A Framework for Group Context Aware Recommendation Systems

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Chapter 1

Introduction

This Ph.D. thesis addresses the problem of Group Recommendation Systems (GRSs) with the aim to define a general framework to integrate in the process of generation of the recommendations for a specific group social aspects related to the interactions between group's members, to the type and the status of the social relationship within the group, and even aspect related to the personality of the group's members. The objective is the realization of techniques that permit to better model the real interactions characterizing the group decision-making process and obtain most suitable recommendations.

1.1 The Addressed Problem

Recommendation Systems (RSs) are software systems supporting users in a decision-making process. An RS provides suggestions for items on which a user have to choose, trying to suggest items that can be of interest for the user in relation to his/her preferences. Such systems can be applied in several domains, as touristic applications that provide suggestions to plan a vacation, or systems that help users choosing movies to watch, music to listen. Recently, RSs have been applied in smart museum scenarios, as a way to improve the users' satisfactions in their visit.

In many of these cases, there is the possibility that not a single user, but a group of people, must choose an activity to perform together. In this case, Group Recommendation Systems (GRSs) give a support to group decision-making giving recommendations to a group of users, trying to suggest items that can be of interest for all considering the preference of all the group's members. General approaches for GRSs starts from the individual recommendations, provided by an individual RS, and merge them in way to determine the best choice for the whole group. Unfortunately, with this approach, it results very difficult to consider aspects that influence the real group decision-making process. Hence, the system has to consider not only the preferences of the group members but also the key factors in such process [38] taking into account the type of control in the group decision-making process [46]. On the basis of these considerations some advanced approaches proposed in literature try to integrate social information about the group members with the classical techniques, in way to derive new strategies more applicable in real scenarios. In this context, the most common approach to integrate such factors in the group recommendation process is to apply weights derived from social interactions between the members of the group.

Hence, the problem on which this work is focused, is to study the social dynamics that occur when a group of people interact to make a group choice, determine the factors that can be useful to consider in the process of generation of the recommendations, and then define advanced aggregation techniques to generate groups recommendations. The aggregation strategies are used to merge individual recommendations obtained from an individual RS for each user in the group and obtain a recommendation for the whole group.

1.2 The Proposed Approach

In this thesis, a two-step approach for the design of a Group Recommendation Systems (GRSs) is proposed. The basic idea is that the general approach, that focuses on how to aggregate individual's utilities to determine the best choices for the group, have a limitation since it only focuses on the merging of the utilities estimated by an individual RS. Our hypothesis is that such utilities should be modified in relation to the specific group in which the users must perform the recommended items since, as suggested by the work about social influence, emotional contagion and other-regarding preferences, individual utilities may change when there are other people that can influence the individual. Hence, we propose an architecture characterized by two subsystems:

- *Group Context Adaptation System*, that has the task to adapt the individuals' utilities to the group's context;
- *Aggregation System*: that must determine the best choice for the group, starting from these adapted utilities, even using information about the social dynamics between group's members and the individual's profile.

Hence, this work is composed of two parts, one for each of the subsystems described. Regarding the adaptation phase, the work is focused on the determination of the factors that can have an impact on the Emotional Contagion phenomenon. It is assumed that individual utilities are determined by individual RS, hence the adaptation system must evaluate the impact, on such utilities, of the presence of other people. Regarding the merging step, instead, two weighted social choice functions are defined, where the weights are determined through a dominance measure, that indicates the most influencing user in the group. Furthermore, a second negotiation-based approach is illustrated. Here, the agents acting in the negotiation replicate the corresponding users behaviour with respect to their conflict management styles, obtained through the Tomas-Kilmann Instrument [47].

1.3 Innovative Aspects of the Work

An important aspect of the proposed work is that is a multidisciplinary work that integrate studies on Economics, Multi-Agent Systems, Psychology, Sociology, and so on. The definition of the two weighted aggregation strategies, introduced in section 4.2.1, apply the concept of Dominance of a person in a group of people, in order to assign a different importance to each user according to it. The negotiation based approach, defined in section 4.2.2, uses a psychological model of Conflict Resolution Styles in way to model the behaviour of the agents that take part in the negotiation. Furthermore, the analysis of the factors that have an influence on the Emotional Contagion phenomenon start from results obtained in psychological field in the study of social behaviours.

Moreover, going beyond these methodological aspects, the obtained results represent the many important parts of this work. The study presented in chapter 5 permit to relate some of the main results on the relation between personality traits and social behaviour, to the study of emotional contagion and how the utilities of an individual change when it is in a group of people. Furthermore, the two proposed aggregation strategies have been showed to outperform their standard implementations, and the negotiation based approach provides high success rate in finding a solution, reporting satisfying results in terms of the negotiation success rate, and of the quality of the recommendations provided.

1.4 List of Publications

1. F. Barile, S. Rossi and Judith Masthoff, *"The Adaptation of an Individual's Satisfaction to Group Context: the Role of Ties Strength and Conflicts"*, in Proceedings of the 25th Conference on User Modeling Adaptation and Personalization (UMAP 2017), 2017.

2. F. Barile, S. Rossi and Judith Masthoff, *"A Detailed Analysis of the Impact of Tie Strength and Conflicts on Social Influence"*, in the 2nd International Workshop on Human Aspects in Adaptive and Personalized Interactive Environments (HAAPIE

2017), in conjunction with the 25th Conference on User Modeling Adaptation and Personalization (UMAP 2017), 2017.

3. S. Rossi, F. Barile, C. Galdi, and L. Russo, *"Recommendation in museums: paths, sequences, and group satisfaction maximization"*, Multimedia Tools and Applications, 2017, pp. 1-25, issn:1573-7721, doi:10.1007/s11042-017-4869-5.

4. S. Rossi, F. Barile, S. Di Martino and D. Improta, *"A comparison of two preference elicitation approaches for museum recommendations"*, Concurrency and Computation: Practice and Experience, issn:1532-0634, doi:10.1002/cpe.4100, 2017.

5. F. Barile, L. Bove, C. Di Napoli and S. Rossi, *"City Parking Allocations as a Bundle of Society-Aware Deals"*, In Agent-Based Modeling of Sustainable Behaviors, Springer International Publishing, ISBN:978-3-319-46331-5, doi=10.1007/978-3-319-46331-5_8, pp.167-186, 2017.

6. S. Rossi, C. Di Napoli, F. Barile, L. Liguori, *"A Multi-agent System for Group Decision Support Based on Conflict Resolution Styles"*, in Conflict Resolution in Decision Making: Second International Workshop, COREDEMA 2016, Revised Selected Papers, 2017, Springer International Publishing, pp. 134-148, isbn=978-3-319-57285-7, doi:10.1007/978-3-319-57285-7_9.

7. S. Rossi, F. Cervone and F. Barile, *"An Off-line Evaluation of Users' Ranking Metrics in Group Recommendation"*, in Proceedings of the 9th International Conference on Agents and Artificial Intelligence (ICAART) Vol. 1, pp.252-259, SCITEPRESS, ISBN:978-989-758-219-6, 2017.

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Summer School (EASSS 2016), Catania, Italy, June 29-30, CEUR-Workshop Proc. (1664), pp. 29-34, 2016.

11. S. Rossi, C. Di Napoli, F. Barile, A. Rossi and M. Staffa, *“Negotiating and Executing Composite Tasks for QoS-Aware Teams of Robots”*, Trends in Practical Applications of Scalable Multi-Agent Systems, the PAAMS Collection, Springer International Publishing, pp. 201-210, isbn:978-3-319-40159-1, doi:10.1007/978-3-319-40159-1_17, 2016.

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20. F. Barile, D.M. Calandra, A. Caso, D. D'Auria, D. Di Mauro, F. Cutugno, and S. Rossi, *"ICT Solutions for the OR.C.HE.S.T.R.A. Project: From Personalized Selection to Enhanced Fruition of Cultural Heritage Data"*, in Proceedings of Tenth International Conference on Signal-Image Technology and Internet-Based Systems (SITIS), IEEE pp.501–507, 23-27 Nov. 2014. doi: 10.1109/SITIS.2014.12.

21. F. Barile, A. Caso, and S. Rossi, *"Group Recommendation for Smart Applications: a Multi-agent View of the Problem"*, Proceedings of the 15th Workshop "From Objects to Agents", Catania (Italy), September 2014, CEUR workshop proceedings, vol 1260 ISSN:1613-0073.

Chapter 2

Recommendation Systems

As suggested by the name, Recommendation Systems (RSs) are software tools that support users in a decision-making process by providing suggestions for items that they have to chose [66]. Examples are systems that suggest movies to watch like Netflix [1], music to listen like Spotify [2], items to buy like Amazon [3], and so on. Hence, RSs can be applied to several different domains and usually try to suggest items that can be of interest for the specific user. The use of RSs can lead advantage both for users and even for the providers of the services to recommend, raising the sales, the users satisfaction and users fidelity, helping to better understand the users needs and to diversify the items bought by the users [66].

Following [66], a RS is characterized by a set of **Users** that interact with the system and a set of **Items** that are the object of the recommendation process. In relation to the specific domain different kinds of items can be considered. The sequence of interactions between a user and the system is denoted as **Transactions**. A transaction can be every interaction that the user has with the system. For example, a transaction can be an explicit rating given by the user to an item, but even a click on a particular web page, a purchase made by the user, a song listened, and so on. Almost every interaction that the user has with the system can be analyzed to better understand what kind of item can be of interest for him.

