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Group recommendation exploiting characteristics of user-item and collaborative rating of users

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Abstract
Recommender Systems have gained popularity in recent years due to their ability to expedite users' selection processes quickly. Traditional recommender systems mainly focus on providing recommendations to a user. However, It is not a suitable recommendation technique for groups of users. A group recommendation system (GRS) addresses this issue of recommendation. GRS is popular in domain, such as health, tourism, movies, etc. A few research is reported in the GRS domain that satisfy each user requirement in a group. The task of GRS can be divided into three subtasks: the formation of the group, rating prediction of individual members in a group, and aggregating them. The state of art technique can not adequately address the issue of group satisfaction. To maximize member satisfaction, we exploit the cluster validation metrics to form suitable groups of users in this paper. We propose a novel technique for rating the prediction of individual members in a group on an item considering the user's characteristics, such as age, gender, and occupation. A Novel aggregation function named Tendency-based Aggregation (TA) is proposed for aggregating the predicted rating of an individual in a group. We conducted the experiments on datasets ML-1M-I, ML-1M-II, and ML-100k to show the efficiency of the proposed method. To validate the proposed approach, we utilize popular evaluation methods used in GRS, such as MAE, RMSE, and group satisfaction metric (GSM). We also report the result of proposed GRS utilizing the newly introduced group satisafction error (SEG). The experimental outcomes show that the proposed method outperforms all the existing methods. The proposed approach improves the GSM by at most 35% compared to the state-of-the-art.

Keywords Group recommender system (GRS) · Aggregation function · Demographic information · Cluster · Content-based filtering (CBF) · Group profile

1 Introduction

Information overload is a problem in the current digital era. Getting relevant recommendations becomes a challenging task. Search engines help tackle the problem to some extent. However,

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personalized information are not provided. A recommendation engine can be used to filter out irrelevant information to provide personalized suggestion. A recommender system (RS) is an excellent tool for e-commerce to sustain customer happiness by studying customers' actions and interests and recommending the most intriguing item. Recommender system supported e-commerce, OTT (over the top), provide effective services. This leads to consumer pleasure and consumer satisfaction [2].

Although majority of recommender system approaches recommend products to users individually. Many activities, such as viewing a movie, going to a restaurant for supper, visiting on tour, watching a movie with family, attending a party, listening to a radio station or music, are usually performed in groups [3]. Recommender systems for these activities should offer services to groups based on members' priorities and interests and their choices. However, traditional recommender systems is useful for individual users. Group recommender system (GRS) is used to recommend items to groups of users. The work in the area of GRS is very limited. With the expanding amount of group activities available over the internet, analysis of the GRS has been increased recently. As a result, researchers have devised several group recommender systems to address this issue [6, 10, 19, 46]. They tried to match specific user expectations to deliver satisfactory recommendations [4]. The task of GRS can be accomplished into three major subtasks: group formation, individual user-item rating prediction, and combining those ratings into group ratings. The clustering technique is often used to form the groups. Subsequently, a prediction technique is used to predict member individual ratings in a group. The aggregation technique is heavily used to combine those individual users' ratings into a group score.

Discovering a common liking or interest in accessible items or actions for all group members is one of the most apparent hurdles in these systems. Many aggregation strategies have been introduced to achieve this goal of constructing the group profile (final group score) [4]. Like individual user recommendation, GRS can be categorized into three major classes: content-based, collaborative filtering, or a combination of these two. Content based has its own drawbacks. It does not focuses on individual choices and relationship of among members. So collaborative filtering has been more popular in the area of GRS. Generally, most of these methods are based on collaborative filtering (CF).

These research focus on enhancing the performance of group recommender systems, suggesting services or activities to groups of people who share a goal or interest. These research focus on several complex issues, such as forming compatible groups, establishing group preferences, improving recommendations, determining social ties, and members' influences [4] on one another. One of the significant issues is the relationship among members'. Hermes [5] developed an approach, which considers the relationships among group members. That is used to influence members to create a compatible profile and enhance the group recommendations. It uses static weights for every relationship such as parents, couple, friends, students, etc. The weight for members' relationship id used to influence other users in a group. However, it still has flaws because of constant weights for different relations. To convey their issues, Hermes demands the users' cooperation. Nozari et al. developed a unique GRS, namely an influence-based group recommender system (IBGR) that implicitly determines dynamic weights of influence for group members [6]. It finds the influence of leader of a group on other members using trust metric. To overcome the deficiency of Hermes an IBGR, Seo et al. [7] develop an approach based on genre preferences to improve the group recommendation. They provide a method to reduce clustering costs and cluster the groups based on genre preference vectors. They provide a new fine-grained item preference value for the aggregation method.

The research gap of the state of the art is as follows. Group formation is the first and vital step in GRS. Researchers utilize various clustering techniques for this purpose. However, the clustering quality is not measured to do the effects of the formed clusters. So, we address this issue. The content information of an individual, along with the collaborative information (ratings), are exploited in the limited work. We revisit to exploit this information. One of the essential steps is the aggregation of GRS. The limitation of GRS is an inadequacy of a convincible aggregation strategy. So, we suggested a new aggregation strategy for this.

We confer the novelty of this paper briefly here. GRS use various clustering techniques previously. In first stage, we use four metrics silhouette measure and within cluster sum of squared error (WCSS), Inter cluster variance (ICV), and intra clusetr correlation (ICC) to check the quality of group formation. Silhouette is used to decide the number of clusters. We propose a method to predict item rating based on a linear combination of user genre and appropriate weights in a group. Subsequently, we provide a method to predict individual user ratings for an item in every group. Additionally, we offer a novel aggregation function to combine personal user-item preferences in a group. To summarise, this paper's essential contributions are as follows:

- Four cluster validation techniques namely Silhouette and WCSS, Inter cluster variance (ICV), and intra clusetr correlation (ICC) are utilized for measuring the quality of the group.
- We combine user characteristics and their appropriate weights linearly to predict item rating and additionally provide a method to achieve user-item preference in each group.
- A novel aggregation function (TA) is proposed to combine user-item preferences in a group.
- We evaluate the group satisfaction of proposed GRS using group satisfaction measure (GSM) and Satisfaction error for group (SEG). Top-n item is recommended based on final group ratings.

Rest of the paper is organized in the following order:

Section 2 presents the literature and context for this study. Section 3 explores the related work of research. The proposed approach is outlined in Section 4, and the study's evaluation results are shown in Section 5. Finally, in Section 6, conclusion is offered.

2 Related work

The performance of GRS mainly depends on group formation, individual member rating prediction, and aggregation of those ratings into a group score. The essential part of GRS is combining individual ratings into group ratings. We discuss here related work for group formation and group member individual rating prediction. After that, we discuss the aggregation method subsequently.

2.1 Group formation

Clustering is frequently used to produce suitable groups in the stage of group formation. Researchers et al. employed fuzzy C-means with Pearson co-relation measure (PCC) to make a compatible group of users [6]. It gives a hard cluster set. One data point can stay in anyone cluster even if it is similar to others. Researchers [19, 23, 48] also used the K-means clustering technique to generate groups. Hyunchul et al. optimized the K-means algorithm using a genetic algorithm (GA) and named the clustering method such as GA K-means [23]. They also proposed an effective market segmentation strategy based on the GA K-means clustering and user characteristics. They divided many users into a few clusters. However, researchers [11, 23] employed the K-means clustering to cluster groups based on item rating vectors due to its simplicity. It clusters similar users in the same cluster. Srivastava et al. develop a hybrid group anomaly detection approach specifically designed for analyzing sequence data with a particular application to trajectory data. The authors present a novel algorithm that integrates both clustering and statistical techniques to identify anomalies within groups of sequences. It helps to enhance the understanding and detection of abnormal patterns in trajectory-based datasets [44].

