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Research Article

Toward a Cognitive Model for Group Recommender Systems

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Abstract: In the contemporary world, the abundance of data and the growing number of users in virtual environments have led to a focus on classifying data and grouping users to create recommendation lists that enhance user experiences. While existing research has explored various methods in developing Group Recommender Systems (GRSs), the role of incoming influence flows and their impact on users' decision-making processes when joining groups remains insufficiently explored. This study introduces a cognitively inspired framework that models user behavior during group formation by explicitly incorporating cognitive theories of decision-making and influence. By mapping users' interactions within complex dynamic networks, the proposed method categorizes users according to the influence of incoming interaction streams. Unlike traditional approaches, the framework naturally supports overlapping group membership, allowing users to belong to multiple groups with varying confidence levels, and constructs corresponding group behavioral profiles. By simulating real-world decision-making processes, the method generates personalized recommendation lists for users within each group. The proposed approach evaluated on four datasets, and the results indicate its effectiveness and robustness compared to established group recommendation methods.

***Keywords*:** recommender systems, group recommender systems, group formation, cognitive model, behavioral group profile

1. Introduction

The field of social networks has become increasingly fascinating due to the abundance of different networks on the internet and people's growing interest in utilizing them. These days, social networks have amassed millions of users and aim to meet the diverse preferences of users by utilizing a range of technologies [1]. It is worth mentioning that online social networks (such as Facebook and Twitter), information networks (like citation networks), and communication networks (e.g., email networks) are recognized as the most widely used networks.

The digital ecosystem is flooded with a vast amount of information, leaving users with a multitude of choices. To simplify the decision-making process, Recommender Systems (RSs) come into play by providing users with recommendation lists, allowing them to make quicker decisions in a shorter amount of time [2]. The popularity of social networks has sparked the development of various algorithms and methods to enhance traditional RSs, ultimately leading to higher user satisfaction. Overall, RSs contribute to an improved user experience and increased business profits by tailoring information to individual users. As a result, RSs have become a prominent topic of interest in both industry and academia [3], [4].

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As the number of users with diverse preferences continues to grow, presenting recommendation lists to individual users becomes expensive, challenging, and, in some cases, even impossible [5]. The provision of personalized services to users by RSs enables the suggestion of suitable items that meet their preferences. However, the focus of existing RSs has primarily been on individual users. With the increasing use of information technology, social activities are increasingly being organized in group settings. Consequently, there is a growing need to recommend items to groups rather than individuals, leading to the emergence of Group Recommender Systems (GRSs) [6]. Given these challenges recent studies in RSs have focused on identifying suitable communities comprising users with similar preferences. The objective of group recommendation is to provide suggestions for a group of users rather than just one individual, taking into account their past behaviors [7]. The concept of "group" serves as a link between the users and the recommended items, and it can be considered as either an integral part of the graph or separate from it [8].

When aiming to enhance the scalability and performance of a recommendation system in a large-scale setting, it is beneficial to present a list of recommendations to a group of users rather than individual users. However, the process of identifying these groups becomes crucial. It is particularly important to identify group members with similar preferences, especially in environments where data is limited. Incorrectly categorizing users can lead to inaccurate recommendation lists. This complexity is further compounded by the fact that users' opinions may change over time intervals and be influenced by different groups. Moreover, users often do not explicitly express their opinions, necessitating the analysis of their behavior [9], [10].

The issue of finding communities in RSs has typically considered constraints such as the number of communities, the average number of members in each community, or prior knowledge about the problem, such as knowing the complete network topology. However, in most cases, community detection lacks prior information and requires the optimal grouping of users. Furthermore, most studies on community detection in RSs have focused on non-overlapping communities. In these methods, users are assigned to a single group, even though, in many real-life situations, users may be interested in participating in more than one community.

The subsequent pivotal endeavor involves the establishment of a group profile. Following the identification of these communities, a suitable behavioral model is formulated for each community, encapsulating the aggregate preferences of its constituent members. Subsequent to the model's development, a recommendation list is systematically furnished to all members within each community, thereby aligning with the discerned preferences encapsulated by the constructed behavioral model.

In this article, we introduce a distinct approach to the community detection problem, diverging from existing research in several key dimensions. Our method is inspired by real-world behavioral patterns and psychological indicators. In everyday life, individuals are influenced by multiple streams when making decisions-such as interacting with friends, following influential figures, or responding to advertising. To model these streams and quantify their impact, we draw on cognitive science theories and embed them within complex dynamic network structures. In a similar spirit, recent intelligent system architectures increasingly adopt Digital Twin frameworks to integrate human behavior directly into virtual environments and system control loops. For example, federated digital twin models with users-or pedestrians-in-the-loop have demonstrated how human decision-making dynamics can be continuously sensed, modeled, and incorporated into virtual systems [11].

Our method employs iterative processes to analyze the level of influence on each individual and group together those with similar susceptibility to different streams into communities. For each community, we develop a behavioral model that predicts and presents future choices as a recommendation list to all members. The fundamental basis of our proposed method lies in comprehending how individuals are influenced by the various streams they encounter when making decisions. By thoroughly examining and evaluating an individual's inclination to join different groups, our aim is to maximize their satisfaction. To summarize our contributions:

- A cognitively informed community-detection framework that models how individuals respond to multiple influence streams, drawing on principles from cognitive science to capture realistic decision-making behavior;
- A mechanism for overlapping group membership, allowing users to belong to multiple communities with different confidence levels, reflecting real-world social dynamics;
- A fully unsupervised grouping method that removes common assumptions such as predefined numbers of groups, fixed network topology, or prior structural knowledge;
- A novel similarity-graph construction strategy that integrates behavioral, structural, and influence-based signals to

improve community identification;

• An empirical evaluation across multiple real-world and structural datasets, demonstrating the effectiveness and robustness of the proposed method.

Based on the aforementioned descriptions, the primary objective of this article is to deliver precise recommendation lists to a vast number of internet users by utilizing the novel method for identifying suitable communities, modeling their behavior, and ultimately presenting recommendation lists.

2. Related work

In general, the development of large-scale RSs encompass the following stages:

2.1 *Pre-processing: converting a sparse matrix into a similarity graph*

First, a series of operations must be performed on the system input. In similar studies, the system input is often a sparse matrix of user-provided ratings for various items. To compute the similarity between two individuals, it is necessary to compare the vectors of ratings assigned by users to items. The accuracy of the recommendation list's results is significantly contingent on the accuracy of the similarity metric employed to identify the most similar users and formulating a group, which serves as the foundation for the predictions generated [12], [13]. Various metrics have been employed to transform this sparse matrix into a similarity graph; the most important ones are summarized in the Table 1.

Table 1. Notable similarity metrics

Metric	Adjusted Cosine Similarity	Pearson Similarity
Use cases	[5], [14]-[19]	[20]-[22]
Formula	$\mathrm{COS}(u,\ v) = \frac{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_i)(r_{vi} - \bar{r}_i)}{\sqrt{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_i)^2} \sqrt{\sum_{i \in I_{uv}} (r_{vi} - \bar{r}_i)^2}}$ (1)	$\mathrm{PCC}(u,\ v) = \frac{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in I_{uv}} (r_{vi} - \bar{r}_v)^2}}$ (2)
Description	I_{uv}: set of items commonly rated by user u and v. r_i: average ratings on item i. r_{ui}: the ratings of the user u on the item i. r_{vi}: the ratings of the user v on the item i.	I_{uv}: set of items commonly rated by both u and v. r_u/r_v: average ratings of the users u/v on item i in I_{uv}. r_{ui}/r_{vi}: ratings of users u/v on the same item i.
Challenges [23]	Single Co-Rated: the result of Cosine Similarity (COS) is always 1. One-Rated Item: the result of COS is always 1. Uniform Rating: the result of COS is always 1.	Single Co-Rated: the result of Pearson Correlation Coefficient (PCC) is either + 1 or -1. One-Rated Item: incompatible as the rating and the mean are equal. Uniform Rating: is not a computable value.

Article [12] provides an overview of similarity metrics for computing the similarity between two users, including improved previous methods including Cosine and Pearson Similarity. Additionally, Article [23] investigates the drawbacks of these metrics.

2.2 *Group formation: identifying groups of users with similar preferences*

Community Detection is a fundamental aspect of group recommender systems especially in large-scale environments and has been extensively studied in the literature. This problem holds significant importance in various domains, such as social sciences, computer science, and E-commerce. While there is no single, universally accepted definition for community identification, it generally involves grouping nodes in a way that nodes within the same group exhibit much denser connections than those between different groups. This problem has garnered significant attention and research efforts, yet it remains unsolved to a satisfactory degree [24]. Here are some previous works related to group identification for the purpose of providing recommendations to groups of users (Table 2).