More formally, we define:

- $A = a_1, a_1, ..., a_n$ as the set of the n users of the system.
- $\Omega = \omega_1, \omega_2, ...\omega_m$ as the set of the m items of the system.

Often, the transactions between the users and the system are used to derive an estimation of the satisfaction of the users with respect to a specific item. We define as $U(a_i, \omega_j)$, or quite

[1] https://www.netflix.com
[2] https://www.spotify.com
[3] https://www.amazon.com/

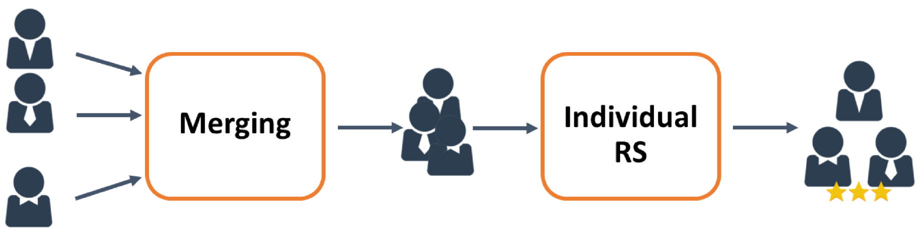
briefly $U_{i,j}$ the *Utility* that a user a_i have with respect to an item ω_j. Following this definition, we can imagine that all the information about the utilities of the users are stored in a matrix, with n row (one for each user) and m columns (one for each item). This matrix is known as *User Item Matrix*. If we could fill out all the cells in the matrix, we could easily determine which are the preferred items for each user. However, usually we only have information about few cells that are often explicit ratings given by the users. Hence, generally the problem is reduced to an estimation of the missing values. In the more simplistic and, at the same time, more used scenario, the utility $U_{i,j}$ coincides with the explicit ratings given by the users a_i to the item ω_j, that we indicate as $r(a_i, \omega_j)$ or, equivalently, $r_{i,j}$. In this case, the problem is usually addressed as a prediction of the missing ratings and a determination of the best item in relation to this prediction.

2.1 Approaches for individual RSs

According to [16, 66], the strategies used to implement an individual RS can be classified into the subsequent categories:

- **Content-based**: the RS recommends items similar to items that the user showed to like in the past, and such similarity is evaluated on the base of the feature used to represent the items in the system;
- **Collaborative filtering**: the system recommends to the user items that are liked by users that are similar to him. Here, the similarity can be defined on the user profiles, based on the transactions with the system;
- **Demographic**: in this case the demographic data of the users are used to generate a recommendation. Generally, recommendations are based on categories of users;
- **Knowledge Based**: this kind of RSs uses a knowledge on a specific domain to infer how determinate item features meet users needs and preferences to derive the utility of the items;
- **Community Based**: here, the system recommends items based on the preferences of a set of friends of the user;
- **Hybrid RSs**: An hybrid RS combines two or more techniques in way to obtain a more robust system that integrate the advantages of all the used strategies.

Two of the most challenging issues related to many of these techniques are the so-called Sparsity and Cold Start problems. The *Sparsity* problem occurs when a similarity based



(a) Merging of Preferences.

(b) Merging of Recommendations.

Fig. 2.1 Approaches for the design of a Group Recommendation System.

system have not enough information to derive similar users (or similar items) or to derive, starting from these, the utility of the items necessary to provide a recommendation. This phenomenon is accentuated when the system starts to work since it has not any transaction and, hence, the traditional techniques cannot be used. Here, the problem takes the name *Cold Start Problem*. Advanced techniques have been proposed to address these problems that, unfortunately, still remains open.

2.2 Group Recommendation Systems

There are many situations in which the system has to recommend items not only to a single user. For instance, a movie to watch for a group of friends, a restaurant for a job dinner, a trip destination for a family. In this case, the problem is to find a solution that can be a good recommendation for all the group's members, meeting all users' tastes. This is a challenging problem because the users' interests can be conflicting.

Group Recommendation Systems (GRSs) are designed to give a support to group decision-making giving recommendations to a group of users. Typically, there are two main approaches to the problem, showed in figure 2.1, and described above:

- **Merging of Preferences**: The system starts from the *Preference Profiles* of each user. Those profiles are merged in a *Group Preference Profile*, on which is applied an individual RS that determines the recommendation for the whole group;

- **Merging of Recommendations**: Even in this case the system starts from users' *Preference Profiles*; for each user the system determines the recommendations with an Individual RS. The recommendations are then merged to find the suggestion for the group.

Intuitively, in the Merging of Preference a sort of "group user" is created, reflecting, in his profile, all the group's members preferences. Hence, we can evidence a first problematic of this approach that is the *flexibility*. If the group changes, the preference profile must be recomputed. For this reason, the most used approach is the Merging of Recommendations, since it provides a greater flexibility in the group formation process. In fact, individual's recommendations are built independently for each group's member, and the users' recommendations are merged at the time of providing the group recommendations (e.g., only once the group is established).

Formally, we define:

- $A = \{a_1, a_1, ..., a_n\}$ as the set of the n users of the system;
- $\Omega = \{\omega_1, \omega_2, ... \omega_m\}$ as the set of the m items of the system;
- $U(a_i, \omega_j) = U_{i,j}$ is the utility of the user a_i for the item ω_j;
- for each $a_i \in A$ we define as $\Omega_i \subset \Omega$ the set of items for which we have an estimation of the utility $U_{i,j}$ derived from the transaction of the user with the system;
- for each $\omega_j \in \Omega$ we define as $A_j \subset A$ the set of users for which we have an estimation of the utility $U_{i,j}$ derived from the transaction of the user with the system;
- for each $a_i \in A$ we have a *User Profile* $UP_i = \{U_{i,j} | \omega_j \in \Omega_i\}$. The profile can be *partial* if $\Omega_i \subset \Omega$, or *complete* if $\Omega_i = \Omega$.

Starting from this definition, we can see an Individual RS as a system that starts from a partial user profile UP_i and derives a complete user profile $\overline{UP_i}$, in way to determine the best item (or the best k items) to recommend to the user. Hence, in the Group Recommendation domain, we have:

- $G \subset A$ as the set of g group's members;
- $U(G, \omega_j) = U_{G,j}$ is the utility for the item ω_j for the whole group;

The Merging of Preferences approach, starting from the user profiles UP_i for each $a_i \in G$, determines a partial Group Profile GP on which applies an Individual RS to obtain a complete Group Profile $\overline{GP} = \{U(G,\omega_j)|\omega_j \in \Omega\}$. On the contrary, in the Merging of Recommendation approach, for each $a_i \in G$ the system applies an Individual RS on the correspondent user profile UP_i obtaining a complete user profile $\overline{UP_i}$. Then, these profiles are merged to obtain a complete Group Profile $\overline{GP} = \{U(G,\omega_j)|\omega_j \in \Omega\}$.

2.2.1 Strategies for Group Recommendations

In a Multi-Agent perspective, the problem of generating a recommendation for a group of users can be addressed defining a set of agents, one for each group member, the utility of which is defined on the bases of the users' one, for each item to recommend. In particular, since we focus on the merging of recommendation approach, we suppose that the utilities that each agent will have for each item is known (computed by an individual recommendation system). Here, we focus on the MAS strategies, that start from a complete user profile (as defined in section 2.2) and derive the group recommendations computing the complete Group profile (containing the utility for the whole group for each item) or determining the group choices as a result of the agents' interactions.

Social Choice Theory

In [51], Social Choice Theory is defined as the study of collective collective decision processes and procedures, resulting in a collection of models and strategies concerning the aggregation of individual inputs, as votes or preferences, into collective outputs. These strategies, according to [71], can be classified as majority-based, mainly implemented as voting mechanisms to determine the most popular choices among alternatives, consensus-based, that try to average among all the possible choices and preferences, and role-based, that explicitly take into account possible roles and hierarchical relationships among members. Here, the most used strategies are described. A more deeply description can be find in [57].

Average Strategy: The average strategy is a consensus-based strategy that, as described in [54, 38], consists in aggregating the utilities of the single agents for an item computing the average of all the utilities. More formally:

$$U(G,\omega_j) = \frac{1}{g} \sum_{a_i \in G} U(a_i,\omega_j) \tag{2.1}$$

where $U(G,\omega_j)$ is the utility for the group of agents $G \subset A$, g is the size of G, and $U(a_i,\omega_j)$ is the utility of the agent a_i with respect to the item $\omega_j \in \Omega$. This strategy is commonly used as a benchmark for comparison or as base to define more complex approaches.

ω	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$U(a_1, \omega)$	1	**5**	3	1	2	$\underline{\mathbf{5}}$	**4**	3
$U(a_2, \omega)$	3	$\underline{\mathbf{4}}$	1	2	**5**	3	2	**4**
$U(a_3, \omega)$	1	3	2	**5**	1	4	**3**	$\underline{\mathbf{2}}$
$U(G, \omega)$	1	7	3	2	5	8	4	6

Table 2.1 An example of fairness strategy application. Users are ordered from 1 to 3 and $K = 3$. The numbers in bold represent the ratings of the user's K preferred items, while the rating values corresponding to the items that causes the least misery are underlined.