Researcher also used a similarity network (SN) to form a groups [10, 12, 14–18]. Flytrap [17] built a network by measuring the similarities across genres. It used group preference to create a voting system to vote for their preferred songs. On the other hand, Flytrap skipped the clustering stage in user preference. Guo et al. established a link between the components to compare all users' evaluations [15]. They grouped the users at random without considering the clustering procedure. They calculated user preferences utilizing PCC between goods and persons to determine similarity. They figured out group priorities by feeding user preferences into a group recommender algorithm. However, they could not fully exploit the benefits of group suggestion since they used a personalized recommendation technique to assess user preferences. Betweenness centrality, a group theory, was used for group formation [16]. They calculated the Betweenness centrality and generated a weighted user similarity network (WUSN) by measuring the similarity between users using COS and Bayesian similarity (BS). The weighted average decides the group choices.

2.2 Members' rating prediction

The main motive of a GRS is to satisfy the maximum members' needs in a group. The effectiveness of member rating prediction in GRS depends on social influence, leader impact, user genre (Age, gender, occupation), item genre (comedy, action, story), etc.

Guo et al. suggested a social influence approach for group user modeling in GRS using personal qualities and relationships to determine users' social influence in a group [15]. This technique creates an influence matrix using social factors such as personality, expertise, susceptibility, and intimacy. It finds group scores using the influence matrix and rating matrix. Zheng et al. introduce a GRS named introduced named Social Influence-based Group Recommender (SIGR) [35]. SIGR uses an attention mechanism to detect a user's social influence and adapt that influence to different groups. SIGN also created a deep learning framework for social influence that uses and combines global and local information from a user's social network. It improves the estimation of a user's social impact drastically. SIGR also applies each member's influence to a user rather than other members. Yang et al. introduced a novel GRS based on attention mechanism [36]. They aggregate the user-item interaction and their general preferences. They learn the user-item interaction through proposed Neural collaborative filtering (NCF). Zhou et al. developed a novel GRS named dynamic connection-based GRS (DCBGRS) [37]. They find the common interest of the subgroup. They compute the connection between users in a subgroup. To obtain a group rating, they use a dynamic aggregation function. It aggregates all the subgroup recommended lists into a final one. Christensen et al. suggested a GRS based on a social relationship in the tourist domain [5]. They use predefined weights as influence factors of all the relationships, such as couples, parents, children, friends, etc. Guo et al. present a unique technique that leverages deep learning algorithms to enhance the accuracy and usefulness of social recommendations in an IoT context (SIoT).

Author address the challenges of ambiguity in social recommendations. By leveraging deep learning techniques, such as CNNs and RNNs, the technique aims to improve recommendation accuracy by capturing complex patterns and context within the IoT environment [45]. Zhou et al. address the challenge of effectively incorporating social information and capturing social interactions. Sociallgn successfully combines social signals into the recommendation process through their proposed method, resulting in improved accuracy and effectiveness [46]. Wang et al. concentrates on CF techniques improved by neural graph models. The authors present a novel approach that combines CF with graph neural networks to improve recommendation accuracy and address the limitations of traditional methods. The proposed approach captures the relationships among users and items in the recommendation process by leveraging the power of graph structures and neural networks [47]. Zhang et al. presents a framework that leverages group embedding techniques and decision aggregation methods to improve the accuracy of group recommendations. The author introduces a decision aggregation strategy that combines individual members' opinions to make group decisions while considering their attentive influence. This aggregation process considers group members' varying expertise and influence levels to arrive at a consensus recommendation [49]. Nozari et al. focused on one of the major problem of GRS, which is relationships and the influence among the group member's [6]. They proposed a method to quantify the impact of members on each other, considering factors such as similarity and trust. Typically, leaders are entrusted with more influence than other group members, and this study aimed to compute the leader's impact on the preferences of other members. One notable aspect of their approach involved utilizing a combination of fuzzy clustering and similarity measures to identify users with similar interests. Additionally, they devised an implicit trust metric to enhance the efficiency of the influence process and leader identification. Other studies [9, 15] have incorporated genre preference or item preference with weighted components in their group recommender algorithms. Joseph et al. used MusicFX to calculate a group's anticipated rating based on genre preference [9]. However, instead of splitting customers with similar likes into several groups, this method treated all users in a fitness center as a single group. It recommends music to a group of users. It has promising results; still, it has limitations. It requires a rating of all radio stations. So it can not be used for movies, books, friends, and tourist recommendations. A few personalized recommendation research [26] included genre features as a primary element in the RS; nevertheless, genre features has a relatively low influence on group recommendation. Researchers [10–12] use UBCF and IBCF for individual rating prediction tasks. Individual member rating prediction method of all other existing methods are provided in Table 1.

Aggregation is an essential part of GRS because of its effectiveness and efficiency [8]. We discuss the literature of existing aggregation methods below.

2.3 Aggregation method

Group Recommendation Systems (GRSs) aim to combine the preferences or forecasts of group members to generate group preferences. Various aggregation approaches have been proposed in the literature to cater to different needs and contexts. The aggregation methods used in previous studies encompass additive utilitarian (AU) [10–12, 42], multiplicative utilitarian (MU) [13], average (Avg) [6, 14, 15, 42], Most pleasure [10], simple count (SC) [17], Borda count (BC) [18], average without misery (AwM) [9, 16], least misery (LM) [10], Approval Voting (AV) [19, 42], hybrid additive (HAU), hybrid approval voting (HAV), and Average without uncertainty [20]. Table 2 exemplifies these aggregation strategies in a

Table 1 Literature of item preference based group recommendations

	Clustering input value	Method	Prediction algorithm	Aggregation Method
Kim and Ahn [23]	user features	Genetic algorithm K-means	CBR	Avg
Baltrunas [14]	item prference	WUSN PCC	UBCF	Avg, LM, BC
Pujahari [10]	item preference	WUSN PCC	IBCF	AU, MP, LM
Boratto [11]	item preference	K-means	UBCF	AU, AV LM, MP, BC
Guo [11]	item preference with social factor	NA	preference relation model	Avg, MP, LM
Mahyar [16]	item preference	WUSN (COS,BS)	centrality based	Weighted AVG
Young-Duk [19]	item preference	K-means	MSD	AU, UL, MP SC, AV, BC CR, AwM, LM
Park [12]	item preference	WUSN (COS, PCC)	UBCF	AU
Amra Delic [24]	non-linear item pref-erecne	NA	centrality based	Avg, Ml, LM, BC
IBGR [6]	item preference	fuzzy c-means (PCC)	Trust based influ-ence rating	Avg
Yalcin [20]	item preference	K-means	NA (baseline)	AU, AV, BC AwU, UL
Yalcin [21]	item preference	Bisecting K-means	SVD++	AU, AV, BC AwM, UL
Yalcin [22]	item preference	Bisecting K-means	MF	UL

user-item matrix. The matrix represents four users forming a group and scoring ten products on a five-star scale. The term "unrated" indicates users who have not yet provided ratings. In GRSs, it is common practice to consider all group members when determining group ratings. AV, however, considers only the ratings of users who have provided ratings above a certain threshold for a particular item within the group [19]. Avg calculates group ratings by averaging individual ratings. AwM is a variation of Avg that disregards ratings below

Table 2 Example for few aggregation strategies

Items	group user score				group preference using aggregation strategies										
	Jitendra	Kusum	Ravi	Ram	MR	AVG	LM	MP	SC	AU	HAU	HAV	PV	AwM	AV
I_1	4	1		3	4	2.66	1	4	3	8	32	27	4	3.5	2
I_2	5	2		4	5	3.66	2	5	3	11	44	36		4.5	2
I_3	4	4		4	4	4	4	4	3	12	48	39	4	4	3
I_4	3	4		3	4	3.33	3	4	3	10	40	33	3	3.66	3
I_5	4		3	2	4	3	2	4	3	9	36	30		3.5	2
I_6	3	2	3	2	3	2.5	2	3	4	10	50	44	3	3	2
I_7			3	3	0	3	3	3	2	6	18	14	3	3	3
I_8			4		0	2	4	4	1	4	8	5	4	4	1
I_9	3	5	3	2	3	3.25	2	5	4	13	65	56	3	3.66	3
I_{10}	4	3	2	5	4	3.50	2	5	4	14	70	60		4	3

a user-defined threshold, effectively ignoring items with ratings below the threshold [29]. AU and MU give substantial weight to such highly-rated products, influencing the GRS to recommend them [30]. They aggregate individual ratings through addition and multiplication, respectively. HAU is a hybrid method that combines AU as the primary influencer and AV as an additional factor in the final group ratings. Conversely, HAV prioritizes AV as the crucial component in determining group ratings, with AU serving as a supplementary influencer [20], as depicted in Table 2.