Table 2. Group identification overview

Use case	Approach	Common input	Weighted?	Graph type	Context
[20], [21]	Group members' influence	Movie-Lens100K	Weighted	Overlapped	Watching movie
[16]	Bisecting *k*-means clustering	Movie-Lens-1M and 100K	Unweighted	Non-overlap	Watching movie
[5], [25]	Group members' influence	Movie-Lens100K	Unweighted	Non-overlap	Watching movie
[22]	Users' relationship type/K-Nearest Neighbor technique	Hermes System	Weighted	Non-overlap	Tourism domain
[17]-[19]	*k*-means	Movie-Lens-1M and 100K	Unweighted	Non-overlap	Watching movie
[26]	Friends Finder	Movie-Lens-1M and 100K	Unweighted	Non-overlap	General
[27]	Neural Attention-based Group Recommendation	User-item interaction matrix	Weighted	Non-overlap	General
[28]	Graph Neural Network (GNN)-based Group Modeling	User-item interaction matrix	Weighted	Overlapped	E-commerce/Social network
[29]	Neural Group Recommendation	User-item interaction matrix	Weighted	Overlapped	Tourism

The approach presented in [20], [21] endeavor to calculate the influence of members on each other by leveraging both similarity and trust. Furthermore, the paper employs a blend of fuzzy clustering and similarity measures to identify users with shared interests. Several other papers leverage the concept of user importance and identify leaders to facilitate group formation [5], [25], and also types of users' relationships [22].

Yalcin and Bilge [16] introduce automated user grouping methodologies through the creation of a binary decision tree using bisecting *k*-means clustering. This approach tries to enhance group formation and impose constraints on group size. Additionally, the article suggests the adoption of a genre-based mapping technique to transform user ratings into a compact and dense vector for user representation.

In the category of methods aiming to identify groups consisting of individuals with similar preferences, many studies have employed the common *k*-means method. For example, the paper by [16], [17] introduces an automated recommendation technology that identifies groups. Boratto [17]-[19] utilize the *k*-means method and employs cosine similarity as a similarity metric among users. Ultimately, a recommendation list based on the preferences of each group's members is provided. Additionally, study [17] reviews methods for harmonizing predicted ratings for users.

Ntoutsi et al. [26] presents a model based on collaborative filtering for group recommendations and utilizes social lists of user recommendations to provide recommendation lists. Initially, users are structured based on the friend-finder algorithm, and then, more precise group structures are formed using a hierarchical clustering algorithm. Neural approaches have recently advanced group recommendation by learning richer representations of user interactions. Attention-based models [27] weight each member's contribution to capture dominant preferences within non-overlapping groups. GNN-based methods [28] use message passing on user-item graphs to model complex and overlapping group structures, especially in social and e-commerce settings. Neural group recommendation models [29] further integrate preference fusion and disentanglement to support overlapping groups in domains such as tourism. Together, these methods highlight the shift toward data-driven, neural architectures for group modeling.

These works have significantly contributed to the field of community group formation within the context of RSs. It should be noted that the output graph of group identification algorithms can be weighed. As observed in the above table, the output of these algorithms is mostly unweighted. Similarly, prevailing prior studies categorize users into distinct groups, with the concept of overlapping groups being less considered in group recommendation systems.

2.3 *Group profile building: aggregating the users' preferences within each group*

After appropriately structuring the members of a group, a profile is created for each group to provide recommendations. Article [30] has delved into analyzing each of the aggregation methods.

2.4 *Promotion of recommendation lists: presentation of a customized list of recommendations*

At this stage, each group is provided with the Top-k popular items among the users within that specific group.

2.5 *Recent advances and research trends in group recommender systems*

Over the past five years, research on GRSs has increasingly shifted toward data-driven and representation-learning paradigms. Recent studies emphasize learning latent group representations through deep neural architectures, attention mechanisms, and graph-based models, aiming to capture complex interaction patterns and social dependencies in large-scale environments [14], [27]-[29]. These approaches reflect a broader trend toward modeling group behavior implicitly through end-to-end optimization rather than explicit behavioral or decision-making processes.

At the same time, recent influence-aware and behavior-oriented methods highlight the growing interest in modeling user impact, leadership, and social influence within groups, particularly in dynamic and large-scale settings [20], [21]. Contemporary surveys further identify scalability, interpretability, and support for overlapping or evolving group structures as key open challenges in modern group recommender systems [30].

In contrast to these recent trends, which are predominantly driven by supervised or end-to-end learning frameworks, the proposed work adopts a cognitively inspired and fully unsupervised perspective. By explicitly modeling decision-making mechanisms, influence streams, and user satisfaction-without assuming predefined group structures or requiring extensive training data-the proposed framework complements recent advances and offers an interpretable alternative for group recommendation in dynamic social environments.

3. Proposed method

This study investigates cognitive science-inspired theories of group formation and leverages them to construct group profiles that enhance the accuracy of recommendations in group recommender systems. We propose a framework that models behavioral profiles by capturing the various influences shaping individual decision-making processes. Specifically, we posit that individuals' product selection behaviors are fundamentally influenced by their susceptibility to the information streams and social interactions within their surrounding environment. Accordingly, the proposed approach is grounded in social events and operates without relying on restrictive assumptions or prior knowledge, such as the number of groups, the average group size, or explicit information about the underlying network topology. Within this framework, suitable groups are first identified using a simulated social interaction graph, followed by the construction of behavioral profiles in a second stage.

3.1 *Problem definition and notation*

The input of most of the classic recommender systems is a user ratings matrix as mentioned in Related works section, from which the following information can be obtained (Table 3).

The output of the system is the number of recommendation lists $RG(g)$ which will be assigned to the group G. A high-quality recommendation list keeps the largest possible number of group members satisfied.

Table 3. Basic definition on GRS

Definitions	
Set of users:	$U = \{u_1, u_2, u_3, \ldots, u_m\}$
Set of items:	$I = \{I_1, I_2, I_3, \ldots, i_n\}$
Set of ratings that given by u_m to i_n:	$r_i^u = \{\text{null}, 0, 1, 2, 3, 4, 5\}$
User ratings matrix:	$R \subseteq U \times I$

3.2 *Cognitive-science foundations for group formation*

The main idea related to recognizing proper groups and finding the best items as a recommended list in this study is established according to cognitive science theories:

Principle 1: Theories on Individuals' Inclination to Join Groups.

According to Social Identity Theory [31]-[33], individuals tend to quickly categorize themselves as members of a group, and they tend to favor the group they belong to over others. Based on this theory, our initial step in providing a recommendation list involves identifying groups comprising individuals with similar preferences. Additionally, the Integrative Theory [34] emphasizes humans' natural inclination to place themselves as members of a group.

Principle 2: Theories Regarding How Individuals Assess Conditions in order to Make Decisions.

Interdependence Theory [35], [36] examine how individuals assess the costs and benefits of a particular relationship. This theory explores how individuals' decision is influenced by these evaluations and ultimately suggests that individuals are more engaged in relationships that provide higher satisfaction compared to others. In essence, the proposed method follows a repetitive selection process, ultimately placing an individual in a group where they derive greater satisfaction compared to other groups.

Principle 3: Theories on Individuals' Susceptibility.

In general, according to the Social Learning Theory [37], [38], learning occurs through three main approaches:

Imitation: Imitation involves copying the behaviors, values, and attitudes of other individuals or groups.

Instruction: Learning occurs intentionally through formal education as well as informally through discussion groups, study groups, and activities such as apprenticeships.

Iteration learning: Motivation for learning appropriate behavior through experience and the trial-and-error process.

Albert Bandura's Social Learning Theory [39] probably one of the most influential theories of learning and development, suggests that people can acquire new information and behaviors by observing others. This type of learning, known as observational (or modeling) learning, can be applied to explain a wide range of behaviors.

While observational learning might seem like a straightforward process at first glance, it is not. Not all observers acquire behavioral patterns from the models they observe. It appears that other users' characteristics such as their credibility and social position, and also their indepdency play a role in this process. Therefore, although observational learning can be a powerful process, it should not be assumed to happen automatically, and the learner is not obliged to imitate others directly.

Hence, Bandura and his colleagues believe that three factors can influence observational learning:

Principle 4: Characteristics of the groups.