Fairness Strategy Even the fairness strategy is a consensus-based approach, and is described in [17, 54]. It is used when a set of k items must be selected for the group. The idea behind the fairness strategy is trying to accommodate everyone in the group. A user can agree to perform activities that he/she does not like so much as long as he/she will be able to do something he/she likes with his/her friends. The strategy needs of an ordering among the users of the group that, in the simplest case, can be random. The strategy is the following:

1. The first agent a_i is selected, and considering the corresponding profile UP_i, the K items with the higher utility value are selected;

2. Among them, the one that causes the least misery to the others is selected (in case of items with the same rating a non-deterministic choice is made), and the process is repeated with the successive user in the rank;

3. The utilities $U(G, \omega_j)$ of the group for each item $\omega_j \in \Omega$ are assigned in a descending order from m to 1.

4. Finally, the group recommendation will correspond to the K item with the highest utility $U(G, \omega_j)$.

The table 2.1 provides an example of a possible application of the fairness strategy. One of the main issues with the use of this strategy is that, by changing the users' ordering, the selection process will produce a different result in the outcome.

Borda Count Strategy The Borda Count is a Majority-based strategy introduced in [27]. As explained in [17, 39, 55], consists into two phases:

1. Initially, the individual utilities of each agent is replaced with scores. Such scores are computed assigning a zero score to the item with the lowest utility, a one score to the next item, and so on. If two or more activities have the same rating they are assigned with the average of the scores that should have.

2. After that, an average strategy is used on those scores to obtain the group utilities.

Plurality Voting Strategy A second majority-based strategy is the Plurality Voting [17, 55]. It is very similar to the fairness strategy hence, even in this case, an ordering among the users is required. Then, the strategy is the following:

1. The first agent a_i is selected, and considering the corresponding profile UP_i, the K items with the higher utility value are selected;
2. Among them, the most voted item from the other agents is selected, and the process is repeated with the successive user in the rank;
3. The utilities $U(G, \omega_j)$ of the group for each item $\omega_j \in \Omega$ are assigned in a descending order from m to 1.
4. Finally, the group recommendation will correspond to the K item with the highest utility $U(G, \omega_j)$.

Least Misery and Most Pleasure Strategies Finally, we present two role-based strategies. The Least Misery strategy [61] can be used when one or more users give a rating particularly low for some activities. In case of small groups, it is reasonable to assume that the satisfaction of the group that performs an activity could decrease if one or more components really dislike the item.

On the contrary, if some user really likes one activity that is acceptable for other group members it should be rational to use, as group rating, the greatest given rating for the activity. Here, the motivation is the opposite, since the satisfaction of the group can increase if one or more component really like an item.

Hence, Least Misery strategy consists in assigning to each activity the minimum of the utilities of the agents:

$$U(G, \omega_j) = \min_{a_i \in G} U(a_i, \omega_j) \tag{2.2}$$

On the other hand, the Most Pleasure strategy assigns the maximum utility among all the agents:

$$U(G, \omega_j) = \max_{a_i \in G} U(a_i, \omega_j) \tag{2.3}$$

Alternative MAS Approaches

Another set of approaches derived from MAS theories to address the group recommendation problem is based on the use of **Negotiation** methodology. Even in this case, a set of agents act on behalf of human group members, participating in a cooperative negotiation for generating the choice for the group. Generally, in negotiation based approaches there is not an estimation of the utility for the whole group for each item; on the contrary, each agent estimates the corresponding user's utility for a set of items and a negotiation protocol is applied since an agreement is find between all agents.

In some cases, group members could have more different interests conflicting with each other. In case of great heterogeneity, the attempt to resolve the conflict by applying a cooperative approach can lead to a failure in the negotiation [21]. In this scenario, it can be reasonable to apply non-cooperative approaches. The idea is that users can be viewed as self-interested agents and the recommendation system can be modelled as a classical **Non-Cooperative Game** in normal form. In this case, group members are viewed as the players of the game, the items to recommend are viewed as game actions, and the recommendation problem is modelled as a problem of finding the Nash Equilibrium for the game.

A different approach is based on the use of coalitions. Since coalitions require the groups formation at run-time, this approach is not straightforward. The idea is to organize group members into smaller and cohesive groups, so it is possible to provide more effective recommendations to each of them. The problem is modelled as a **Coalitional Game**, where people are grouped into disjoint coalitions to maximize the social welfare function of the group [20]. The payoff function considers the similarity between coalition members' ratings, and a weighting factor for the coalition size. The approach is compared with a classic K-Means clustering, on randomly formed groups, and the results show better performances in the formation of larger coalitions. In some cases, however, this approach is not applicable, because it is not possible to reorganize the group into more cohesive sub-groups, but it is necessary to provide a recommendation for the whole group of users.

2.3 Context-Aware Recommendation Systems

Recent studies evidenced one of the most important and, at the same time, neglected aspect of RSs, that is the context in which the recommended items have to be used [4]. Generally speaking, when we talk about context-aware computing, we refer to systems that use information about the context to adapt dynamically their behaviors [28]. RSs, in most cases, use very simplistic models, ignoring the fact that the users interact with the system in a particular context [4] (e.g., the external environment, or the user's internal state, such as, for example, the mood).

Context-aware recommender systems (CARSs) try to adapt recommendations to the specific contextual situation of the user, to generate more relevant recommendations [4]. It is a relative recent field of recommendation systems, and is based on the consideration that users' preferences may vary in relation to the context, even for the same item [83]. The question of what we have to consider as context in recommendation systems is still an open problem [4]. For example, a RS that suggests places to visit should consider that same destination can be more or less valuable in relation to the time of the year. In the same way, a system that recommends music should consider the mood of the user. As we can see from these basic examples, we have many possible factors that can be considered as context.

To consider contextual information in the recommendation process it is necessary to extend the traditional model, that usually considers only Users and Items, to multi-dimensional settings [3]. In [82], authors recall that there are different kinds of contextual information that can be considered, and, in relation to the activity to perform, we should focus on some of them, and [2] shows that by extending the traditional collaborative filtering approach to take into consideration the contextual information, such as when, where and with whom a movie is seen, the resulting recommender system could outperform the pure traditional collaborative filtering method.

In [4], starting from an analysis of the characteristics that a context can have, different classifications are proposed, and a survey of research in CARS is provided. The context is classified in *Partially Observable*, *Fully Observable* and *Unobservable* in relation to the knowledge of the RS about it, and can even be *Static* or *Dynamic*, if the factors that characterize it changes seldom or often. Four types of context are considered:

- *Physical Context*, that refers to the conditions in which the recommendations are supposed to be used;
- *Social Context*, that is the presence and role of other people when the recommendations are used;
- *Interaction Media Context*, which refers to the device used to access the system;
- *Modal Context*, representing the mental state of the person that uses the recommendations.

As for individual RS, also in Groups Recommendation Systems (GRS) the context is a key factor that must be considered in the recommendation process. Nevertheless, few studies on GRS consider these aspects, usually trying to determine factors that can be used as weights in the aggregation process, or to determine the best strategies to apply for the specific group on the basis of the characteristics of the relationship between group's members [57]. Here, we can assume that the *Social Context* should be always considered by the GRS, since the presence of other people, and the satisfaction of the other group's members, can influence the other individual ones [58, 31, 10].

2.4 Evaluation of GRSs

One of the major problems in designing group recommendation techniques relates to the difficulty of evaluating the effectiveness of group recommendations. As for Individual Recommendation Systems, also for group recommendations the principal evaluation strategies are on-line and off-line evaluation. However, in case of GRSs, since the evaluation should consist in comparing the generated recommendations for a group with the true preferences of real groups, there are problems for both the approaches:

1. The on-line evaluation consists in interviewing real users. It is clear that such evaluation can be performed on a very limited set of test cases and cannot be used to extensively test alternative algorithms. Furthermore, it may require a beta implementation of the real system since aspects like the user interface and the presentation of the recommendations can influence on users final choices and even supposing to not consider this factor, each test case requires more subjects, hence to reach a reasonable set of evaluations can be very difficult and expensive;

2. In off-line evaluations, the recommendations generated by the GRS is compared with a real choice stored in a dataset. This approach is largely used in the evaluation of Individual Recommendation Systems, since there are many datasets available for different application domains. Unfortunately, up today, no freely available dataset exists that consider groups choices.

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An approach to get round the problem is to compare the predicted group recommendations with the individual observed in a dataset for individual RS. As shown in [8], the most popular datasets (e.g. Movielens or Netflix) that contain just evaluations of individual users can be used to perform a such evaluation of GRSs. In fact, in [8], the Authors analyzes the effectiveness of group recommendations obtained aggregating the individual lists of recommendations produced by a collaborative filtering system.

2.5 Personality and Social Influence

As final part of this introduction chapter, the concept of Social Influence is introduced, considering works on Personality. In [45], *Social Influence* is defined as a *"change of* *attitudes, beliefs, opinions, values and behaviour as a result of being exposed to other individuals' attitudes, beliefs, opinions, values and behaviour"*, and it is divided into two categories, *Incidental* and *Deliberate* Social Influence. The evidence of such influence is confirmed by studies in psychology fields [81]. In [81], authors show that the presence of others can lead to improving performances or, on the contrary, can even lead to performance impairment, in relation to the difficulty and the knowledge of the task to perform, hence, Social Influence affects many aspects of an individual, from behaviours to evaluations and opinions.