The extreme ratings are essential to the aggregation procedures in this area. These extreme evaluations can be classified as either the highest or lowest ratings, and they correspond to the Most pleasure (MP), Least misery (LM), and Plural voting (PV) aggregation approaches, respectively. MP [31] selects the item with the highest ratings among the group members, while LM [32] chooses the item with the lowest rating. When a group consists of a large number of members, MP (and LM) tends to assign the same high (and low) rating to practically every item, as it is highly likely that at least one member of the group will provide a high (or low) rating for each item. In such cases, these approaches fail to differentiate between items that the group genuinely prefers. Table 2 illustrates the group ratings computed by MP and LM. Plurality Voting (PV) [27] also emphasizes the highest ratings for aggregation. However, PV differs from MP in that it considers the highest rating for each user rather than for each item. PV generates a list of recommended items based on the top ratings, while the aforementioned systems aggregate the preferences of group members. PV begins by placing the item with the highest rating from each member at the top of the recommendation list. It then selects the item with the highest rating from the remaining items, provided it is not already in the favorite sets of the group members. This process continues by considering the item with the top rating from each user in the group for the remaining items, adding it to the second-best recommendation list. This process repeats until the recommendation list is finalized. To better understand how PV operates, please refer to Table 2. Another approach in this category is the aggregation function called most respected person (MR) [13], which relies on the ratings of the most influential person in the group. However, relying solely on the opinions of a single user while disregarding the views of other group members is not typically the most effective aggregation function, especially in the case of larger groups. Moreover, it is often challenging to determine who should be designated as the most respected group member. The selection of the most respected person in MR can be based on various criteria, such as the highest average, highest median, highest standard deviation, etc. To comprehend the functioning of MRP, please refer to Table 2, where Jitendra is selected as the most respected person. Additionally, Upward leveling (UL), introduced by Seo et al. [19], takes into account the distribution of ratings for each item. UL calculates the standard deviation (SD) of an item's ratings and combines it with the item's Avg and AV values to generate the final aggregation. This combination is performed using a weighted average, with the weights randomly selected from a predefined set. UL transforms the original ratings into a [0, 1] scale and applies min-max normalization techniques to the AV group scores. To illustrate how UL operates in practice, an example is provided in Table 2.

As discussed in Section 2.2, most studies ignore the genre or characteristics of user and item. We focused on user genre or characteristics to predict individual ratings. A significant amount of aggregate function is reported to combine members' ratings. But we observed from Section 2.3 that none of them focused on characteristics of user and item (user tendency and item tendency). So, we provide a novel aggregation function to combine them into a group. It helps to satisfy maximum members' needs in a group.

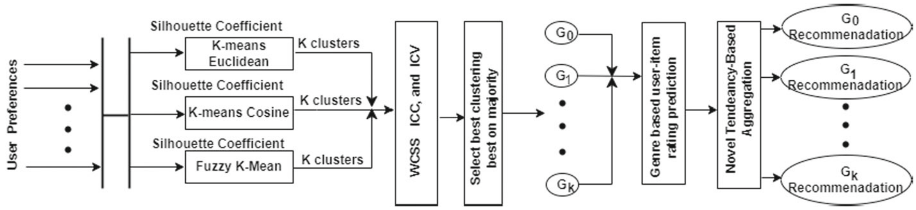

Fig. 1 Block diagram of proposed GRS

3 Proposed approach

in Fig. 1. In the first subtask, we use three techniques (K-means Eucledian, K-means cosine, and Fuzzy K-mean) to form suitable groups of users. Finally, we select the best out of these three techniques. Many researchers use these widely to form suitable groups in GRS and have proven effective [4, 6, 34]. GRS requires the number of clusters as input. We use silhouette measure to decide the number of clusters. Subsequently, the within-cluster sum of squares (WCSS), Intra-cluster correlation (ICC), and Inter-cluster variance is utilized to validate the best cluster. So, we select the K-means cluster with cosine measure over the K-means clustering with Euclidean to avoid the ineffectiveness of Euclidean distance. Angle-based distance similarity measure is effective when handling high dimensionality and sparse dataset.

Predicting individual user-item rating on an item i is an essential part of GRS in the second subtask. We first predict rating on an item i, which is the same for all users in the system. Subsequently, an individual's user average is combined to obtain an individual's user rating on the item i.

We propose a feed forward neural network to compute the item rating (Fig. 2). In order to compute item rating, we combine user features such as age, gender and occupation linearly

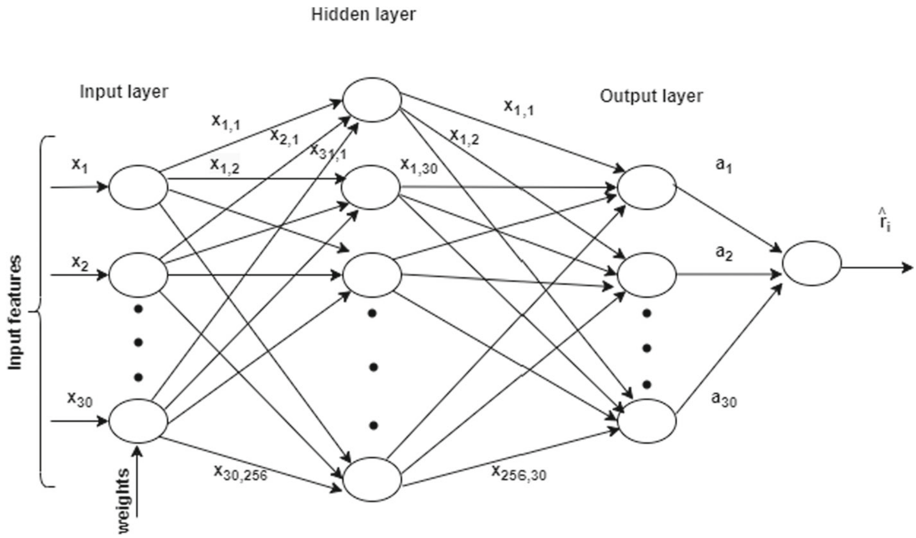

Fig. 2 Feed forward neural network with a single hidden layer

to calculate item rating using (1).