The characteristics of the models can influence our inclination to imitate them. These influential characteristics include similarity between the model (group) and user, age and gender similarity, as well as authority and fame.

Principle 5: Characteristics of the Observers.

The characteristics of the observers also determine the effectiveness of observational learning. Individuals with low self-esteem are much more likely to imitate others with high self-esteem.

Principle 6: Consequences and Rewards Associated with Behaviors.

The consequences or rewards associated with specific behaviors can affect the extent to which observers imitate them. A model with a higher status may lead to imitative behavior, but if the rewards are not meaningful to the observers, they may not continue the behavior.

Principle 7: Social Impact level.

According to Social Impact Theory [40], the level of social influence and the susceptibility of individuals depend on three factors: the number, strength, and immediacy of the sources. When the number of individuals is higher, their impact is stronger, and a reduction in physical distance leads to increased susceptibility of recipients. This power and influence result from access to resources and facilities such as rewards, punishments, and information. Furthermore, these resources and facilities can be either the social status of individuals in society or the interest and admiration of others.

To summarize, the explanations provided above, along with the cognitive theories, highlight the factors that can influence modeling and susceptibility to social influence. These factors play a crucial role in shaping an individual's behavior and decision-making processes.

In this paper, we have discussed the aforementioned principles and how they relate to complex dynamic networks through mapping (Table 4).

Table 4. Mapping cognitive sciences theories to complex dynamic networks

#	Principle	Addressing in proposed method	Use cases
P1	Individuals' inclination to join groups	Assigning each individual to a group for decision-making purposes	[41]-[43]
P2	Conditions evaluation	The possibility of group modification during successive iterations	[44]
P3	Individuals' susceptibility	Various information flows received by decision-makers based on weighted relationships	[45]
P4	Importance of groups' characteristics	Defining group profile based on its member choices	[41]
P5	Importance of observers' characteristics	Defining a satisfaction factor for each user	[45]
P6	Importance of the sequence of behaviors	Defining iteration-based process for choosing proper group	[46]
P7	Social impact level	Using weighted graph for simulating the level of similarity and impact (section 3.3)	[5], [22], [25]

3.3 *Preprocessing: create the user similarity graph*

This paper attempts to model the interactions that each user faces in the decision-making process. Additionally, it discusses how individuals are influenced by these interactions and make their final choices. The main stages of the proposed method depict in Figure 1.

As mentioned in Related Work Section, the methodology of the similarity graph significantly influences the recommendation list's result. This study employs the Adjusted Cosine Similarity (COS) (Formula (1)), a common choice in prior research [5], [14]-[19]. Our unique contribution is the development of a weighted similarity graph to consider Principle 7 as well as enhance the precision of the recommendation list.

Upon computation of the similarity measures for each user u, the corresponding similarity interval $\mathrm{SimInt}(u)$ with other users is subsequently determined. The upper bound of this interval signifies the maximum similarity with other users, while the lower bound represents the minimum degree of similarity that the target user with others. So, $\mathrm{SimInt}(u) = \left[\min_{u \neq v,\, v \in U} \mathrm{COS}(u, v), \max_{u \neq v,\, v \in U} \mathrm{COS}(u, v) \right]$ will be established.

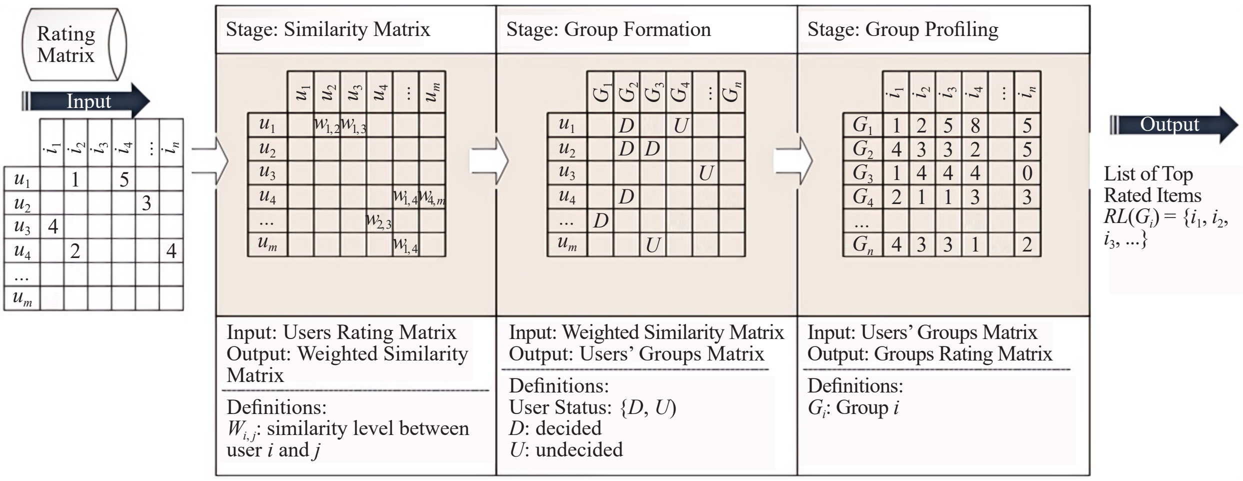

Figure 1. Main stages of proposed method

The range of similarity of each user is divided into two distinct categories. The lower half, representing limited similarity, are deemed insignificant and thus excluded from further consideration. The remaining range, representing higher degree of similarity, will be assigned weights according to below formula:

$$Adj(u, v) = \begin{cases} \omega, & \mathrm{COS}(u, v) \geq \mathrm{SimInt}(u)/2 \\ 0, & \text{Otherwise.} \end{cases} \tag{3}$$

Where $W(u, v)$ represents the weight between two user u and v.

$$\omega = \begin{cases} 3, & \mathrm{COS}(u, v) \geq 5 * \mathrm{SimInt}(u)/6 \\ 2, & 5 * \mathrm{SimInt}(u)/6 > \mathrm{COS}(u, v) \geq 2 * \mathrm{SimInt}(u)/3 \\ 1, & 2 * \mathrm{SimInt}(u)/3 \geq \mathrm{COS}(u, v) \geq \mathrm{SimInt}(u)/2. \end{cases} \tag{4}$$

-Zero Level: If the similarity between two users falls within the lower half of similarity, the similarity level of those users will be zero. This level indicates an unacceptable similarity between the two users and, as a result, the absence of an edge in the graph.

-Non-Zero Level: If the similarity falls within the upper half of similarity, the presence of an edge in the graph is guaranteed. At this stage, the remaining range is divided into three equal levels. Thus, if the similarity falls within the upper one-third, it is assigned a similarity level of 3; if it falls within the second one-third, it is assigned a similarity level of 2, and in any other case, it is assigned a similarity level of 1. Based on this, the weights of the graph edges are determined proportionally to the assigned levels. The obtained similarity can be represented as an adjacency matrix $Adj(u, v)$. According to the provided explanations, the permissible values for edge weights form the set $\{1, 2, 3\}$, denoted as ω. Furthermore, users who are connected to each other are considered neighbors. Figure 2 shows the similarity graph that recognized by the above approach:

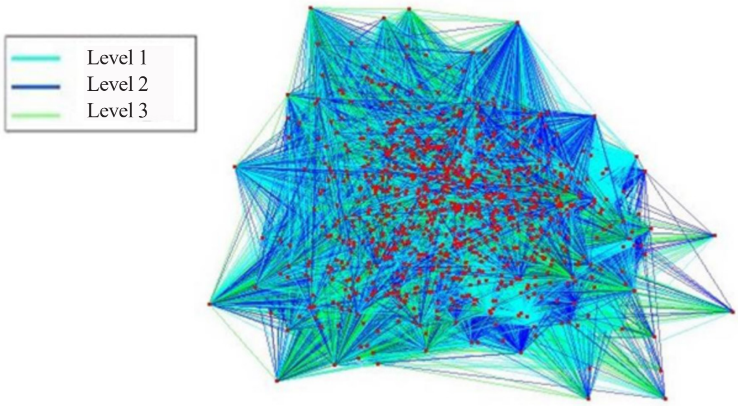

Figure 2. Similarity graph based on proposed method

3.4 *Group formation*

The input for this section is the users' similarity graph, in which each individual is neighbors with the most similar individuals in terms of preferences, and edge weights represent the level of similarity between users. In this context, it is necessary to develop models for influence propagation and sender behavior, aligning with Principle 4, user behavior in information reception, aligning with Principle 5 and the modeling of user acceptance mechanisms, based on Principle 1, 2, 3, and 6 is further elaborated in sections 3.4.1, 3.4.2, and 3.4.3, respectively.