Recent studies on Opinion Shifting assume the possibility of positive and negative interpersonal influence [75], and the individual's personality is a key factor to understand how an individual is incline to be influenced by others. Positive influence occurs when the initial opinion of an individual shifts towards the opinion of another person, when the individual is exposed to it, while, on the contrary, when Negative influence happens, the individual shifts his opinion increasing the difference with the opinion of another person [75]. In the case of Negative influence, there is the possibility that opinion differences between groups intensify, leading groups to positions that are the two extremes of an opinion spectrum, in the phenomenon known as *Bi-polarization* [53]. Bi-polarization can be amplified if the model supports *homophily*, the process with whom people like similar people, and *heterophobia*, that, on the contrary, is the disliking of dissimilar others [75]. The authors of [75] also analyze the opinion shift in relation to the initial differences in the evaluation of specific items, showing that the largest positive shift occurs when the initial differences between individuals' ratings are higher. Unfortunately, no studies show a robust explanation on how Negative Influence works.

There are many models proposed in psychological studies to model different aspects of the human beings personalities. Here, we introduce two widely used models. The first one is the Five Factor Model (FFM), that models the personality through five factors also known as the "Big Five". The second one is the Thomas-Kilmann, that models people's conflict resolution profiles.

2.5.1 Five Factor Model

The Five Factor Model (FFM), also referred as the *Big Five* personality traits, is a personality framework identifying five major dimension of personality [42]. Despite some opposition based on the lack of theoretical rationale, the Five Factor model has reached a good deal of consensus in psychological communities [45], and several studies find empirical evidence to support this classification [34]. The taxonomy indicates five personality factors [23]:

- *Neuroticism* is the tendency to experience negative emotions (anxiety, depression, anger), while calm and relaxted personalities are related to low Neuroticism;
- *Extraversion* is related to impulsiveness, assertiveness, and a tendency toward social behaviour and to experience positive emotions, while low Extraversion (or Introversion) characterizes quiet and restrained people;
- *Openness to Experience* refers to the tendency to experience new sensations and ideas or to engage in intellectual activities;
- *Agreeableness* represent a friendly, considerate and modest behaviour, and a high level of this factor describes people with a general predisposition to prosocial behaviour;
- *Conscentiousness* is generally associated with proactivity, responsibility and self-discipline, that reflect in an efficient, organized and determined person.

To evaluate Big Five personality traits several inventories have been proposed. The NEO Personality Inventory [24, 25] is composed of 60 items, but recently alternative methods have been presented, in order to provide shorter personality instruments requiring few time to be completed. In [65], a short version based on 10 items is presented. A valuable alternative, validated as accurately measuring the FFM, is the *Personality Sliders* method [72]. This is based on a series of stories, two stories for each personality trait, illustrating person that was low or high for that trait. Hence, participants use a slider to indicate which person they were most like, resulting in a value for each trait between 18 and 162.

2.5.2 Conflict Management Style

The Conflict Management Style describes the human beings' strategies to resolve conflicts arising during negotiation. In literature, several models of conflict management have been proposed. In 1974 H. Kilmann and W. Thomas [47] identified five different categories of interpersonal conflict management styles. Such styles are identified with respect to two fundamental dimensions: *cooperation*, i.e., the extent to which the individual attempts to satisfy the other person's interests, and *assertiveness*, i.e., the extent to which the individual attempts to satisfy his/her interests. These two dimensions are used to define five methods of dealing with conflicts, as follows:

- *Accommodating*: this style prioritizes cooperation at the expense of assertiveness. A person with this conflict resolution style will generally put aside its own goals, allowing the other person to achieve their own;

- *Avoiding*: this style avoids conflicts by searching for a solution in a diplomatic way, i.e. going forward in the decision process until a solution is found, but withdrawing or postponing any threatening issue;
- *Collaborating*: this style models a collaborative approach that aims to resolve conflicts by making the involved parties working together;
- *Compromise*: this style models people that aim to build a solution in such a way to meet both parties preferences;
- *Competitive*: this style relies on assertiveness, so each member of the group tries to pursue its own interests.

In order to assess the conflict management style of users, the Thomas-Kilmann Conflict Mode Instrument (TKI) is used, a powerful tool to measure a person's behavior in conflicting situations, rather than the user's competence in managing conflicts. It is based on interviews consisting in a questionnaire of 30 questions that allow to associate user's preferences for different styles in handling conflicts to a specific profile.

Chapter 3

Related Works

In this section a survey of the most recent techniques proposed in literature to address the group recommendation problem is presented. We focus on the techniques based on the *Merging of Recommendations* approach. The problem has been widely analyzed in Mathematics, Economics and Multi-agent systems (MAS). In section 2.2.1 the most commonly used approaches, based on MAS techniques, have been showed. Here, the more recent work presented in literature are illustrated. In particular, techniques that take into account social influence between users are illustrated, from an Economic point of view, with the definition of the Other-Regarding Preferences (ORP) models, and from a Psychological perspective, talking about the Emotional Contagion phenomenon and the possible factors that have an impact on it.

3.1 Integrate Social Factors in Group Recommendations

The results presented in the literature showed that there is no strategy can be defined as the "best", but different approaches are better suited in different scenarios, depending from the characteristics of the specific group. Besides, traditionally MAS techniques do not seem to capture all the features of real-world scenarios. For example, automatic voting/ranking mechanisms often require that all the agents involved have the same influence on the decision procedure, while real group interactions take into account intra-group roles and mutual influences. Again, some members of the group could have a particular influence on the others, based on their personal experiences or on the strength of their mutual relationship. Furthermore, there may be situations where the participants follow a democratic process in order to find a possible solution, and cases where the group is supported by a human leader. Usually the decision of a group member whether or not to accept a given recommendation may depend not only on his/her own evaluation of the content of the recommendation, but also on his/her beliefs about the evaluations of the other group members [17]. Recommendation systems for groups need to capture both the preferences of the group members but also these key factors in the group decision process [38] taking into account the type of control in the group decision-making process [46].

On the basis of these considerations some advanced approaches try to integrate information from the social relationships among group members with the classical MAS techniques and so to derive new strategies more applicable to the considered settings.

PolyLens [61] has been one of the first approaches to include social characteristics (such as the nature of a group, the rights of group members, and social value functions for groups) within the group recommendation process. It uses a Collaborative Filtering (CF) approach to produce recommendations for each user of the group, and a Least Misery (LM) strategy to aggregate these recommendations. Moreover, in [6] intra-group relationships, such as children and the disabled were contemplated; each group is subdivided into homogeneous subgroups of similar members that fit a stereotype, and recommendations are predicted for each subgroup and an overall preference is built considering some subgroups more influential. An approach that provides group recommendations with explicit relationships within a family is proposed in [13], while in [5], the authors propose to use the disagreement among users' ratings to implement an efficient group recommendation algorithm. The problem of defining the proper decision strategy is crucial in group decision support systems. In Choicla [74], for example, a decision support system is proposed that provides users with the possibility to choose among different decision strategies for independent decision tasks, so allowing to personalize the application to the user's preferences by providing different heuristic functions and trustworthiness levels to the group members.

3.1.1 Weighted Utility functions

The most common approach to integrate social factors in the group recommendation process is to apply weights derived from social interactions between the members of the group. In this context, a very interesting work is proposed by Gartrell et al. in [38]. Here, authors starts to evaluate the group members' weights, in terms of their importance or influence in a group, for movies recommendations. The work introduces some important concept:

1. the use of a "social value", determined from questionnaires on the social interactions between group members, used to determine the aggregation strategy to use for the specific group.

2. the use of weights for the individual utilities in the aggregation procedure. In particular, they rely on the concept of "expertise", computed as the percentage of item used (e.g. the movie watched).

3. finally, a "group dissimilarity" factor is introduced, to consider the possibility of high disagreement between group's members.

The work was then used in an application helping users to find an agreed solution regarding the choice of a restaurant, the Social Dining system [37], with the peculiarity that recommendations are generated by collecting real data from social networks.

3.1.2 Advanced Negotiation

In [11] there is a negotiation agent for each group member. An individual recommendation system gives recommendation for a set of items, and, in addition to this, an individual utility of each product for each user is evaluated, introducing a user preference model. The Negotiation protocol is different according to the size of the group. For groups of two people, the used protocol is the *alternating offers*, while for groups of more people, a *merging ranks* protocol is used, with a mediator agent that uses strategies to help in choosing among proposals and offering an agreement to the group (i.e, by maximizing the average utilities of group members or maximizing the utility of the least happy member). The framework is tested by simulating the negotiation protocols.

Even in [36] an *alternating offers* protocol is used. In this approach there is not a mediation, but groups size is restricted to two users. There is an agent for each user, and there is a two-level user profiling, which includes a *recommendation profile*, containing personal information and preferences, and a *negotiation profile*, used to distinguish agent behaviors in the negotiation among three degrees of collaboration (self-interested, collaborative and highly collaborative). If the negotiation finishes with an agreement among all the agents, the result is a list of constraints that match the preferences of the group members.