$$\hat{r_i} = \sum_{i=1}^{n} a_i x_i \tag{1}$$

where, $\hat{r_i}$ denotes the predicted rating for an item i. There are three features available gender, age, and occupation. The total number of the category is thirty (n = 30), two category in gender features, six category in age features, and 21 category in occupation features. These thirty categories are denoted as symbol $x_1,\ x_2,\ x_3, ..., x_{30}$. Where, x_1, and x_2 denotes average rating based on the category of gender, x_3 to x_8 represent user means based on age category, and x_9 to x_{30} represent the user means ratings based on the category of occupation. Weights are initialized randomly for all the categories (a_i). The weights are updated using the gradient descent approach. Gradient descent is a well-known first-order optimization technique that confines the minimum of an objective function by taking steps proportional to the current point's negative gradient. The weights are calculated by computing partial loss derivatives concerning features vector at each position and ending when the error function hits the minimum. For this loss function is defined as per (2). The weights are updated using loss function as given in (3).

$$loss_i = (\hat{r_i} - r_i)^2 \tag{2}$$

where, $loss_i$ is loss, $\hat{r_i}$ is predicted rating, and r_i is overall actual rating for the item i.

$$a_i = a_i + \lambda \times \Delta loss_i \tag{3}$$

where, a_i is assigned weight for each item, $\Delta loss_i$ is change in loss with respect to a_i, and λ is learning parameter. We assume the value of λ = 0.001 Finally, we compute predicted ratings for individual user to an item using (4). The α is considered as 0.5 for calculation of individual user-item predicted rating.

$$\hat{p}_{ui} = \alpha \times Avg_u + (1 - \alpha)\,\hat{r_i} \tag{4}$$

where, $\hat{p}_{ui}$ is predicted individual user rating on item i. Avg_u is average rating for user u, and $\hat{r_i}$ is predicted item rating for an item i, which is obtained by using (1). We combine these individual user ratings to an item in a group. The combined rating is a group score. We propose an aggregation technique based on the tendency approach.

Having predicted individual user-item rating in a group, we compute group rating by using proposed tendency-based aggregation (TA). We adopt user tendency and item tendency proposed by Cacheda et al. [28] due to its clarity and usefulness in this work. The user tendency is computed as per (5).

$$T_u = \frac{\sum_{i \in I}(r_{ui} - \bar{r}_i)}{I_u} \tag{5}$$

where, T_u is user tendency in a group, r_{ui} indicates user u provides rating on item i, $\bar{r}_i$ is average rating of an item and I_u is the set of item ratings received from the user u. Similarly item tendency is calculated as per (6).

$$T_i = \frac{\sum_{u \in U}(r_{ui} - Avg_u)}{U_i} \tag{6}$$

where Avg_u is the average rating of user u and U_i is the set of users received ratings from an item i. Group tendency is the average of all the user tendency in a group. The tendency of group is computed as per (7).

$$T_g = \frac{\sum T_u}{u_g} \tag{7}$$

where, T_g denotes group tendency, T_u is user tendency in a group and u_g indicates the number of users in the group.

There are various ways of predicting the final group rating given here. In this modeling approach predicting rating for the group is calculated based on the value of group tendency (T_g) and item tendency (T_i).

1. Group tendency (T_g) and item tendency (T_i) in a group are positive: This is evaluated by combining the user predicted rating average value and maximum of item tendency and group tendency, the final predicted rating is calculated as mentioned in (8).

$$\hat{p}_{gi} = \hat{p}_{avg_i} + max(T_i, T_g) \tag{8}$$

   where, $\hat{p}_{gi}$ is the predicted group rating on item i, $\hat{p}_{avg_i}$ is the average of the predicted rating of all individual users in the group who predict the rating on item i.
2. Group tendency (T_g) and item tendency (T_i) in a group are negative: It is computed by combining the user predicted rating average value and a minimum of item tendency and group tendency, From the above observations the predicted rating calculated as per (9).

$$\hat{p}_{gi} = \hat{p}_{avg_i} + min(T_i, T_g) \tag{9}$$

3. If group tendency (T_g) is positive and item tendency (T_i) is negative or group tendency (T_g) is negative and item tendency (T_i) is positive then the predicted rating for the group is computed as per (10).

$$\hat{p}_{gi} = \hat{p}_{avg_i} + \frac{T_g + T_i}{2} \tag{10}$$

3.1 Running example

This subsection shows how the novel tendency modeling estimates group ratings in the aggregation phase. Aggregation is third subtask of GRS. It combines the individual's user rating into a group rating. To understand this subtask, we create a sample group of four individuals who predict the preferences for ten items on a [1-5] scale, as shown in Table 2. We apply this novel technique on predicted preference of individual group member rating. It combines the predicted rating of individual's member into a group score.

A novel TA computes an overall group tendency towards every item. Here, a group tendency is the average aggregation of a user tendency in a group. There is four members' group in a given example in Table 2. The (5) computes the group member tendency 0.5104, −0.2738, −0.2083, −0.1018, respectively. The (7) calculates group tendency. The group tendency of a sample group is −0.0183. After that, TA calculates the item tendency of all the items using (6). Table 3 presents a group member and group tendency. Table 4 presents item tendency of a given group.

To understand the process of predicting the group rating to an item. We demonstrate here how to calculate group rating to an item. Here, the group tendency is negative, and item i_1 tendency is positive, So it lies in the third case. The average of an item i_1 is 2.66, and the average of group and tendency of an item i_1 is $(0.018 + 0.62)/2 = 0.319$. So, group rating

Table 3 Group member and group tendency

Jitendra	Kusum	Ravi	Ram	group
0.51	−0.27	−0.21	−0.10	−0.018

Table 4 Item tendency

i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
0.62	0.38	0.71	0.05	−0.29	−0.72	−0.06	1.00	0.03	0.28

to an item i_1 is $2.66 + 0.319 = 2.979$. To predict the group rating of an item i_5 in a given example, The group tendency and item tendency are negative. So, this item lies in the second case. The average of an item i_5 is 3, So group rating to an item i_5 is $3 + 0.0.18 = 3.018$. Table 5 shows the group rating to all the items of given example.

4 Experimental evaluation

To evaluate the significance of propose method, we implement CF-AV [14], Hermes [5], and IBGR [6]. We use K-means cluster with cosine measure for forming suitable groups. We propose a way to predict user-item individual rating. Lastly, we introduce a novel aggregation function to combine individual rating into group ratings.

4.1 Experimental setup

This study split the total number of ratings into training and testing using random subsampling cross validation step.[1] The training set contains roughly 80%, and the test set includes 20% of the total number of ratings. The training dataset is used to identify the groups, while the test dataset is used for evaluating the suggested aggregation function.

To predict the individual user-item rating in (4), the value of alpha is considered as 0.5. Threshold value for aggregation function AwM and AV is considered as 3.

4.2 Data preparation

MovieLens-1M (ML-1M-I), (ML-1M-II), MovieLens-100K (ML-100K) datasets are used, which are benchmark dataset in the field of RS.[2] In this well-known dataset, users can rate items on a scale of 1 to 5. Where score of 1 indicates the least interest and a score of 5 means the maximum interest. Also, a user with 20 item rating is considered. The brief description of dataset can be found in Table 6.

This work is related to group recommendations system. Experimented datasets do not have group information. Ground truth value for the group is also not available. We discuss the computation of ground truth value for each metric in next subsection.

4.3 Evaluation metric

To assess the efficacy of the proposed strategy. The mean absolute error (MAE) is the most common benchmark metric for evaluating a system's ability to forecast a user's interest in a specific item [6, 41]. As seen in (11), this standard measures computes the difference between

[1] https://machinelearningmastery.com/training-validation-test-split-and-cross-validation-done-right/

[2] https://grouplens.org/datasets/movielens/

Table 5 Group rating

i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
3.301	0.38	0.71	0.05	−0.29	−0.72	−0.06	1.00	0.03	0.28

the actual and predicted values. It evaluates the prediction method in GRS. It estimates the error of every group.

$$MAE_{G_g} = \frac{\sum_i^{MAX} (\hat{p}_{rat} - act_{rat})}{MAX} \tag{11}$$

where, MAE_{G_g} is mean absolute error for a group g, $\hat{p}_{rat}$ is predicted rating for a particular user-item of a group, act_{rat} is actual rating for corresponding user-item, and MAX is the number of predicted rating rating in a group.