3.4.1 *Interactions modeling*

After constructing the user graph, cognitive science theory is utilized for modeling in each iteration. According to [37], user decision-making is significantly impacted by the viewpoints of individuals within the same age bracket (Stream 1), same social position (Stream 2), and same gender (Stream 3) as the target user.

Additionally, based on the theories of [32], [34] and [37], individuals are often influenced by the opinions of the vast majority of their closest neighbors and share the most influence with them (Stream 4).

Also, [39] and [43] emphasize on the role of influential individuals in decision making process. In order to calculate the users' importance, this study relies on one of the most renowned complex network measures [47], referred to as Betweenness centrality that firstly introduced by [48] represents in Formula (5). Considerable research has been conducted on this metric; in this article, we opt for the Local Betweenness centrality [49] to manage time complexity effectively.

$$I(u) = \sum_{u \neq v \neq s} \frac{\delta_{vs(u)}}{\delta_{vs}}. \tag{5}$$

In this context, u, v, and s, all belonging to the set U. The symbol δ_{vs} represents the total number of shortest paths originating from node v and reaching node s. Furthermore, $\delta_{vs(u)}$ is the number of those paths that pass-through u. In contrast to the conventional Betweenness centrality, which considers the entire network, the local Betweenness centrality measure concentrates on shorter paths. This study confines its analysis to the paths of only the immediate neighbors of each user. In other words, it considers a version that exclusively takes into account pairs directly connected to the specified node u. Moreover, user u will be influenced by neighbors who have higher importance than them (Stream 5).

Since the role of advertising streams in influencing individuals is not negligible, this algorithm takes this parameter into account. In each iteration, a group label is randomly assigned as the advertising stream and is included in the algorithm's calculations. According to [50], people who are less important are more influenced by external factors during their decisions. Therefore, in this article, the influence of advertising streams is taken as the inverse ratio of the importance of each user (Stream 6).

The effective streams in decision making process are illustrated in Figure 3.

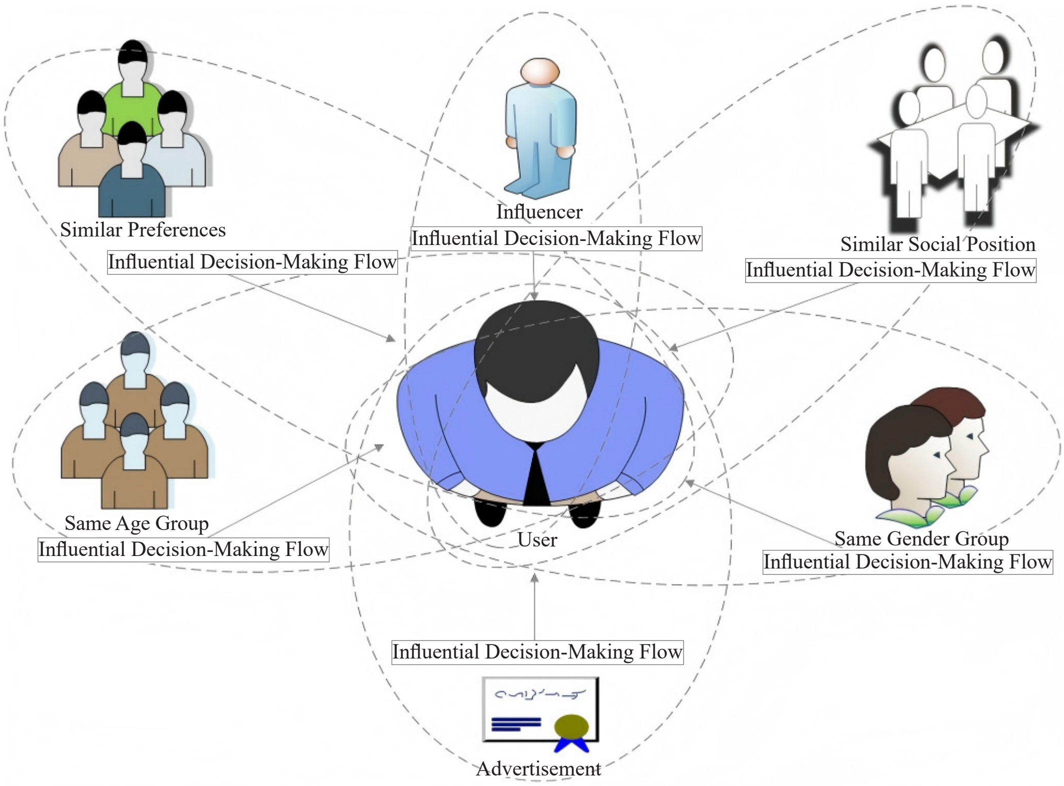

Figure 3. Effective streams in decision-making process

The proposed method assigns a confidence coefficient to each of these streams based on their impact on the target user. Table 5 represents the confidence coefficient calculation.

Table 5. Confidence coefficient calculation

#	Streams	Confidence Coefficient (CC)	Formula
1	Same age group	$\mathrm{CC}(u, A) = \mathrm{AVE}(w(u, Nu)) * Nu(\mathrm{sameAge}, A)/Nu(\mathrm{sameAge})$	(6)
2	Same social position	$\mathrm{CC}(u, A) = \mathrm{AVE}(w(u, Nu)) * Nu(\mathrm{samePosition}, A)/Nu(\mathrm{samePosition})$	(7)
3	Same gender	$\mathrm{CC}(u, A) = \mathrm{AVE}(w(u, Nu)) * Nu(\mathrm{sameGender}, A)/Nu(\mathrm{sameGender})$	(8)
4	Majority of neighbors	$\mathrm{CC}(u, A) = \mathrm{AVE}(w(u, Nu)) * Nu(A)/Nu$	(9)
5	Influential neighbors	$CC(u, A) = \mathrm{AVE}(w(u, Nu)) * \mathrm{AVE}(I(Nu)) * Nu(A)/Nu$	(10)
6	Advertisements	$\mathrm{CC}(u, A) = 1 - I(u)$	(11)

Where CC(u, A) denotes the confidence coefficient of user u from a specific group(A). Additionally, AVE(w(u, Nu)) represents the average weight (similarity) of user u with its neighbors in the similarity graph. Also, Nu(sameAge), Nu(samePosition), and Nu(sameGender) show neighbors that are same age, same social position and same gender, respectively. In the same way, $Nu(A)$, $Nu(\text{sameAge}, A)$, $Nu(\text{samePosition})$ and $Nu(\text{sameGender}, A)$ denote, respectively, total neighbors user u, neighbors that are same age, same social position and same gender that belong to the group A. $I(u)$ denotes the level of influence exerted by user u and also $\text{AVE}(I(Nu))$ represents the average influence of the neighbors of user u.

3.4.2 *User satisfaction modeling*

In this method, a satisfaction level θu is assigned to each user u. This satisfaction level is randomly distributed among users. Additionally, for each user, two states are defined. If the Confidence Coefficient of each stream for a user is higher than the user satisfaction, the user is considered satisfied or Decided (D); otherwise, they are considered dissatisfied or Undecided (U):

$$\text{Status}(u) = \begin{cases} D, & CC(u, \text{ group } A) \geq \theta u \\ \\ U, & \text{Otherwise.} \end{cases} \tag{12}$$

3.4.3 *Social-Cognitive Label Propagation Algorithm (SC-LPA)*

In this approach, users are assigned labels that are constantly updated based on dynamic interaction rules from incoming streams. This method is derived from the Speaker-Listener Label Propagation Algorithm [51]. The below algorithm represents how the users' groups are changed over the iterations:

Algorithm 1: SC-LPA.
Input: Weighted Similarity Graph
Output: G_i as a proper group of user u
Variables:
Label (*u*, *t*): label (group) user u in iteration t
***Nu*:** neighbors of user u
User Satisfaction (US) (*u*, *g*, *t*): estimated satisfaction of user u from group g in iteration t
Initialization:
  for each u
Label $(u, 0) \leftarrow$ unique label   /In initial stage each user will have a unique and random label
Findingproper groups ineach iteration:
For $t = 1$ to n;
  for each u;
    calculate CC (u, g),   /According to Formulae (6)-(11)
    calculate US (u, g),   /According to Fomula (13)
    label $(u, t) \leftarrow$ label (max (US (u, g), t-1)   /retuns the label (group) with the highest US among received streams in previous iteration
$t = t + 1$
Termination conditions:
For each u:
  If label (u, t_n) = label (u, t_{n-1}) or US (u, g, t_n) > US (u, g, t_{n-1})
Break.

