendation model based on personalized measurement and game theory," Chinese J. Electron., vol. 32, pp. 1-10, October 2022.

[9] W. Gong, and Q. Yu, "A deep music recommendation method based on human motion analysis," IEEE Access, vol. 9, pp. 26290-26300, February 2021.

[10] D. Sun, "Using factor decomposition machine learning method to music recommendation," Complexity, vol. 2021, pp. 1-10, May 2021.

[11] B. Sheng, and G. Sun, "Matrix factorization recommendation algorithm based on multiple social relationships," Math. Probl. Eng., vol. 2021, pp. 1-8, February 2021.

[12] Z. Yang, and J. Cheng, "Recommendation algorithm based on knowledge graph to propagate user preference," Int. J. Comput. Int. Sys., pp. 1-25, January 2021.

[13] M. F. Aljunid, and M. D. Huchaiah, "An efficient hybrid recommendation model based on collaborative filtering recommender systems," CAAI Trans. Intell. Technol., vol. 6, pp. 1-13, May 2021.

[14] Y. Gao, A. Xu, P. J. H. Hu, and T. H. Cheng, "Incorporating association rule networks in feature category-weighted naive Bayes model to support weaning decision making," Decis. Support Syst., vol. 96, pp. 27-38, January 2017.

[15] Y. Wu, J. Lin, and Y. Ma, "A hybrid music recommendation model based on personalized measurement and game theory," Chinese J. Electron., vol. 32, pp. 1-10, October 2022.

[16] S. Xiao, Y. Hu, J. Han, R. Zhou, and J. Wen, "Bayesian networks-based association rules and knowledge reuse in maintenance decision-making of industrial product-service systems," Proc. CIRP, vol. 47, pp. 198-203, December 2016.

[17] W. Rao, L. Zhu, S. Pan, P. Yang, and J. Qiao, "Bayesian network and association rules-based transformer oil temperature prediction," J. Phys. Conf., vol. 1314, pp. 1-8, November 2019.

[18] M. R. Siddiquee, S. Rahman, S. U. I. Chowdhury, and M. R. Rahman, "Association rule mining and audio signal processing for music discovery and recommendation," Int. J. Softw. Innov., vol. 4, pp. 71-87, April 2016.

[19] F. F. dos Santos, M. A. Domingues, V. A. Sundermann, V. O. de Carvalho, M. F. Moura, and S. O. Rezende, "Latent association rule cluster based model to extract topics for classification and recommendation applications," Expert Syst. Appl., vol. 112, pp. 34-60, June 2018.

[20] T. Li, "Selection of audio materials in college music education courses based on hybrid recommendation algorithm and big data," J. Phys. Conf. Ser., vol. 1774, pp. 1-8, January 2021.