Root mean squared error is another well-known statistic for GRS evaluation (RMSE). Every group's RMSE is determined using the (12).

$$RMSE_{G_g} = \sqrt{\frac{\sum_{i=1}^{MAX} (\hat{p}_{rat} - act_{rat})^2}{MAX}} \tag{12}$$

where $RMSE_{G_g}$ defines the root means squared error for group g.

Evaluating member satisfaction is vital to Group Recommendation Systems (GRS). It involves assessing the effectiveness of the proposed technique, which combines individual predicted scores into a group score. To measure the satisfaction level of groups based on each member, a Group Satisfaction Metric (GSM) has been introduced [6]. The GSM is designed to quantify the degree of satisfaction of groups with the recommendations provided. The calculation of the GSM is represented by (13):

$$GSM_{G_g} = \frac{\sum_{u \in G_g} \| I_u^{sat} \cap I_{rec} \|}{N_{G_g} \times N_{I_{rec}}} \tag{13}$$

where, I_u^{sat} is an set of item that is satisfied or has received rating 3.5 or greater than 3.5. I_rec is the set of recommended item. N_{G_g} is number of user in a group G_g, and $N_{I_{rec}}$ is number of recommended items for the group. This metric enables the evaluation of how well the recommendations align with the preferences and expectations of group members, providing valuable insights into the performance of the recommendation algorithm.

There have been limited evaluation measures to evaluate member satisfaction in GRS. Group satisfaction is essential in GRS. Therefore, SEG is used to check group satisfaction in terms of error. This metric relies on the standard deviation. This metric checks how much user preference deviates from a group. The (14) defines SEG.

$$SEG_{G_g} = \frac{\sum_{i=1}^{MAX} \| \hat{p}_{rat,i} - \mu_i \|}{MAX} \tag{14}$$

Table 6 Data preparation

Dataset	# of user	# of item
ML-1M-I	6040	3900
ML-1M-II	6000	3000
ML-100K	943	1682

Table 7 Result of silhouette coefficient for ML-1M

Cluster algorithm	Silhouette coefficient ML-100K				Silhouette coefficient ML-1M -1M-I				Silhouette coefficient ML-1M-II			
	K=4	K=6	K=8	K=12	K=4	K=6	K=8	K=12	K=4	K=6	K=8	K=12
K-means Eucledian	0.2683	0.2649	0.2633	0.2604	0.2797	0.2788	0.2783	0.2772	0.2847	0.2796	0.2848	0.2842
K-means cosine	0.8785	0.8672	0.8576	0.8462	0.5769	0.5740	0.5697	0.5643	0.5729	0.5620	0.5642	0.5648
Fuzzy c-means	0.1684	0.1669	0.1650	0.1585	0.1891	0.1887	0.1877	0.1830	0.1841	0.1774	0.1727	0.1742

where, $\hat{p}_{rat,i}$ is predicted rating on item i, and μ_i is the mean of actual rating of a group G_g on item i.

5 Results and discussion

To assess the performance of the proposed method of GRS, we used metrics: MAE, RMSE, SEG, and GSM. We analyze the performance of the proposed method in this section. We showed the result here and compared it with state-of-the-art techniques in this section.

As we discuss in Section 3, to decide an optimum number of clusters for group formation, we use the silhouette coefficient. The result of the silhouette coefficient is given in Table 7. For ML-100K, the silhouette coefficient value of K-means using Euclidean measure are 0.2649, 0.2649, 0.2633, 0.2604 respectively at the value of K= 4, 6, 8 and 12. We achieve the silhouette coefficient value of K-means using Euclidean measure are 0.8785, 0.8672, 0.8576, 0.8462 respectively at the value of K= 4, 6, 8 and 12. We obtain the silhouette coefficient value of fuzzy c-means are 0.1684, 0.1669, 0.1660, 0.1585 respectively at the value of K= 4, 6, 8 and 12. Similarly, the result of silhouette coefficient for ML-1M-I and ML-1m-II is presented in Table 7. We observe from table, all the clustering techniques are suitable for forming groups at K=4.

Intra-cluster correlation (ICC) is a metric that quantifies the similarity or correlation between data points within the same cluster. It indicates how well the data points within a group are together. The average pairwise similarity is commonly used to calculate the intra-cluster correlation. It is also known as intra-cluster similarity or cohesion. Suppose there is a clustering scenario with a dataset with N data points and K clusters. For each cluster k, we calculate the intra-cluster correlation using (15):

$$ICC = \frac{1}{N(k) * (N(k) - 1)} * \sum SIM_k(i, j) \tag{15}$$

where $N(k)$ is number of data point in cluster k. $SIM_k(i, j)$ is the similarity between pair of i, and j in cluster k. Inter-cluster variance (ICV) defines the separation between different clusters. It refers to the average distance or dissimilarity between different clusters. It measures how the clusters are separated from each other. The inter-cluster distance can be computed using the (16):

$$ICV = (\frac{1}{(K * (K - 1))}) * \sum \sum dissim(k1, k2) \tag{16}$$

where K is the total number of clusters, and $dissim(k1, k2)$ is the distance computed between clusters $k1$ and $k2$. In the above equation, the double summation iterates over all pairs of clusters. For each pair, the dissimilarity measure between the clusters is computed. The dissimilarity measure can be a distance metric, such as Euclidean distance, Manhattan distance, or other appropriate measures relying on the nature of the data and the clustering techniques used.

Cluster	WCSS			ICV		
	ML-100k	ML-1M-I	ML-1M-II	ML-100k	ML-1M-I	ML-1M-II
K-means Euclidean	0.0285	0.2021	0.1724	1124.3254	2845.2345	2648.3249
K-means Cosine	0.0150	0.0056	0.0046	1043.2145	2483.0990	2284.5590
Fuzzy C-mean	0.0382	0.3024	0.2842	21574.224	37100.2345	37406.2599

Algorithm/Group	Inter Cluster Corelation (ICC)			
	G0	G1	G2	G3
K-means Euclidean	5.2637	5.1825	5.346	5.3905
K-means Cosine	1.7750	6.7601	6.6853	1.4139
Fuzzy C-mean	5.3245	5.2346	4.2586	5.2849

As we decide the optimum value of cluster (4) by using silhouette coefficient. Now, we use the within-cluster sum of squares (WCSS) for different datasets to decide similarity measure with K-means. We show the result of WCSS in Table 5. The result of K-means using Euclidean measure is 0.02850, 0.2021, and 0.1724 for the dataset ML-100K, ML-1M-I, ML-1M-II respectively. The result of K-means using cosine mesasure is 0.0150, 0.0056, and 0.0046 for the dataset ML-100K, ML-1M-I, ML-1M-II respectively. We observe here, K-means using cosine measure is giving better results. The result of within cluster sum of squares (WCSS) and inter cluster variance is in Table 5 and intra cluster correlation in Table 5. The result of K-means using Euclidean measure is 0.02850, 0.2021, and 0.1724 for the dataset ML-100K, ML-1M-I, ML-1M-II respectively. The result of K-means using cosine mesasure is 0.0150, 0.0056, and 0.0046 for the dataset ML-100K, ML-1M-I, ML-1M-II respectively. We observe here, K-means using cosine measure is giving better results. Similarly, inter cluster variance also shows that k-means cosine is better than other clustering methods. Table 5 shows the result of inter cluster correlation. It also shows that K-means cosine is better than other methods. So, we have chosen K-means cosine for clustering purpose and proceeded for further experiment.