The original idea was then developed in a subsequent work [35], where user agents are configurable in order to exhibit the desired behavior of the corresponding user. The negotiation model is a multi-party negotiation that centralize the communications through a negotiator agent, acting as mediator. It receives the proposals of the user agents, combines them into a single proposal, which is later broadcast by the negotiator agent and analyzed by the user agents. The system uses a domain ontology to describe the user's likes and the items to recommend. The user agent is responsible for building and updating a user profile, of obtaining the individual preference model, of participating in the negotiation process and of informing the user about the result of the negotiation. Besides, there are two support

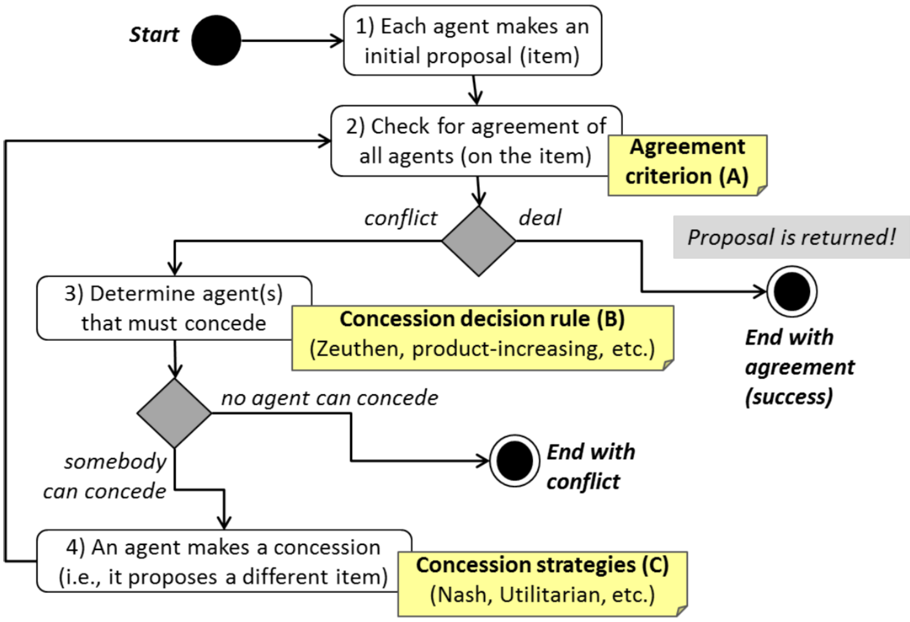


Fig. 3.1 MCP Negotiation proposed in [78].

agents that help in computing the individual preference model (preferences agent) and in selecting the list of items that satisfy the group preferences, given the group preference model (items selector agent). The protocol used in the negotiation is a generalization of the bilateral alternating offers protocol [68] for the multi-party negotiation.

A different approach is proposed in [77, 78] where a Monotonic Concession Protocol (MCP) is used [32]. As in previous cases, an agent for each group member is present that is responsible for computing the utility of the corresponding user for the necessary items. Furthermore, agents compute the “willingness” to risk a conflict and a concession strategy based on this value. There is even a Moderator agent that is responsible in checking the agreement or to select the agents that must concede. The protocol is summarized in figure 3.1 [78].

3.2 Not Self-Interested Agents

The approached displayed until now show how to model aggregation functions with the aim to obtain a group utility or a group shared choice. Another recent field of research in Economics and Multi-Agent System regards the necessity to define utility models where the agents voluntary fail to maximize their utility [29]. Even if this seems to be in contrast with the *Rationality Assumption* used in the modelling of Rational Agents, there are many evidences of such behaviours in the observation of human being [73]. This phenomenon can be studied under different perspective.

An interesting work is proposed by Salehi and Boutilier in [69] and explore the Consensus decision-making in social networks. Here, the authors introduce the concept of *empathetic utility* on social networks: the satisfaction of an individual depends from both his intrinsic utility and his *empathetic utility* deriving from the happiness of his neighbors in the social network [69]. Based on this idea, individual preferences are aggregated in a weighted social choice function that takes into account local relationships with neighborhoods in the network. However, in [69] the Authors do not specify how to evaluate such numerical relationships, while they focus on computational aspects of scaling up with large networks of friends.

Other approaches that try to model this phenomenon are described under an Economic view, with the works on "Other-Regarding Preferences" models [29, 73] and, from a Psychological point of view, with the studies on the "Emotional Contagion" phenomenon. In our view, these are two different aspect of the same story and we introduce them in the following sections.

3.2.1 Other-Regarding Preferences

Only recently Economists have begun to recognize the need for explicit models considering the possibility that an agent will bear a personal cost in terms of payoff to increase that of another one [26]. There are many aspects that can have an impact on this phenomenon, in particular [26] evidence that the **status** of the relationship can have an impact and even the possibility of reciprocity, that means that an agent can concede to another if there is the possibility that the favour will be returned in the future. There is, also, the possibility of Negative reciprocity, since an agent can be glad in decreasing another agent's payoff if it is viewed as enemy [26].

Other-Regarding Preferences (ORP) models try to consider these possibilities, modelling agents that do not maximizes their own utilities in way to give a greater (or, in some cases, lower) payoff to some other agents. In this section, an overview of the principal models proposed is presented.

Inequality Aversion

The Inequality Aversion model is the simplest ORP model. A first version of the model, known as Fehr-Schmidt model [33] is in equeation 3.1. For simplicity we refer on a two-agent version.

$$U(m,y) = \begin{cases} m - \alpha * (y - m) & \text{if } m < y \\ m - \beta * (m - y) & \text{if } m \geq y \end{cases} \tag{3.1}$$

where $U(m,y)$ indicates the ORP utility for the agent when m is the payoff of the agent (m stands for "my payoff") and y is the payoff of the other agent (y stands for "your payoff"). The parameters α and β are denoted as *marginal rate of substitution* and must satisfy $0 \leq \beta \leq \alpha$ and $\beta < 1$. In this model, the considered agent is interested in its own income, and the sign of the marginal rate of substitution between its income and that of the other agent depends on which has higher income [26].

An alternative model is the Bolton-Ockenfels two-player model [14], that also assumes that an agent like its own income and dislike income inequality. Here, the the utility function is defined as in equation 3.2.

$$u(m,y) = v(m, m/(m+y)) \tag{3.2}$$

Again, m is the agent's payoff, and y is the payoff of another agent. The equation present a non-linear form and assume that the function v is globally non-decreasing and concave in the first argument, strictly concave in the second argument, that is the *relative income* $m/(m+y)$ [26].

Interdependent Preferences

The Interdependent Preferences model can be viewed as a generalization of inequality aversion models [73]. Supposing to have a set $A = \{a_1, ..., a_n\}$ of agents. Indicating with $\Omega(s) = \{x_1, ..., x_n\} = x$ the payoff of each agent, the utility is defined as in equation 3.3

$$U_i(x) = x_i + \sum_{i \neq j} \lambda_{i,j}(x_i - x_j) * x_j \tag{3.3}$$

Here, the parameter $\lambda_{i,j}$ can define altruistic or, on the contrary, spiteful behaviours, assigning to it a positive or a negative constant value. Other variants can give a non-constant value to the parameter $\lambda_{i,j}$ [73]. In his work [73], Sobel specifies the relation between this model and the Inequality Aversion models seen before. In the Fehr-Schmidt model, $\lambda_{i,j}$ is positive if $x_i > x_j$ and negative if $x_i < x_j$, in way to have an agent that cares about his payoff but, at the same time, would like to reduce the inequality in payoffs between the two players. On the contrary, in the Bolton-Ockenfels model the utility of the agent a_i is a non-linear function of is payoff x_i and its relative income.

Fairness and Reciprocity

An alternative approach try to define the reciprocity in terms of agents' beliefs regarding the intentions of the other agents [26, 73]. The model proposed by Rabin [64] evaluates the utility of an agent a_i in terms of his strategy s_i, the beliefs about the strategy of a second agent a_j, denoted as b_j, and the beliefs of the agent a_i about the beliefs of the agent a_j about its strategy, denoted as c_i. Hence, the utility is modelled as in equation 3.4. We use the definition provided in [26].

$$U_i(s_i, b_j, c_i) = \pi_i(s_i, b_j) + \bar{f}_j(b_j, c_i)[1 + f_i(a_i, b_j)] \tag{3.4}$$

Here, $\pi_i(s_i, b_j)$ is the payoff of the agent a_i, while $\bar{f}_j(b_j, c_i)$ is the belief of the agent a_i about how kind the agent a_j is being to him and $f_i(a_i, b_j)$ is how kind agent a_i is being to player j.

3.2.2 The Emotional Contagion

The model presented in the previous section consider the possibility in which the utility of an agent depends not only on its own payoff but also on those of other agents, with the possibility of altruistic or egoistic behaviours. In the psychology field, the phenomenon for which the satisfaction of an individual is influenced by the satisfaction of other people is known as **Emotional Contagion**, that is defined as "the process by which a person or group influences the emotions or behavior of another person or group through the conscious or unconscious induction of emotion states and behavioral attitudes" [70, 31]. Many empirical studies show the evidence of this influence between people [58], but how this influence works is very difficult to explain, and so many theories have been proposed. However, the motivations, mechanism of working, and many other aspects, are still open research problems in the psychology field [31]. It is recognized that understanding the sharing process of emotions that occurs in groups is necessary, and to limit the analysis on how people share ideas in group dynamics is not enough [10].

Empirical studies showed that factors like the personality or the type of relationship between people can influence the willingness of a person to be affected by the emotional contagion. For example, in [56] has been showed that it is easier that a person is influenced by people with whom they have a good and strong relationship, with respect to other people.

Another factor that could influence the emotional contagion between two individuals is the type of relationship between them and the state of this relationship. In [58], different types of relationship and the relative influence between members are analyzed, divided into four types: communal sharing, authority ranking, equality matching, and market pricing. Each type corresponds to different parameters in a model of variation of the individual satisfaction on the basis of other group members' satisfaction.