According to the above algorithm, in the first iteration, each node is initially labeled as distinct. In this method, the label of each node is considered as the community of that user. It aims to select the most suitable community in each iteration, one that is likely to satisfy the user the most. According to Confidence Coefficient of streams in each iteration, the probability of US with each group is estimated using Formula (13).

$$\text{US}(u, A) = P(A \mid D) = \frac{P(A \cap D)}{P(D)} \tag{13}$$

where $P(D)$ represents the probability of Status D with communities in general based on Formula (12). Additionally, $P(A \cap D)$ is the probability of Status D with specific community like A.

After calculating this probability, the community with the highest value is selected as the output for that iteration. For better understanding, consider the following example as the received streams in one iteration (Figure 4).

	Ads	Influential neighbors			Majority of neighbors			Same position				Same gender		Same age		
g	*B*	*A*	*B*	*D*	*A*	*D*	*E*	*B*	*C*	*D*	*E*	*A*	*B*	*A*	*C*	*E*
CC (u, g)	0.5	0.6	0.7	0.2	0.4	0.5	0.7	0.7	0.6	0.4	0.6	0.8	0.3	0.5	0.5	0.8
Status (u)	*U*	*D*	*D*	*U*	*U*	*U*	*D*	*D*	*D*	*U*	*D*	*D*	*U*	*U*	*U*	*D*

Figure 4. Example of received streams and user satisfaction calculation in each iteration for user u with $\theta u = 0.6$

In the example above, user u in iteration t received 5 labels from defined streams with varying confidence coefficients. According to Formula (13), the probability of user satisfaction associated with the label (group) A would be:

$$\mathrm{US}(u,\ A) = P(A \mid D) = \frac{P(A \cap D)}{P(D)} = \frac{0.6 + 0.8}{0.6 + 0.7 + 0.7 + 0.7 + 0.6 + 0.6 + 0.8 + 0.8} \approx 0.25 \tag{14}$$

Similarly, the likelihood of other labels' user satisfaction are calculated: US(u, B) = 0.25, US(u, C) = 0.12, US(u, D) = 0 and US(u, E) = 0.38.

According to the results of user satisfaction calculation (Formula (14)), the label with the highest satisfaction probability is selected as the most suitable community for the user in each iteration. At these stage two exceptions may occur:

Exception 1 (lack of satisfaction): When the user is not satisfied by any of the flows in a particular iteration CC(u, g) < θu and has the status "U", meaning that the user is still undecided, the algorithm selects the community with the highest probability of satisfaction from among the received labels, even though the user's status remains "U".

Exception 2 (Maximum Satisfaction Probability): When the probability of user satisfaction from more than one group is equal and maximized, the algorithm considers the number of times each of these communities has been presented to the user. The community that has been presented to the user the most times is selected as the user's chosen community. This ensures that the community with the highest frequency of presentation is chosen as the final community.

3.4.4 *Finalizing the groups*

The process of determining the final community for each user involves specific conditions to terminate the algorithm based on user behavior and community satisfaction. There are two main termination conditions: stable user behavior, where all users do not change communities in the last two iterations, or higher satisfaction in the chosen community, where all users have a higher probability of satisfaction than in their previous communities. Figure 5 depicts the memory of user at the end of the algorithm.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
g	*B*	*E*	*B*	*A*	*E*	*E*
Status (u)	*D*	*D*	*U*	*U*	*U*	*D*

Figure 5. User's memory state at the Algorithm's convergence after 6 iterations

After the algorithm stabilizes, decisions are made for each user based on the received labels. Each user's memory is proportional to their satisfaction level θu and the number of iterations. To make a decision, the last element of each user's memory is examined, and based on below criteria, the appropriate community for the user is selected:

1. Status (u, last iteration) = D: it indicates that the individual is in a state of satisfaction after the algorithm has stabilized, so this community will be suitable for them. Additional criteria to consider in this case include:

• If the user has been kept in memory in more than one community in the D state, these communities can be selected as suitable for the user. This indicates the user's satisfied with these groups, and as none of them have a preference over the others, the user will be placed in both groups.

2. Status (u, last iteration) = U: it is necessary to examine the states of the elements preceding the last element:

• If the user, in the elements before the last one, alternately belonged to one of the groups in the D state and the last element is different from that group, the user will be placed in both groups.

• If the user, in previous iterations, was in the D state for multiple groups, besides the group in the last element, the group with the highest probability of satisfaction should also be considered, and the user will be placed in both of these groups.

• If the previous elements were a combination of U and D states, where they do not follow any patterns, the group with the highest probability of satisfaction should be considered.

• If the previous elements were alternately in the form of U, the decision is made based on the highest repetition of the groups. If this number is equal, the user is included in both groups.

3.5 *Building the group behavioral profile*

As discussed in the previous section, users may simultaneously belong to multiple groups. This section focuses on constructing behavioral profiles for groups with overlapping memberships. To achieve this, different user roles are defined, and these roles determine the extent to which each user contributes to the group profile (Table 6).

Table 6. Users' status in building a group profile

Joining group status	Users' status	Impact on group profile	Received recommendation
One group	"*D*"	Involved in constructing the group profiles	Receive recommended lists from the group
	"*U*"	Do not have any direct impact on the profile	Receive recommended lists from the group
Two groups	"*D*" in both groups	Involved in constructing both group profiles	Receive recommended lists from both groups
	"*U*" and "*D*"	Will contribute to the group that made them satisfied	Receive recommended lists from both groups
	"*U*" in both groups	Do not have any direct impact on the profiles	Receive recommended lists from both groups

After identifying the groups, the profile of each group will be calculated using the weighted average strategy as Formula (3).

3.6 *Time complexity*

In the group formation stage, processing is performed on each user's neighbors per iteration to examine incoming information flows. Let Δ denote the maximum node degree, m the number of users, and k the number of iterations. The resulting computational complexity of this stage is $O(mk\Delta^2)$. Additionally, for each user, a memory structure of bounded size E is maintained to store historical group assignments. Processing this memory incurs a time complexity of $O(mE)$. Similarly, for the group profile construction component, the computational cost depends on G (the number of identified groups), S (the maximum group size), and n (the number of items), resulting in a time complexity of $O(GSn)$.

4. Experimental evaluation

4.1 *Dataset*

To conduct a comprehensive evaluation of the proposed method, we employed a diverse set of datasets. The primary experiments use the MovieLens 100K (MLP) and MovieLens 1M (MLM) datasets, which are among the most widely adopted benchmarks for assessing recommender system performance and scalability. In addition, the Southern Women and Karate Club datasets-both lacking rating matrices and containing minimal structural information-are included to evaluate the algorithmic behavior of the proposed method under controlled, interpretable conditions.

I. MovieLens Dataset:

The MovieLens datasets, curated by the GroupLens research team, are extensively used for benchmarking recommender systems. In this study, we utilize the 100K (MLP) and 1M (MLM) versions. Detailed statistics, including the number of users, items, and ratings, are provided in the accompanying table. Both datasets also include demographic attributes such as age, gender, and occupation, enabling a richer analysis of user behavior and the impact of the proposed approach on preference modeling (Table 7).

Table 7. MovieLens dataset details

Dataset	# Of ratings	# Of users	# Of items	Sparsity	Ratings	Other points
MLP	100K	943	1,682	93.70%	{1 to 5}	Each user has rated at least 20 items
MLM	1 Mil	6,040	3,952	95.75%	{1 to 5}	

II. Southern Women Dataset:

This dataset consists of 18 women who attended 14 social events over a period of nine months. It represents a bipartite graph with two types of nodes: women and events. The dataset captures the social interactions between women attending these events.

III. Karate Club Dataset:

The Karate Club Dataset is a well-known social network dataset that represents friendships between members of a university Karate club. It has been widely used in network analysis and social network research. 34 nodes (representing club members) and 78 edges (representing friendships between members). The dataset is often used for network analysis and community detection tasks.