To show the superiority of the proposed member rating individual prediction technique and proposed aggregation function. We show the experimental results of ML-1M-I in Table 8, ML-1M-II in Table 9, ML-100K in Table 10. We analyze the performance of the proposed method on four different groups. The result for state of the art techniques are also promising. Baltrunas et al. [14] achieves MAE of 0.7770, and RMSE of 1.0981 for group G_0. The group satisfaction metric (GSM) of G_0 is 80.6615%, and SEG is 0.6787. Christensen et al. [5]

Table 8 Result of four groups on ML-1M-I

Group	Method	MAE	RMSE	GSM	SEG
G0	CF-AV	0.7770	1.0981	80.6615	0.6787
	Hermes	1.1983	1.6083	82.6442	0.9344
	IBGR	0.8568	1.2409	91.6886	0.8660
	LightGCN	0.7963	0.9084	62.8426	0.9835
	NGCF	0.4856	0.6825	80.3282	0.7486
	Proposed	**0.8379**	**1.095**	**95.2384**	0.6409
G1	CF-AV	0.8209	1.1889	78.4442	0.8496
	Hermes	0.9816	1.4815	82.6616	0.9639
	IBGR	0.8039	1.2044	88.0121	0.8445
	LightGCN	0.8124	1.0248	64.3254	0.9424
	NGCF	0.4758	0.6625	79.3582	0.7668
	Proposed	**0.6918**	**1.0335**	**90.9090**	0.5943
G2	CF-AV	0.6786	1.0906	80.8458	0.7742
	Hermes	1.0690	1.5178	84.6296	0.9483
	IBGR	0.7724	1.1757	90.8539	0.8416
	LightGCN	0.8324	1.1256	66.5214	0.9365
	NGCF	0.5215	0.7248	77.3295	0.7894
	Proposed	**0.5627**	**0.9642**	**94.7491**	0.5386
G3	CF-AV	0.6762	1.0413	80.8238	0.8378
	Hermes	0.9502	1.4065	82.6276	0.9592
	IBGR	0.7437	1.1741	88.0482	0.7862
	LightGCN	0.8328	1.1264	62.8024	0.9624
	NGCF	0.4832	0.6782	75.2482	0.7088
	Proposed	**0.5568**	**0.9351**	**92.7366**	0.5225

The result of the proposed method is highlighted.

Table 9 Result of four groups on ML-1M-II

Group	Method	MAE	RMSE	GSM	SEG
G0	CF-AV	0.7524	1.0284	81.6424	0.6684
	Hermes	1.1648	1.5220	82.8844	0.9024
	IBGR	0.8424	1.1424	90.6246	0.8584
	LightGCN	0.7432	0.9814	68.8224	0.7832
	NGCF	0.3586	0.5068	72.6482	0.7468
	Proposed	**0.5386**	**0.8420**	**95.2280**	**0.5912**
G1	CF-AV	0.8120	1.0284	77.8624	0.8624
	Hermes	0.9721	1.4815	82.6616	0.9639
	IBGR	0.8039	1.2044	88.0121	0.8445
	LightGCN	0.8821	1.2230	70.4424	0.7604
	NGCF	0.3368	0.4984	78.6248	0.7458
	Proposed	**0.5182**	**0.8205**	**88.8888**	**0.6022**

Table 9 continued

Group	Method	MAE	RMSE	GSM	SEG
G2	CF-AV	0.6986	0.9890	82.8628	0.7824
	Hermes	1.002	1.4684	82.6224	0.9242
	IBGR	0.7812	1.0826	**91.0532**	0.8216
	LightGCN	0.8782	1.1924	72.4212	0.7824
	NGCF	0.3456	0.4892	80.3258	0.7346
	Proposed	**0.5920**	**0.8426**	91.9490	**0.5424**
G3	CF-AV	0.6834	0.9242	80.6224	0.8242
	Hermes	0.9246	1.3840	80.6224	0.9442
	IBGR	0.7324	1.1044	86.4428	0.7786
	LightGCN	0.8149	1.2248	68.3284	0.7825
	NGCF	0.3284	0.4542	73.7248	0.7345
	Proposed	**0.5246**	**0.8123**	**91.4428**	**0.6637**

The result of the proposed method is highlighted.

Table 10 Result of four groups on MovieLens-100k

Group	Method	MAE	RMSE	GSM	SEG
G0	CF-AV	0.7912	0.9882	80.2624	0.7180
	Hermes	1.0446	1.2460	82.4840	0.7842
	IBGR	0.8024	0.9424	90.8424	0.8342
	LightGCN	0.7432	0.9814	68.8224	0.7832
	NGCF	0.3586	0.5068	72.6482	0.7468
	Proposed	**0.5782**	**0.7892**	**93.4628**	**0.6242**
G1	CF-AV	0.8342	0.9984	79.4680	0.8546
	Hermes	0.9422	1.3424	83.6212	0.9432
	IBGR	0.8428	1.1982	89.2042	0.8648
	LightGCN	0.8821	1.2230	70.4424	0.7604
	NGCF	0.3368	0.4984	78.6248	0.7458
	Proposed	**0.6482**	**0.8240**	**92.6666**	**0.6424**
G2	CF-AV	0.6828	0.9648	81.0862	0.7912
	Hermes	0.9824	1.0424	83.2642	0.9024
	IBGR	0.7024	0.9812	88.1022	0.8646
	LightGCN	0.8782	1.1924	72.4212	0.7824
	NGCF	0.3456	0.4892	80.3258	0.7346
	Proposed	**0.6428**	**0.8986**	**92.6940**	**0.6824**
G3	CF-AV	0.6924	0.8824	82.2824	0.8028
	Hermes	0.9064	1.1840	79.4680	0.9084
	IBGR	0.7437	1.1741	88.0482	0.7862
	LightGCN	0.8149	1.2248	68.3284	0.7825
	NGCF	0.3284	0.4542	73.7248	0.7345
	Proposed	**0.5846**	**0.7896**	**92.8420**	**0.6240**

The result of the proposed method is highlighted.

achieves MAE of 1.1983, and RMSE of 1.6083. The group satisfaction level with the value of GSM is 82.6442%, and SEG is 0.9344 for group G_0. This may get more better result in tourist domain. Nozari et al. achieves MAE of 0.8568, and RMSE of 1.2409. The group satisfaction level with the value of GSM is 91.6886%, and SEG is 0.8660 for group G_0. The best result is achieved by the proposed method with MAE of 0.8379, and RMSE: 1.0950, The best group satisfaction level with the value of GSM is 95.2384%, and SEG of 0.6409 for group G_0. Similarly, The result for ML-1M-I dataset are presented for all the other groups in Table 8.

We show the performance analysis of proposed method on ML-1M-II dataset (6000 users and 3000 items) here in Table 9. Acoording to the table Baltrunas et al. [14] achieves MAE of 0.7524, and RMSE of 1.0284, The group satisfaction level with the value of GSM is 81.6424%, and SEG: 0.6684 for group G_0. Christensen et al. [5] proposed a GRS approach in a tourist domain that achieves MAE of 1.1983, and RMSE 1.6083, The group satisfaction level with the value of GSM is 82.6442%, and SEG 0.9344 for group G_0. This may get better result in tourist domain. Nozari et al. [6] achieves MAE of 0.8568, RMSE of 1.2409, The group satisfaction level with the value of GSM is 91.6886%, and SEG 0.8660 for group G_0. The best result is achieved by the proposed method with MAE of 0.8379, RMSE of 1.0950, The group satisfaction level with the value of GSM is 95.2384%, and SEG 0.6409 for group G_0. Similarly, the result for all the other groups of ML-1M dataset is presented for all the other groups in Table 9. Similarly, the result of ML-1M-I, Ml-1M-II for all the groups for LightGCN, and NGCF are presented in Tables 8 and 9.