Chapter 4

A Framework for Context-Aware GRS

In this thesis, a two-step approach for the design of Group Recommendation Systems (GRSs) is proposed. Generally, the common approach in GRSs focuses on how to aggregate individual's utilities to determine the best choices for the group, while the most recent studies try to replicate the real dynamics in small groups decision-making. In our view, this approach has a limitation, since it only focuses on the merging of the utilities estimated by an individual RS. Our hypothesis is that such utilities should be modified in relation to the specific group in which the users must perform the recommended items. As suggested by the work about social influence, emotional contagion and other-regarding preferences introduced in the chapter 3, individual utilities may change when there are other people that can influence the individual, and this aspect should be considered by the GRS before aggregating the utilities.

The proposed architecture is showed in figure 4.1, and it is characterized by two subsystems, a *Group Context Adaptation System* and an *Aggregation System*. The first one has the task to adapt the individuals' utilities to the group's context, while the second one must determine the best choice for the group, starting from these adapted utilities, even using information about the social dynamics between group's members and the individual's profile. We suppose that individual utilities are determined by individual CARS, hence the adaptation system must evaluate the impact, on such utilities, of the presence of other people.

The work presented in this thesis is divided into two parts, corresponding to the two steps of such architecture. In the rest of this chapter an overview of the methodology is presented. In particular, regarding the adaptation phase, the work is focused on the determination of the factors that can have an impact on the Emotional Contagion phenomenon, with the future aim to define a ORP model to perform the adaptation; on the contrary, regarding the merging step, two weighted social choice functions are defined, where the weights are determined through a dominance measure, that indicates the most influencing user in the group. Furthermore, a second negotiation-based approach is illustrated. Here, the agents acting in the negotiation

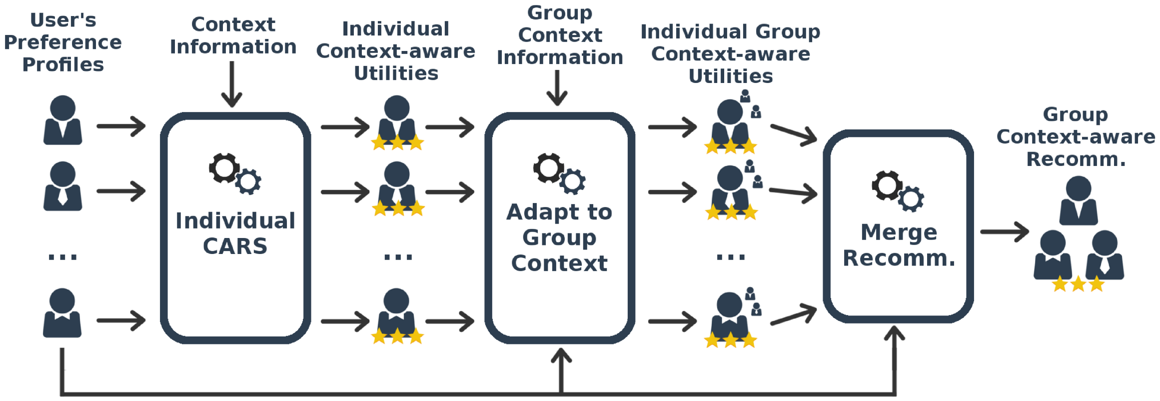


Fig. 4.1 The proposed architecture for Context-Aware Group Recommendation Systems.

replicate the corresponding users behaviour with respect to their conflict management styles, obtained through the Tomas-Kilmann Instrument [47].

4.1 The Adaptation Phase

This part of the work focuses on an analysis of some of the possible factors that can determine a modification of individuals' utility with respect to determinate activities when they must perform such activities with a determinate group of people. The objective is the definition of an ORP model that can be used to perform the adapted utilities, before aggregating them. The idea is to define a model to predict the adapted utility, that we denote as $U^{new}(a_i, \omega_j)$ with respect to a user a_i and an object ω_j, on the base of the old utility $U(a_i, \omega_j)$, and of the utilities of the other people in the group (the set $\{U(a_t, \omega_j) | i \neq t \wedge t \in G \wedge \omega_j \in \Omega\}$. The idea is to apply a model inspired by the *Interdependent Dependences* hence the general form of the adapted utility function is defined in equation 4.1.

$$U_{i,j}^{new} = U_{i,j} + \sum_{i \neq k} \lambda_{i,k}(U_{i,j} - U_{k,j}) * U_{k,j} \tag{4.1}$$

It is also possible to define multiple models, as in [38], and apply each model to a specific case according to the characteristics of the specific group. A key factor in this model is the definition of the parameters $\lambda_{i,k}$ since from their formulation derives the altruistic or egoistic behaviour of the user a_i with respect to the user a_k. As seen in previous sections, many aspects come into play, hence, it is necessary to identify the factors that can have an impact on the phenomenon, and to quantify their influence on the phenomenon. We start analyzing the dynamics of the relationship between two people, focusing the attention on the impact of ties strength and the status of the relationship. Then, we analyze the impact of users' personalities, investigating possible relations between them and the changing in individual utilities.

4.1.1 Tie Strength

The concept of ties strength was introduced in [43] as a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the ties. It can be viewed as the importance of a social relationship between two individuals [7], and, despite there being a great amount of research in this field, the evaluation of this concept still results in being a great research problem. Recent studies try to estimate the strength of the tie using information derived from Online Social Networks [67]. In [40], an approach to distinguish between strong and weak ties is proposed. A similar classification was proposed in [43], where tie strength is distinguished between *weak*, *intermediate* and *strong*.

It appears reasonable that the variation in individuals' utilities deriving from the Emotional Contagion can be influenced by the strength of the tie between them. Our starting hypothesis is that the tie strength directly impacts on the variation in the individuals' utility, determining how the individuals can be influenced by each other in a pair. We start from the assumption that the "perceived tie strength" is not bidirectional, hence the same tie could have a different "strength value" for each person in the pair.

4.1.2 The State of a Relationship: Conflict and Negative Influence

Many studies analyze the problem of how to model social influence between people, especially in social dynamics field, and, in recent years, theories of opinion dynamics assume the possibility of positive and negative interpersonal influence [75]:

- **Positive influence** occurs when the initial opinion of an individual shifts towards the opinion of another person, when the individual is exposed to it;
- When **Negative influence** happens, the individual shifts his opinion increasing the difference with the opinion of another person [75].

In the case of Negative influence, there is the possibility that opinion differences between groups intensify, leading groups to positions that are the two extremes of an opinion spectrum, in the phenomenon known as *Bi-polarization* [53]. Bi-polarization can be amplified if the model supports *homophily*, the process with whom people like similar people, and *heterophobia*, that, on the contrary, is the disliking of dissimilar others [75].

A factor that can influence the opinion shift between two individuals is the type of relationship between them and the state of this relationship. In [58], different types of relationship and the relative influence between members are analyzed, divided into four types: communal sharing, authority ranking, equality matching, and market pricing. Each type corresponds to different parameters in a model of variation of the individual satisfaction on the basis of other group members' satisfaction.

The literature on Social Influence evidences that in presence of a peaceful and friendly relationship, Positive Influence, usually, occurs. The authors of [75] also analyze the opinion shift in relation to the initial differences in the evaluation of specific items, showing that the largest positive shift occurs when the initial differences between individuals' ratings are higher. Unfortunately, no studies show a robust explanation on how Negative Influence works.

Hence, an objective of the study conducted in this work focuses in particular on the analysis of the impact of the presence of conflicts in the variation of individual's utility. It is clear that the problem is close to the Opinion Shifting problem, but not exactly the same. Hence, it is reasonable to expect that, in case of peaceful relationships, a positive variation of utility should occur, as in the Positive Opinion Shifting phenomenon. On the contrary, a Negative variation may take place when there is a conflict between people. Hence, a second objective of this study is trying to underline such considerations.

4.1.3 The Impact of Personality

Since the purpose of this part of the work is to model the changing in individual's utilities with respect to determinate activities when they must perform such activities with a group of people, considering the mutual influences between group's members, an analysis of the relation between individual's personality and their propensity to positive and negative variations has been performed. To do this, it is necessary to consider a standard framework to model the personality traits of individuals and then to relate them to the considered pro-social and antisocial behaviours. In the Psychological field, the *Five Factor Model* (FFM), described in section 2.5.1, has been mostly recognized as the basic model on the number and nature of traits that are necessary to describe the basic psychological differences between individuals [45]. Furthermore, many Psychological studies analyze the relation between the five factors and social behaviours.

Prosocial and Antisocial Behaviour

Prosocial behaviour refers to action intended to improve the situation of the help-recipient, not motivated professional obligations and not based on an organization, and a particular case is characterized by *altruism*, where the ultimate goal of the helper is to benefit another person [45]. In general, prosocial behaviour could be egoistically motivated, when the motivation is a benefit for oneself, or altruistically motivated, when the goal is to benefit another person [45]. There are many psychological studies that try to relate personality factors with prosocial behaviours. In most cases, the magnitude of such relations is relatively small [19]. This because the relations between traits and behaviour can be mediated by motives, and traits can interact with each other and even with motives to jointly influence behaviours [19, 18]. However, an empirical evidence of a relation between Agreeableness and prosocial behavior has been shown in [44], while [19] evidences a correlation between prosocial behaviour and Agreeableness and Extraversion factors, and this is also showed in [63]. Finally, in [44], authors conceptualize prosocial behavior as a form of Agreeableness.