4.2 *Evaluation metric*

In order to evaluate the quality of predictions made by the proposed algorithm, we will use the Root Mean Square Error (RMSE) as a measure. RMSE is a standard metric for evaluating model error and is based on the differences between predicted and actual scores. The RMSE is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{r=0}^{n}\left(r_u^i - e_g^i\right)^2}{n}} \tag{15}$$

where e_g^i represents the estimated score for item "i" in group "Gg". This estimated score can be obtained in the prediction or recommendation stage using the proposed methods. Furthermore, r_u^i represents the actual score given to item "i" by user "u" who is a member of group "Gg". In this formula, "n" represents the number of items with known scores in the test dataset.

4.3 *Evaluation results*

Experiment 1 Analyzing the stability of the proposed algorithm.

The algorithm under consideration underwent 25 times on the MovieLens-100K dataset. Notably, in 92% of these instances, the algorithm achieved a stable state, disregarding the termination condition, involving 8 and 9 iterations. It is noteworthy that the number of iterations in the remaining cases closely approximates this outcome as well.

Figure 6a and b illustrate the algorithm's error rate in both mentioned cases. As observed, in the initial iterations, the algorithm's error rate is very low because each user has a unique label in the graph. As the algorithm progresses and users are placed in different communities, the error rate gradually increases. However, during this process, there are instances where the error decreases due to finding more suitable communities.

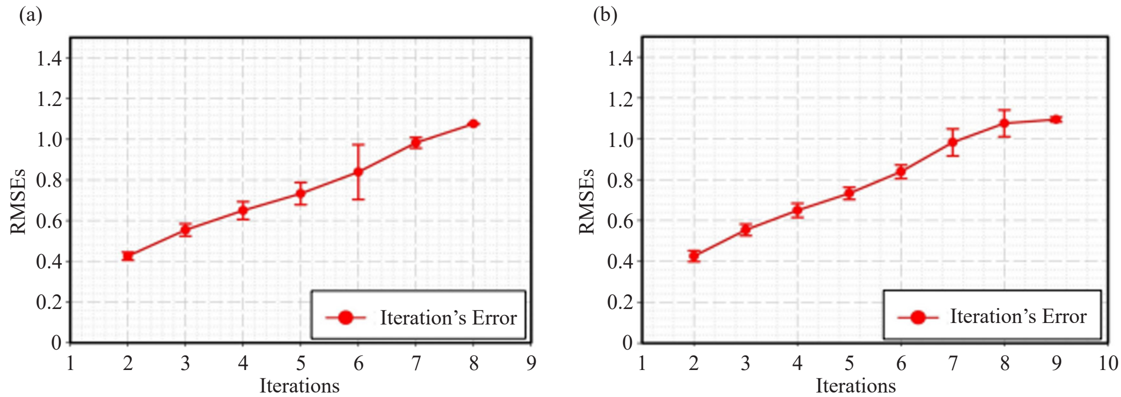

Figure 6. The error upon the algorithm's termination after (a) 8 iterations and (b) 9 iterations

Experiment 2 Accuracy of the proposed algorithm.

The final results of the algorithm on the specified datasets, considering the termination condition, are illustrated through Figure 7a and b. Across three datasets, this maximum number of iterations satisfying the termination condition is identified as six. Notably, the proposed algorithm exhibits commendable performance in datasets encompassing user information, such as MovieLens, along with simulations and their results.

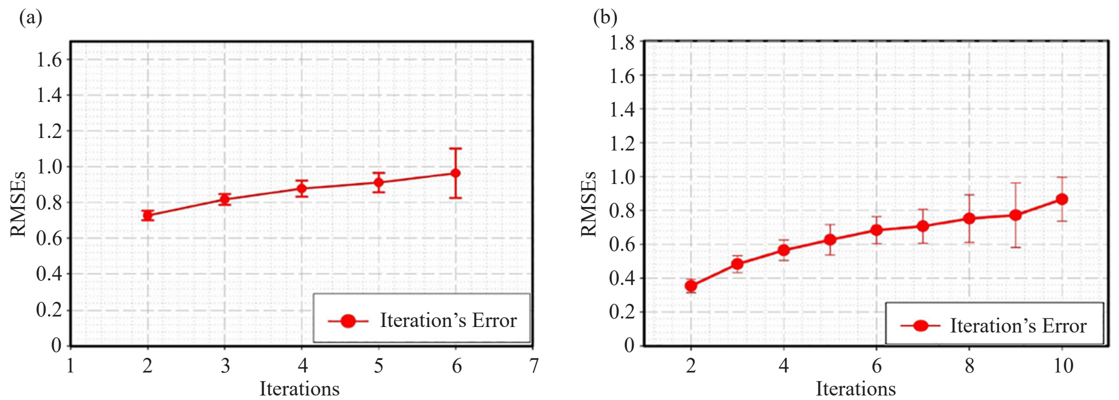

Figure 7. (a) MovieLens Dataset-100K (MLP) and (b) MovieLens Dataset-1Mil (MLM)

Several studies in the literature have reported RMSE values for group recommendation or community-based prediction tasks on datasets comparable to those employed in this study. Specifically, Reference [17] reported an RMSE of 1.05, Reference [18] reported 0.97, Reference [19] obtained 0.95, and Reference [5] achieved 0.91. By comparison, the proposed method attained an RMSE of 0.86, indicating superior predictive accuracy relative to these previously reported results. Although additional studies discussed in the related work section differ in terms of methodological assumptions and dataset configurations, this comparative analysis nevertheless provides a meaningful indication of the effectiveness and competitiveness of the proposed approach. It is important to clarify that the comparative evaluation focuses on baseline models that are methodologically aligned with the proposed framework. Specifically, the selected baselines represent classical and influence-based GRSs that do not rely on end-to-end supervised learning, large-scale model training, or predefined group structures. Many recent group recommendation approaches are based on deep neural or graph neural architectures and require extensive labeled interaction data and task-specific training objectives. As such, they are not directly comparable to the proposed cognitively inspired, fully unsupervised framework, which addresses a different problem setting.

The goal of this evaluation is therefore not to demonstrate superiority over all recent neural models, but to show that incorporating cognitive theories, influence streams, and overlapping group membership can yield substantial performance improvements over established group recommendation paradigms while maintaining interpretability and minimal data requirements.

Additionally, an assessment of the proposed method is conducted in scenarios where user information is absent, exemplified by the Southern Women and Karate Club datasets. In these instances, the algorithm relies on structural characteristics. Figure 8a and b depict that even in the absence of user information, the algorithm continues to yield satisfactory results.

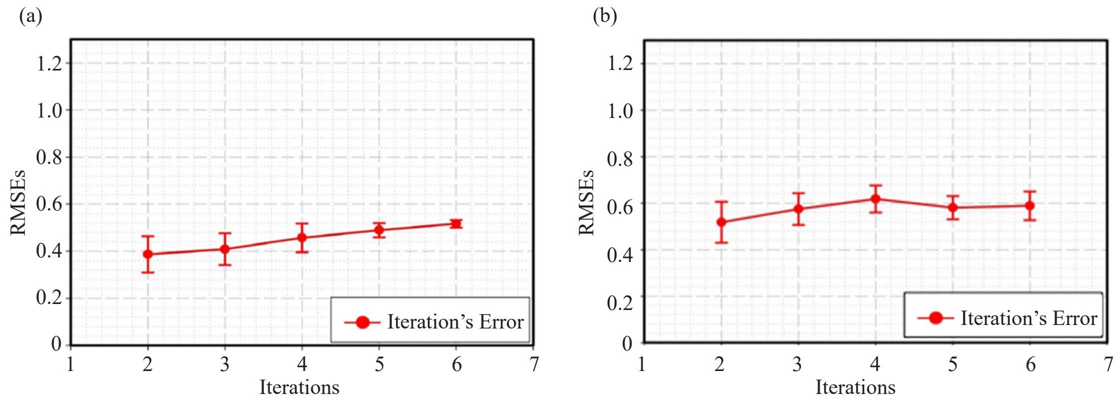

Figure 8. (a) Southern women dataset and (b) Karate club dataset

Experiment 3 Number of groups analysis.

In this section, our analysis aims to find the correlation between the number of identified groups and RMSEs. Table 8 depicts the count of identified groups in the Movielens-100K (MLP) dataset, incorporating termination conditions for the proposed method. Notably, the table reveals that in the final iteration (iteration 6), all 943 users are categorized into approximately 51 groups, demonstrating an average grouping result.

Table 8. Number of identified groups in each iteration

Iteration #	1^{st} iteration	2^{nd} iteration	3^{rd} iteration	4^{th} iteration	5^{th} iteration	6^{th} iteration
# Of groups	≈ 588	≈ 426	≈ 331	≈ 266	≈ 111	≈ 51

Experiment 4 Examining the influence of incorporating overlapping communities.