We analyze the performance of the proposed method on ML-100K datasets here. Acoording to the table, Baltrunas et al. [14] achieves the MAE, and RMSE, for group G_0 is 0.7912, 0.9882 respectively, and SEG is 0.7180. The group satisfaction level with the value of GSM for G_0 is 80.2624%. Hermes [5] achieves MAE, and RMSE for group G_0 is 1.0446, 1.24600 respectively, and SEG is 0.7842. They achieve level of group satisfaction with the value of GSM is 82.4840%. IBGR [6] achieves MAE, and RMSE, 0.8024, 0.9424, respectively and SEG is 0.8342. This technique achieves a 93.4628% level of group satisfaction. Our proposed techniques achieve the best MAE, and RMSE, 0.5782, 0.7892, and SEG is 0.6242. The proposed method achieves the best group satisfaction level of 93.4628% for group G_0 compared to state of the art techniques. The result for all the groups for the

Table 11 P-test and t-test on ML-1M-I

	CF-AV	Hermes	IBGR	LightGCN	NGCF	Proposed
CF-AV						
Hermes	1.2611, 0.2540					
IBGR	5.4261, 0.0016	5.5379, 0.0014				
LightGCN	−15.2775, 4.96e-06	−18.9134, 1.41e-06	−19.7586, 1.08e-06			
NGCF	−2.2620, 0.0643	−4.1777 0.0058	−7.3902 0.0003	7.1899, 0.0003		
Proposed	7.3616, 0.0001	7.5348, 0.0001	1.7794, 0.1183	22.1263, 5.57e-07	9.3896, 8.2e-05	

Table 12 P-test and t-test on ML-1M-II

	CF-AV	Hermes	IBGR	LightGCN	NGCF	Proposed
CF-AV						
Hermes	1.2214, 0.2677					
IBGR	5.4261, 0.0016	5.6274, 0.0013				
LightGCN	−7.6203, 0.0002	−11.4677, 1.41e-05	−13.2895, 1.12e-05			
NGCF	−2.0594, 0.0851	−3.0333, 0.0229	−5.8831, 0.0010	3.0449, 0.0226		
Proposed	7.3616, 0.0001	7.5348, 0.0001	1.7794, 0.1183	13.6997, 9.40e-06	9.3896, 8.2e-05	

ML-100K dataset is presented in Table 10. It shows the superiority of the proposed method. Similarly, the result of ML-100k for all the groups for LightGCN, and NGCF are presented in Table 10. The result of performed p-test and t-test on ML-1M-I and ML-1M-II for various techniques are presented in Tables 11 and 12 respectively. Result shows that the proposed approach outperforms the state of the art techniques.

We validate three clusters and select the best one for MovieLens datasets. K-means cosine is selected best one with help of WCSS, ICC, ICV. Later, we consider the content information or user characteristic such age, gender, occupation, etc. These information is combined with collaborative ratings for predicting individual rating. While predicting individual rating, we take the advantage of content information as well as collaborative rating of users. Finally, new aggregation strategy is suggested for aggregation of individual ratings. So, our proposed approach performed better than state of the art according to result.

6 Conclusion and future work

In this paper, the formed clusters are validated using cluster-validated measures. In this paper, we exploit the user content information along with the collaborative rating of the systems to recommend the group of users. This paper also proposed a novel aggregating mechanism called tendency-based aggregation (TA). It combines the predicted individual rating into a group. Experimental evaluation of real-world datasets demonstrated the effectiveness of our approach. For future research, we include item content information to categorize items. It can be combined with collaborative ratings provided by the users for further enhancement. Researchers can use individual user and item characteristics to form suitable future groups.

Declarations

Conflicts of interest The authors declare that they have no known competing financial interests or personal relationship that could have appeared to influence the work reported in this paper.

References

1. Agarwal A, Chakraborty M, Chowdary CR (2017) Does order matter? Effect of order in group recommendation. Exp Syst Appl 82:115–127. https://doi.org/10.1016/j.eswa.2017.03.069
2. Villegas NM, Sánchez C, Díaz-Cely J, Tamura G (2018) Characterizing context-aware recommender systems: A systematic literature review. Knowle-Based Syst 140:173–200. https://doi.org/10.1016/j.knosys.2017.11.003
3. Nozari RB, Koohi H (2021) Novel implicit-trust-network-based recommendation methodology. Exp Syst Appl 186:115709. https://doi.org/10.1016/j.eswa.2021.115709
4. Dara S, Chowdary CR, Kumar C (2020) A survey on group recommender systems. J Intell Inf Syst 54:271–295. https://doi.org/10.1007/s10844-018-0542-3
5. Christensen I, Schiaffino S, Armentano M (2016) Social group recommendation in the tourism domain. J Intell Inf Syst 47:209–231. https://doi.org/10.1007/s10844-016-0400-0
6. Nozari RB, Koohi H (2021) A novel group recommender system based on members' influence and leader impact. Knowl-Based Syst 205:106296. https://doi.org/10.1016/j.knosys.2020.106296
7. Seo YD, Kim YG, Lee E, Kim H (2021) Group recommender system based on genre preference focusing on reducing the clustering cost. Exp Syst Appl 183:115396. https://doi.org/10.1016/j.eswa.2021.115396
8. De Pessemier T, Dooms S, Martens L (2014) Comparison of group recommendation algorithms. Multimed Tools Appl 72:2497–2541. https://doi.org/10.1007/s11042-013-1563-0
9. McCarthy JF, Anagnost TD (1998) MusicFX: an arbiter of group preferences for computer supported collaborative workouts. In: Proceedings of the 1998 ACM conference on Computer supported cooperative work, pp 363–372. https://doi.org/10.1145/289444.289511
10. Pujahari A, Padmanabhan V (2015) Group Recommender Systems: Combining user-user and item-item Collaborative filtering techniques. In: Proceedings of the 2015 International Conference on Information Technology (ICIT), pp. 148–152. https://doi.org/10.1109/ICIT.2015.36
11. Boratto L, Carta S, Fenu G (2016) Discovery and representation of the preferences of automatically detected groups: Exploiting the link between group modeling and clustering. Future Gener Comput Syst 64:65–174. https://doi.org/10.1016/j.future.2015.10.007
12. Park J, Nam K (2019) Group recommender system for store product placement. Data Mining Knowl Discov 33:204–229. https://doi.org/10.1007/s10618-018-0600-z
13. Masthoff J (2015) Group Recommender systems: Aggregation, satisfaction and group attributes. Recommender systems handbook,"Boston, MA", pp 743–776. https://doi.org/10.1007/978-1-4899-7637-6_22
14. Baltrunas L, Makcinskas T, Ricci F (2010) Group recommendations with rank aggregation and collaborative filtering. In: Proceedings of the 4th ACM conference on Recommender systems, pp 119–126. https://doi.org/10.1145/1864708.1864733
15. Guo J, Zhu Y, Li A, Wang Q, Han W (2016). A social influence approach for group user modeling in group recommendation systems. IEEE Intelligent systems, IEEE, pp 40-48. https://doi.org/10.1109/MIS.2016.28
16. Mahyar H, Ghalebi KE, Morshedi SM, Khalili S, Grosu R, Movaghar A (2017) Centrality-based group formation in group recommender systems. In: Proceedings of the 26th International conference on world wide web companion, pp 1187–1196. https://doi.org/10.1145/3041021.3055363
17. Crossen A, Budzik J, Hammond KJ (2002) Flytrap: intelligent group music recommendation. In: Proceedings of the 7th international conference on Intelligent user interfaces, pp 184-185. https://doi.org/10.1145/502716.502748
18. Sacharidis D (2019) Top-n group recommendations with fairness. In: Proceedings of the 34th ACM/SIGAPP symposium on applied computing, pp 1663–1670. https://doi.org/10.1145/3297280.3297442
19. Seo YD, Kim YG, Lee E, Seol KS, Baik DK (2018) An enhanced aggregation method considering deviations for a group recommendation. Exp Syst Appl 93:299–312. https://doi.org/10.1016/j.eswa.2017.10.027
20. Yalcin E, Ismailoglu F, Bilge A (2021) An entropy empowered hybridized aggregation technique for group recommender systems. Exp Syst Appl 166:114111. https://doi.org/10.1016/j.eswa.2020.114111
21. Yalcin E, Bilge A (2021) Investigating and counteracting popularity bias in group recommendations. Inf Process Manag 58:102608. https://doi.org/10.1016/j.ipm.2021.102608
22. Yalcin E, Bilge A (2021) Novel automatic group identification approaches for group recommendation. Exp Syst Appl 174:114709. https://doi.org/10.1016/j.eswa.2021.114709
23. Kim KJ, Ahn H (2008) A recommender system using GA K-means clustering in an online shopping market. Exp Syst Appl 28:1200–1209. https://doi.org/10.1016/j.eswa.2006.12.025