Antisocial behaviours include crime, substance abuse and truancy, and has been wider analyzed from researchers in psychological fields. Here, generally, the aim is to derive models to predict these behaviours. Low Conscientiousness has been used to predict conflict between adolescents, substance abuse and criminal acts [23]. Antisocial behaviour has also been associated with low Agreeableness [59]. It has been also showed that, contrary to what one could imagine, prosocial and antisocial behaviours are uncorrelated tendencies stemming from different sources, and not two opposite extremes of the same dimension [23, 48]. This is supported also by the absence of a negative correlation between them, that could be observable otherwise, while antisocial behaviours seem to be correlated mostly to low Conscientiousness and low Neuroticism [23].

The main correlations evidenced in psychological studies are reported in figure 4.2 [23]. However, these studies presented quite low correlations, and more complex models are needed. For the purpose of the present work, we have a phenomenon, the variation in individual utility, that can be related to both prosocial and antisocial behaviours. Hence, a third objective of the present work is to explore the possible correlations between personality traits and utility variations, to investigate the factors related to the Emotional Contagion phenomenon.

4.1.4 Extended Social Graph

As final part of the section on the Adaptation step, an extended social graph is defined, to extend the formal definition introduced in section 2.2. Such graph contains the information

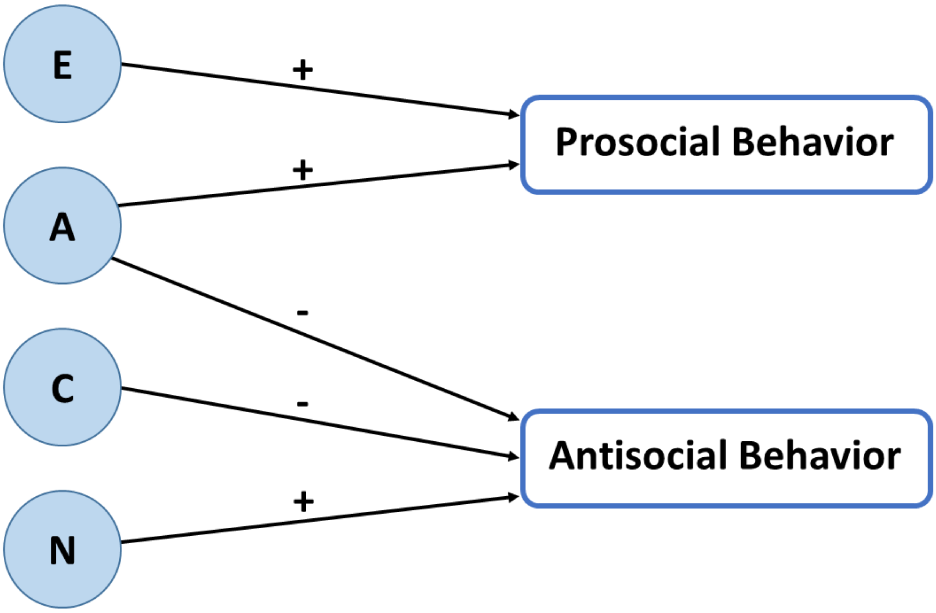


Fig. 4.2 Personality and Social Behaviour [23].

about the relationship between group members necessary to the adaptation of individual utilities. More formally, we define:

- $SN = (A, E)$ as the Social Graph of the users of the system. Here, $A = a_1, \ldots, a_n$ is the set of the users, and $E \subset A \times A$ is the set of the edges in the graph that indicate the social relation between the users, hence, if $(a_i, a_k) \in E$ there is a social relation between the user a_i and the user a_k;

- $\forall (a_i, a_k) \in E$, we define:

  - $ts(a_i, a_k) = ts_{i,k} \in \{\text{weak}, \text{intermediate}, \text{strong}\}$ is the tie strength of the relation between the user a_i and the user a_k, *as perceived from the user* a_i. This means that for the same social relation we can have two different values of tie strength;

  - $c(a_i, a_k) = c_{i,k} \in \{\text{dislike}, \text{intdifferent}, \text{like}\}$ is the state, intended as conflictual or peaceful, of the relation between the user a_i and the user a_k, *as perceived from the user* a_i. Even in this case, the same social relation can have two different state;

- Given the group $G \subset A$ of users, we can derive the graph $SN_G(A, E^G)$ as subgraph of SN induced from G.

- $\forall a_i \in A$ we define:

- $P(a_i) = P_i = (conc, extr, agre, open, neur)$ as the *Big Five Personality Profile* of the user a_i, where $conc \in [0,1]$, $extr \in [0,1]$, $agre \in [0,1]$, $open \in [0,1]$ and $neur \in [0,1]$;
- $CM(a_i) = CM_i \in \{Accommodating, Avoiding, Collaborating, Compromise, Competitive\}$ as the *Conflict Management Style* of the user a_i;

• Finally, we define:

- $U^G(a_i, \omega_j) = U^G_{i,j}$ as the utility of the user a_i for the item ω_j adapted to the specific group G.
- $\forall a_i \in A$, $UP^G_i = \{U^G_{i,j} \| \omega_j \in \Omega\}$ is the user adapted utility profile.

4.2 The Merging phase

The second part of this work consist of the definition and evaluation of advanced aggregation techniques to apply on the adapted utilities. In particular, two approaches have been designed. The first one is based on weighted social choice functions. Starting from a measure of dominance between group members, used as weight, two aggregation strategies have been realized, one based on the weighted average defined in [38] and the other defined as variant of the basic fairness strategy. Regarding the second approach, we decide to define a negotiation based approach, where each agent replicate the conflict management style of the corresponding user. The strategies are illustrated in the next sections.

4.2.1 Two Dominance Weighted Social Choice Functions

In section 3.1.1 some of the most interesting works applying weighted social choice functions has been illustrated. The first two aggregation strategies defined in the present work follow this direction. Here, we suppose to have a complete adapted utility profile $UP^G_i = \{U^G_{i,j} | \omega_j \in \Omega\}$ for each user $a_i \in G$. The objective is to define an aggregation strategy to derive the complete group profile $GP = \{U(G, \omega_j) | \omega_j \in \Omega\}$. Regarding the choice of the aggregation strategies, according to [56], users involved in real interaction seem to care about fairness and to avoid misery. For these reasons we decided to use a fairness strategy and one based on average satisfaction, weighting such functions with a measure of the influence of each user on the other group's members, and, consequently, on the group's final decision. We start discussing how information about the social interactions on Online Social Networks (OSNs) can be used to derive the influences between group's members. Then, we describe a

Dominance ranking on social networks, defined in [22]. These Dominance values are, hence, used as weights into the two social choice strategies.

Estimate Social Interactions Weights With Online Social Networks

Online Social Networks (OSNs) are widely recognized as effective ways to interact, communicate and collaborate with friends, but also to drive people's opinions. Moreover, OSNs interaction analysis can provide a viable way to obtain, without intruding the users with questionnaires, information about the social relationships and pattern of activities among the group's members. Some recent work has seen the emergence of a class of socially enhanced applications that leverage relationships from OSNs, especially to improve security and performance of network applications and online advertising [79]. While the attempt to infer meaningful relationships from social networks connectivity is often criticized from sociology researchers, the analysis of the interaction graphs in controlled situations (e.g., small and close groups) may provide useful insight. Furthermore, social networks analysis may lead to a misinterpretation of popularity as leadership that sometimes are highly correlated, but sometimes they are not. It was shown that cohesiveness of a group determines the correlation between these two concepts [76]. Moreover, the cohesiveness of a group is a fundamental issue in facilitating the decision process. In a cohesive group, users self-needs can be sacrificed for the well-being of the whole group. OSNs keep tracks of the type of interaction among the users that can be used for modelling intra-user relationships [80] and considering some of the communication activities between couple of users on a OSN, as, for example, *Facebook.com*, is it possible evaluate the weight of the relationship between pairs of users, deriving a measure of the influence that an user can have on the other in the pair.

A Dominance Ranking

In order to define our social choice functions, we analyze the possibility to evaluate, in a first approximation, the "role" of a specific relationship from the analysis of interactions on a social network, without the help of semantic features. In [1], the Authors showed that the analysis of only the user behaviors is practically equivalent, in terms of ability to determine the different types of relationships between pairs of individuals interacting in social media, to methods based on text analysis. Information exchanges between actors are dependent on social attachments that produce expectations of trust and reciprocity.

In particular, in this work, we are interested in dominance and relationship-focused leadership or influence, from the analysis of group members' interactions in a social network. Many social networks analysis approaches assume binary, symmetric relationships of equal value between all directly connected users with the main focus in analyzing big networks, while, in our approach, we deal with small groups of friends that are, most of the time, totally connected one to the others. Moreover, differently from binary networks, in reality, an individual has relationships of varying quality [9, 41].

There is a number of attempts to generalize the three node centrality measures to weighted networks [60, 62]. Here, to compute the users' ranking, we decided to use a simple "non-semantic" approach defined in the work of Caso et al. [22]. For each user $a_i \in G$ we evaluate his/her dominance value, as the value $D(a_i) \in [0,1]$. Dominance values are computed by analyzing the popularity of each user within the group, and evaluating the number of directed interactions of each user towards the other group's members. Such popularity values are obtained implementing an extension of the well-known *PageRank* algorithm [15] starting from the users' interactions on the social network *facebook.com*.