Figure 9 depicts the repercussions of accounting for overlapping groups. In this experimental setup, Case 2 denotes the implementation of the proposed algorithm without considering overlapping groups, whereas Case 1 incorporates this feature. Given that individuals in non-overlapping groups can exclusively belong to a single group, the initial iterations show a superior error performance for Case 2 compared to Case 1. However, the chart illustrates that, with a progression in iterations, an enhancement in the accuracy of overlapping groups becomes evident.

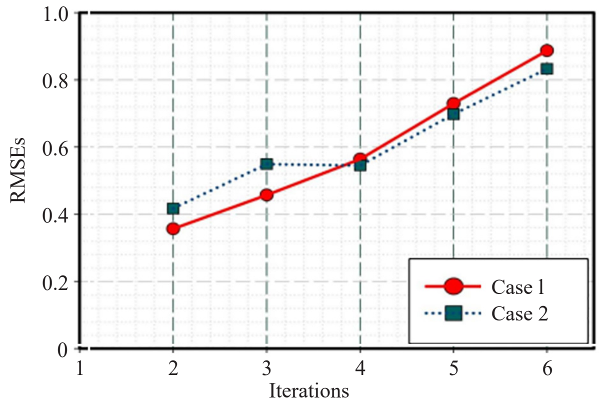

Figure 9. Comparing the error of proposed method in two cases considering overlapped-communities and non-overlapped communities

Experiment 5 Analysis of time complexity with users' growth.

In this section, we aim to analyze the time complexity of the proposed method with users' growth. The execution time of the proposed method is assessed on a 16-core system with 16 gigabytes of available memory, operating on Windows Server 2008. The following table shows the execution time data for the proposed method. Figure 10 is dedicated to comparing the execution time of each iteration of the algorithm with an increasing number of users. This comparative analysis provides insights into the scalability of the algorithm.

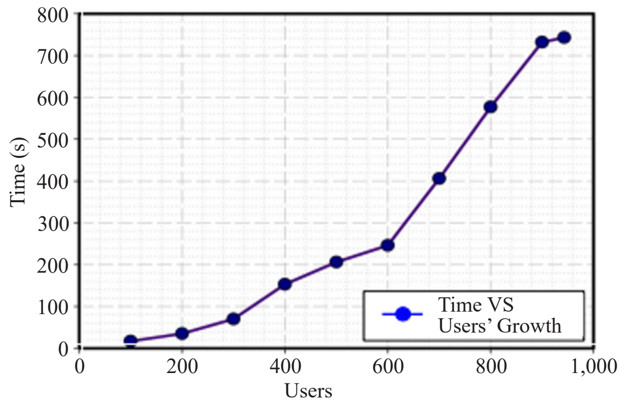

Figure 10. Time analysis VS users' growth

Experiment 6 Error analysis with users' growth.

In addition to the above analysis, the error rate in this method is also examined based on the growth rate of users in each iteration. Figure 11 will illustrate this comparison.

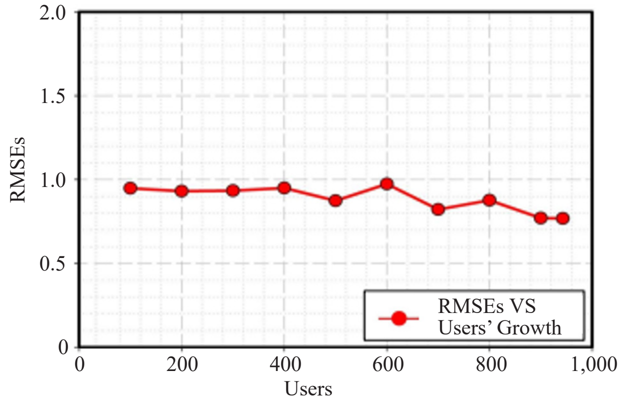

Figure 11. Error analysis with the users' growth

5. Conclusion and future work

This article endeavors to provide accurate recommendation lists by eliminating restrictive assumptions such as a predefined number of groups or explicit knowledge of user network topology, while requiring only minimal input information. By adopting a cognitively inspired perspective, the proposed framework identifies groups of users with similar preferences through an iterative process grounded in well-established cognitive theories. User satisfaction levels, incoming influence streams during decision-making, and the impact of each stream on individual users are explicitly modeled. Moreover, allowing users to belong to overlapping groups enhances the expressiveness of group behavioral profiles and ultimately improves the accuracy of the generated recommendation lists.

While the proposed framework assumes cooperative information exchange among users during the iterative interaction process, real-world environments may involve more complex, strategic, or even adversarial behaviors. An important direction for future work is to extend the current interaction modeling to game-theoretic formulations, particularly repeated coalition formation games, where users strategically adapt their group affiliations over time. In addition, the proposed cognitive model relies on human-centric attributes such as age, gender, and social position to estimate confidence coefficients and influence dynamics. When deploying such models in real-world systems, particularly at scale, it is essential to address privacy and data protection concerns associated with sensitive personal information.

Author contributions

"Conceptualization, Mojdeh Morshedi and Mehdi Sadeghi, Hanieh Morshedi; methodology, Mojdeh Morshedi; software, Amir Fazelinia; validation, Amir Fazelinia; formal analysis, Mojdeh Morshedi; investigation, Mojdeh Morshedi; resources, Mojdeh Morshedi and Mehdi Sadeghi; writing-original draft preparation, Mojdeh Morshedi, Alireza Morshedi and Mehdi Sadeghi; writing-review and editing, Mojdeh Morshedi; visualization, Mojdeh Morshedi. All authors have read and agreed to the published version of the manuscript".

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] D. M. Boyd and N. B. Ellison, "Social network sites: Definition, history, and scholarship," *Journal of Computer-*

Mediated Communication, vol. 13, no. 1, pp. 210-230, 2007.

[2] A. Agarwal, M. Chakraborty, and C. R. Chowdary, “Does order matter? Effect of order in group recommendation,” *Expert Systems with Applications*, vol. 82, pp. 115-127, 2017.

[3] C. Gao, Y. Zheng, N. Li, Y. Li, Y. Qin, J. Piao, Y. Quan, J. Chang, D. Jin, X. He, et al., “A survey of graph neural networks for recommender systems: Challenges, methods, and directions,” *ACM Transactions on Recommender Systems*, vol. 1, no. 1, pp. 1-51, 2023.

[4] Z. Guo, L. Tang, T. Guo, K. Yu, M. Alazab, and A. Shalaginov, “Deep graph neural network-based spammer detection under the perspective of heterogeneous cyberspace,” *Future Generation Computer Systems*, vol. 117, pp. 205-218, 2021.

[5] H. Mahyar, K. E. Ghalebi, S. M. Morshedi, S. Khalili, R. Grosu, and A. Movaghar, “Centrality-based group formation in group recommender systems,” in Proc. WWW 2017 Companion: 26th Int. World Wide Web Conf. Companion, Perth, Australia, 2017, pp. 1187-1196.

[6] K. Yu, Z. Guo, Y. Shen, W. Wang, J. C. W. Lin, and T. Sato, “Secure artificial intelligence of things for implicit group recommendations,” *IEEE Internet of Things Journal*, vol. 9, no. 4, pp. 2698-2707, 2021.

[7] Z. He, C. Y. Chen, and J. D. Zhang, “GAME: Learning graphical and attentive multi-view embeddings for occasional group recommendation,” in Proc. SIGIR 2020: Int. ACM SIGIR Conf., Xi’an, China, 2020, pp. 649-658.

[8] S. Wu, F. Sun, W. Zhang, X. Xie, and B. Cui, “Graph neural networks in recommender systems: A survey,” *ACM Computing Surveys*, vol. 55, no. 5, pp. 1-37, 2022.

[9] J. Monsalve-Pulido, J. Aguilar, E. Montoya, and C. Salazar, “Autonomous recommender system architecture for virtual learning environments,” *Applied Computing and Informatics*, vol. 20, no. 1-2, pp. 69-88, 2024.

[10] J. Dong, J. Hu, Y. Zhao, and Y. Peng, “Opinion formation analysis for expressed and private opinions models in group decision-making systems,” *Expert Systems with Applications*, vol. 236, pp. 121292, 2024.

[11] X. Li, J. Wei, H. Wang, L. Dong, R. Chen, C. Yi, J. Cai, D. Niyato, and X. Shen, “Towards intelligent transportation with pedestrians and vehicles in-the-loop: A surveillance video-assisted federated digital twin framework,” *IEEE Network*, vol. 39, no. 6, pp. 305-315, 2025.