24. Delic A, Ricci F, Neidhardt J (2019) Preference networks and non-linear preferences in group recommendations. In: Proceedings of IEEE/WIC/ACM International Conference on Web Intelligence, pp. 403–407. https://doi.org/10.1145/3350546.3352556
25. Ismailoglu, Firat (2021) Aggregating user preferences in group recommender systems: A crowdsourcing approach", Decision Support Systems, pp 1–10. https://doi.org/10.1016/j.dss.2021.113663
26. Qian X, Feng H, Zhao G, Mei T (2013) Personalized recommendation combining user interest and social circle. IEEE Trans Knowl Data Eng 26:1763–1777. https://doi.org/10.1109/TKDE.2013.168
27. Salehi-Abari A, Boutilier C (2015) Preference-oriented social networks: Group recommendation and inference. In: Proceedings of the 9th ACM Conference on recommender systems, pp 35–42. https://doi.org/10.1145/2792838.2800190
28. Cacheda F, Carneiro V, Fernández D, Formoso V (2011) Comparison of collaborative filtering algorithms: Limitations of current techniques and proposals for scalable, high-performance recommender systems. ACM Transactions on the Web (TWEB) 1:1–33. https://doi.org/10.1145/1921591.1921593
29. McCarthy K, Salamó M, Coyle L, McGinty L, Smyth B, Nixon P (2006) Cats: A synchronous approach to collaborative group recommendation. In: Proceedings of the Florida Artificial Intelligence Research Society Conference (FLAIRS), pp 86–91. https://www.aaai.org/Papers/FLAIRS/2006/Flairs06-015.pdf
30. Christensen IA, Schiaffino S (2011) Entertainment recommender systems for group of users. Exp Syst Appl 38:14127–14135. https://doi.org/10.1016/j.eswa.2011.04.221
31. Quijano-Sánchez L, Bridge D, Díaz-Agudo B, Recio-García JA (2012) A case-based solution to the cold-start problem in group recommenders. International Conference on Case-Based Reasoning, pp 342–356. https://doi.org/10.1007/978-3-642-32986-9_26
32. O'connor M, Cosley D, Konstan JA, Riedl J (2001) PolyLens: A recommender system for groups of users. In: ECSCW 2001: Proceedings of the Seventh European Conference on Computer Supported Cooperative Work 16–20 September, Bonn, Dordrecht, Germany, pp 199–218. https://doi.org/10.1007/0-306-48019-0_11
33. Hartigan JA, Wong MA (1979) Algorithm AS 136: A k-means clustering algorithm. J R Stat Soc Ser C Appl Stat 28:100–108. https://doi.org/10.2307/2346830
34. Boratto L, Carta S (2015) ART: group recommendation approaches for automatically detected groups. Int J Mach Learn Cybern 6:953–980. https://doi.org/10.1007/s13042-015-0371-4
35. Yin H, Wang Q, Zheng K, Li Z, Yang J, Zhou X (2019) Social influence-based group representation learning for group recommendation. In: IEEE 35th International Conference on Data Engineering (ICDE), pp 566–577. https://doi.org/10.1109/ICDE.2019.00057
36. Cao D, He X, Miao L, An Y, Yang C, Hong R (2018) Attentive group recommendation. In: Proceedings of the 41st International ACM SIGIR conference on research & development in information retrieval, pp 645–654. https://doi.org/10.1145/3209978.3209998
37. Qin D, Zhou X, Chen L, Huang G, Zhang Y (2018) Dynamic connection-based social group recommendation. IEEE Trans Knowl Data Eng 32:453–467. https://doi.org/10.1109/TKDE.2018.2879658
38. Patra BK, Launonen R, Ollikainen V, Nandi S (2015) A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data. Knowledge-Based Systems 82:163–177. https://doi.org/10.1016/j.knosys.2015.03.001
39. Liu S, Li G, Tran T, Jiang Y (2016) Preference relation-based Markov random fields for recommender systems. In: Proceedings of asian conference on machine learning, pp 157–172
40. Gazdar A, Hidri L (2020) A new similarity measure for collaborative filtering based recommender systems. Knowl-Based Syst 188:105058. https://doi.org/10.1016/j.knosys.2019.105058
41. Zhang Q, Lu J, Wu D, Zhang G (2018) A cross-domain recommender system with kernel-induced knowledge transfer for overlapping entities. IEEE Trans Neural Netw Learn Syst 30:1998–2012. https://doi.org/10.1109/TNNLS.2018.2875144
42. Ceh-Varela E, Cao H, Lauw HW (2022) Performance evaluation of aggregation-based group recommender systems for ephemeral groups. ACM Trans Intell Syst Technol, pp. 1–25. https://doi.org/10.1145/3542804
43. Belhadi A, Djenouri Y, Djenouri D, Michalak T, Lin JC (2020) Deep learning versus traditional solutions for group trajectory outliers. IEEE Trans Cybern 52:4508–4519. https://doi.org/10.1109/TCYB.2020.3029338
44. Belhadi A, Djenouri Y, Srivastava G, Cano A, Lin JC (2022) Hybrid group anomaly detection for sequence data: application to trajectory data analytics. IEEE Trans Intell Transp Syst 23(7):9346–9357. https://doi.org/10.1109/TITS.2021.3114064
45. Guo Z, Yu K, Li Y, Srivastava G, Lin JC (2022) Deep learning-embedded social internet of things for ambiguity-aware social recommendations. In: IEEE Transactions on network science and engineering, vol 9, no. 3, pp 1067–1081. https://doi.org/10.1109/TNSE.2021.3049262
46. Liao J, Zhou W, Luo F, Wen J, Gao M, Li X, Zeng J (2022) SocialLGN: Light graph convolution network for social recommendation. Inf Sci 589:595–607. https://doi.org/10.1016/j.ins.2022.01.001

47. Wang X, He X, Wang M, Feng F, Chua TS (2019) Neural graph collaborative filtering. In: Proceedings of the 42nd international ACM SIGIR conference on research and development in information retrieval, pp 165–174. https://doi.org/10.1145/3331184.3331267
48. Wang Y, Ma W, Zhang M, Liu Y, Ma S (2023) A survey on the fairness of recommender systems. ACM Tran Inf Syst 41(3):1–43. https://doi.org/10.1145/3547333
49. Yu L, Leng Y, Zhang D, He S (2023) Collaborative group embedding and decision aggregation based on attentive influence of individual members: A group recommendation perspective. Decis Support Syst 165:113894. https://doi.org/10.1016/j.dss.2022.113894

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