[12] F. Fkih, “Similarity measures for collaborative filtering-based recommender systems: Review and experimental comparison,” *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 9, pp. 7645-7669, 2022.

[13] A. Bellogín and A. P. De Vries, “Understanding similarity metrics in neighbour-based recommender systems,” in Proc. Conf. Theory of Information Retrieval, ACM, Copenhagen, Denmark, 2013, pp. 48-55.

[14] X. Chen, L. Yao, J. McAuley, G. Zhou, and X. Wang, “Deep reinforcement learning in recommender systems: A survey and new perspectives,” *Knowledge-Based Systems*, vol. 264, pp. 110335, 2023.

[15] Z. Liu, S. Wen, and Y. Quan, “Deep reinforcement learning based group recommender system,” *arXiv*, 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2106.06900. [Accessed June 13, 2021].

[16] E. Yalcin and A. Bilge, “Novel automatic group identification approaches for group recommendation,” *Expert Systems with Applications*, vol. 174, pp. 114709, 2021.

[17] L. Boratto, “ART: Group recommendation approaches for automatically detected groups,” *International Journal of Machine Learning and Cybernetics*, vol. 6, no. 6, pp. 953-980, 2015.

[18] L. Boratto and S. Carta, “State-of-the-art in group recommendation and new approaches for automatic identification of groups,” in *Information Retrieval and Mining in Distributed Environments*, A. Soro, E. Vargiu, G. Armano, and G. Paddeu, Eds. Berlin, Germany: Springer, 2011, pp. 1-20.

[19] L. Boratto and S. M. Serra, “Groups identification and individual recommendations in group recommendation algorithms,” in Proc. PRSAT Workshop, ACM RecSys 2010, Barcelona, Spain, 2010, pp. 27-34.

[20] R. B. Nozari, H. Koohi, and Z. Kobti, “IBGR: Influence-based group recommendation system,” *Software Impacts*, vol. 19, pp. 100597, 2024.

[21] R. B. Nozari and H. Koohi, “A novel group recommender system based on members’ influence and leader impact,” *Knowledge-Based Systems*, vol. 205, pp. 106296, 2020.

[22] I. Christensen, S. Schiaffino, and M. Armentano, “Social group recommendation in the tourism domain,” *Journal of Intelligent Information Systems*, vol. 47, no. 2, pp. 209-231, 2016.

[23] M. Al-Shamri, “Similarity measures for recommender systems: Drawbacks and neighbors formation,” *Preprint*, 2022. [Online]. Available: https://doi.org/10.21203/rs.3.rs-2091938/v1. [Accessed September 23, 2022].

[24] S. Fortunato, “Community detection in graphs,” *Physics Reports*, vol. 486, no. 3-5, pp. 75-174, 2010.

[25] S. M. Morshedi, H. Mahyar, and A. Movaghar, “Influence-based community detection in social recommender

systems," in Proc. European Conf. Social Networks (EUSN), Paris, France, 2016.
[26] E. Ntoutsi, K. Stefanidis, K. Nørvåg, and H. P. Kriegel, "Fast group recommendations by applying user clustering," in *Conceptual Modeling*, Berlin: Springer, 2012, pp. 126-140.
[27] D. Cao, X. He, L. Miao, Y. An, C. Yang, and R. Hong, "Attentive group recommendation," in Proc. ACM SIGIR, Ann Arbor, MI, USA, 2018, pp. 645-654.
[28] W. Fan, Y. Ma, Q. Li, Y. He, E. Zhao, J. Tang, and D. Yin, "Graph neural networks for social recommendation," in Proc. World Wide Web Conf., San Francisco, CA, USA, 2019, pp. 417-426.
[29] Z. Huang, Y. Liu, C. Zhan, C. Lin, W. Cai, and Y. Chen, "A novel group recommendation model with two-stage deep learning," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 9, pp. 5853-5864, 2021.
[30] S. Dara, C. R. Chowdary, and C. Kumar, "A survey on group recommender systems," *Journal of Intelligent Information Systems*, vol. 54, no. 2, pp. 271-295, 2020.
[31] M. A. Hogg, "Understanding peace and conflict through social identity theory," in *Social Identity Theory*, Cham, Switzerland: Springer International Publishing, 2016, pp. 3-17.
[32] H. Tajfel, *Social Identity and Intergroup Relations*. Cambridge, U.K.: Cambridge University Press, 2010.
[33] S. McLeod, "Social identity theory," *Simply Psychology*, 2008.
[34] H. Tajfel and J. C. Turner, "An integrative theory of intergroup conflict," in *The Social Psychology of Intergroup Relations*. Monterey, CA, USA: Brooks/Cole, 1979.
[35] P. A. Van Lange and D. Balliet, "Interdependence theory," in *APA Handbook of Personality and Social Psychology*. Washington, DC, USA: American Psychological Association, 2015, pp. 1-29.
[36] L. K. Guerrero, P. A. Andersen, and W. A. Afifi, *Close Encounters: Communication in Relationships*, 3rd ed. Thousand Oaks, CA, USA: SAGE Publications, 2021.
[37] A. N. F. Rumjaun, "Social learning theory-Albert Bandura," in *Science Education in Theory and Practice: An Introductory Guide to Learning Theory*. Cham, Switzerland: Springer, 2020, pp. 85-99.
[38] J. B. Rotter, "Social learning theory," in *Expectations and Actions*. New York, NY, USA: Routledge, 2021, pp. 241-260.
[39] A. Bandura, *Social Learning Theory*. New York, NY, USA: General Learning Corporation, 1971.
[40] B. Latané, "The emergence and evolution of social realities," in *Pillars of Social Psychology: Stories and Retrospectives*. Cambridge, U.K.: Cambridge University Press, 2022.
[41] M. H. T. Stoica, "A social identity theory perspective on sustainable brand recommendation: The case of professional service providers," *Journal of Brand Strategy*, vol. 12, no. 3, pp. 300-318, 2023.
[42] R. Ma, J. Cherian, W.-H. Tsai, M. Sial, L. Hou, and S. Álvarez-Otero, "The relationship of corporate social responsibility on digital platforms, electronic word-of-mouth, and consumer-company identification: An application of social identity theory," *Sustainability*, vol. 13, no. 9, pp. 4700, 2021.
[43] N. K. Steffens, P. A. M. Van Lange, K. Kessler, J. F. Dovidio, M. J. Platow, and S. A. Haslam, "Advancing the social identity theory of leadership: A meta-analytic review of leader group prototypicality," *Organizational Psychology Review*, vol. 11, no. 1, pp. 35-72, 2021.
[44] J. Schoeffer, J. Jakubik, M. Vössing, N. Kühl, and G. Satzger, "On the interdependence of reliance behavior and accuracy in AI-assisted decision-making," in Proc. HHAI, Amsterdam, The Netherlands, 2023, pp. 46-59.
[45] M. Lamia, M. Hafidi, and S. Aouidi, "Towards recommendation using learners' interest in social learning environment," in *Innovations in Smart Cities Applications Edition 3*. Cham, Switzerland: Springer, 2020, pp. 183-199.
[46] M. Mansoury, H. Abdollahpouri, M. Pechenizkiy, B. Mobasher, and R. Burke, "Feedback loop and bias amplification in recommender systems," in Proc. 29th ACM Int. Conf. Information and Knowledge Management (CIKM), Galway, Ireland, 2020.
[47] F. Bloch, M. O. Jackson, and P. Tebaldi, "Centrality measures in networks," *Social Choice and Welfare*, vol. 61, pp. 413-453, 2023.
[48] L. C. Freeman, "A set of measures of centrality based on betweenness," *Sociometry*, vol. 35, no. 1, pp. 35-41, 1977.
[49] K. Yamaoka, Y. Kumakoshi, and Y. Yoshimura, "Local betweenness centrality analysis of 30 European cities," in *Urban Informatics and Future Cities*. Cham, Switzerland: Springer, 2021, pp. 527-547.
[50] K. Nelson-Field, "Who should you impress (and where are they hiding)?," in *The Attention Economy and How Media Works*. Singapore: Palgrave Macmillan, 2020, pp. 123-138.
[51] J. Xie, B. Szymanski, and X. Liu, "SLPA: Uncovering overlapping communities in social networks via a speaker-listener interaction dynamic process," in *Proc. IEEE Int. Conf. Data Mining Workshops*, 2011, pp. 344-349.