Given a group $G \subset A$ of users, and the corresponding graph $SN_G(A, E^G)$ (that is the subgraph of *SN* induced from *G*), we define:

- $\forall (a_i, a_k) \in E^G$, $w(a_i, a_k) = w_{i,k}$ is the weight of the communications from the agent a_i to the agent a_k;
- $\forall a_i \in G$, $w(a_i) = w_i$ is the weight of all the communications from the agent a_i to all the other agents.

Hence, the ranking function is defined as follows:

$$D(a_x) = \frac{1-d}{|G|} + d \sum_{a_i \in G} \frac{w_{i,x}}{w_i} D(a_i) \tag{4.2}$$

where, $|G|$ is the total number of friends in the group and d (with $0 \leq d \leq 1$) is a dampening factor set to 0.85 (this value is often considered the default value for PageRank calculations [49]). In the second part of Equation 4.2, the user a_x inherits a portion of popularity from the other a_i group's members. In detail, this proportion is calculated by considering both the popularity of the user a_i and the weight of the communication activity of the user a_i towards the user a_x ($w_{i,x}$), normalized with respect to the total communication activity of the user a_i with all the members of the group (w_i). The rationale of this choice is that the frequency of directed communication (or interaction) from the user a_i towards the user a_x is an index of influence that the user a_x have on the user a_i. Hence, $w_{i,x}$ evaluates the edges from the user a_i to the user a_x, which represent the activities with a_i as source and a_x as receiver.

ω_x	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$U(a_1,\omega_x)$	1	**5**	3	1	2	$\underline{\mathbf{5}}$	**4**	3
$U(a_2,\omega_x)$	3	$\underline{\mathbf{4}}$	1	2	**5**	3	2	**4**
$U(a_3,\omega_x)$	1	3	2	**5**	1	4	**3**	$\underline{\mathbf{2}}$
$U^{fair}(G,\omega_x)$	1	7	3	2	5	8	4	6

Table 4.1 An example of application of the weighted fairness strategy. Users are ordered from 1 to 3 and $K = 3$. The numbers in bold represent the ratings of the user's K preferred items, while the rating values corresponding to the item that causes the least misery are underlined.

Weighted Fairness Strategy

The first proposed approach is based on the Fairness Strategy illustrated in section 2.2.1. the idea behind the fairness strategy is trying to accommodate everyone in the group, since a user can agree to perform activities that he/she does not like so much as long as he/she will be able to do something he/she likes with his/her friends. One of the main issues with the use of this strategy is that, by changing the users' ordering, the selection process will produce a different result in the outcome. Hence, we propose to use the $D(a_i)$ values to provide a ranking and use such ranking to sort the users.

Average Satisfaction Strategy

As a second strategy, we developed an average satisfaction strategy inspired by [38]. We defined a strategy that takes into account the dominance as a weight for the utility provided by the user (note that the sum of the dominance values in a group is equal to one). Moreover, a second factor which can be considered in the evaluation is a measure of dissimilarity among the users individual utilities. The proposed strategy to evaluate the group utility for the item ω_x is:

$$U^{avg}(G,\omega_x) = \alpha \cdot \frac{1}{g} \sum_{a_i \in G} [D(a_i) \cdot U(a_i,\omega_x)] + \beta \cdot [1 - \sigma^2_{U(a_i,\omega_x)}] \tag{4.3}$$

where, $U(a_i,\omega_x)$ is the utility for the item ω_x, made by the user a_i, $D(a_i)$ is evaluated according to [22], and $\sigma^2_{U(a_i,\omega_x)}$ is the variance of $U(a_i,\omega_x)$ that accounts for the dissimilarity among the ratings of all the $a_i \in G$ for the item ω_x. α and β are weights. Once that all the groups' utilities of each item are computed, they are normalized, and the items with the higher value are given as result of the recommendation process. An example of a possible application of this strategy is provided in Table 4.2.

ω_x	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$U(a_1, \omega_x)$	1	5	3	1	2	5	4	3
$U(a_2, \omega_x)$	3	4	1	2	5	3	2	4
$U(a_3, \omega_x)$	1	3	2	5	1	4	3	2
$U^{avg}(G, \omega_x)$	0.51	**1.21**	0.61	0.16	0.45	**1.14**	0.88	**0.94**

Table 4.2 An example of the group choice selection using an average satisfaction evaluation. The considered dominance values are $D(a_1) = 0.44$, $D(a_2) = 0.41$ and $D(a_3) = 0.15$.

4.2.2 Negotiation Approach based on Thomas Killman Conflict Management Styles

As second strategy a consensus approach based on a negotiation mechanism is proposed. Hence, a Multi-Agent System (MAS) is defined, composed of a set of agents, called *User Agents* (UAs), each one acting on behalf of a group member, and of a special agent, called *Mediator Agent* (MA), acting as a mediator that interacts with the others to build a recommendation for the group. A key aspect of this work is that the UAs represent users with different behaviors in conflict resolution. Even in this case, it is assumed that there is a group G of g users and a set Ω of m items. In this case, we consider the possibility to have a complete user profile for each user or, alternatively, to only have a restricted set of utilities, but the possibility to estimate the utilities for each user in each moment if requested. Finally, we suppose that the agents chose a subset of K items, hence, there is the possibility to find a compromise among the users' preferences, i.e. a solution that maximizes the group satisfaction also guaranteeing a minimum utility value for each member of the group.

Interaction Protocol

The proposed negotiation process is based on an alternation of a *Merging Ranks* step, made by the MA, to aggregate preferences and compute a subset of POI to propose to the group, and a *Negotiation* step, where each UA may accept the received proposal or reject the suggested solution, and reply with an alternative proposal. The process is showed in figure 4.3- In detail, such alternating protocol is composed of the following steps:

1. the MA generates a suggested solution for the group, denoted as $P(t)$, where t is the negotiation round, hence, initially $t = 0$;

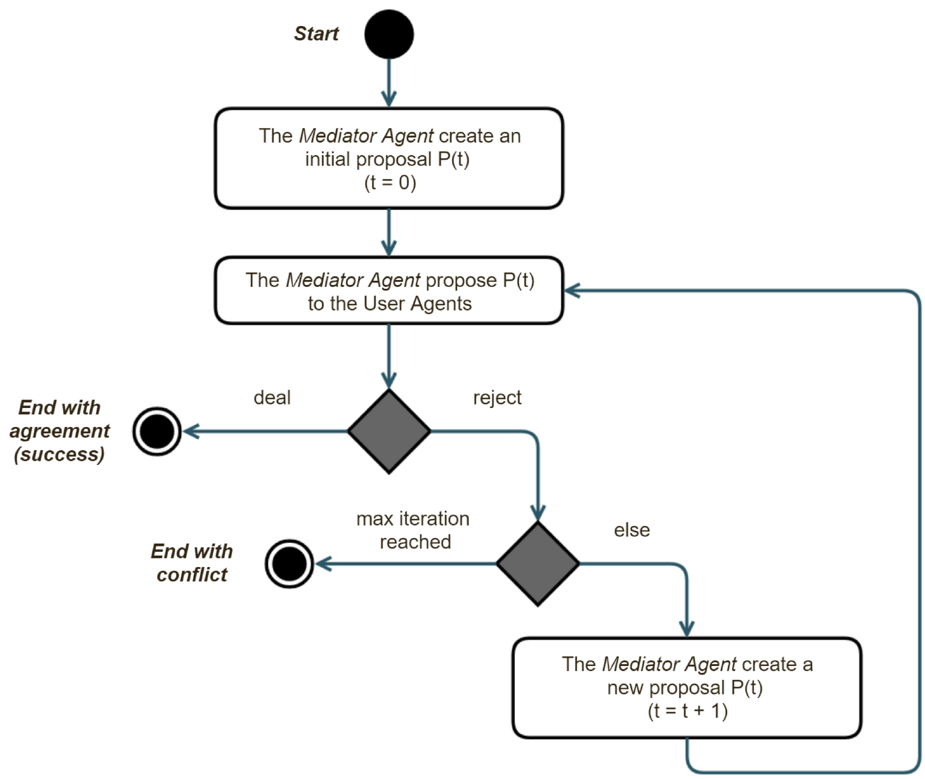


Fig. 4.3 Negotiation protocol proposed.

2. the MA send the proposal to the UA, and each one of them can accept or reject the received proposal;

   2.1 if the proposed solution is accepted by all user agents, such solution is the output of the system;

   2.2 if an UA reject the proposal, it generates a counteroffer;

      2.2.1 if the maximum number of rounds is reached, the negotiation ends with a conflict;

      2.2.2 otherwise, the MA aggregates the received counteroffers generating a new solution for the group, and it starts a new negotiation round.

The negotiation process may be iterated for a number of rounds set by the MA at the beginning of the negotiation. The agents' negotiation strategies are detailed in the following sections.

The Mediator Agent Strategy

The MA is responsible for building and sending proposals to the group members. Such proposal is a set of items $P(t) \subset \Omega$, where $|P(t)| = K$ and t indicates the negotiation round. If this solution is accepted by all the UAs, it becomes the group solution. In order to build a proposal, the MA refers to a set of item it is aware of, that is defined *Mediator Domain*. To provide a larger flexibility, we consider the case in which the MA do not have a complete knowledge of the user agent preference profiles. This can happen when the individual RS, used to estimate the individual utilities, is not used on all the items in the set Ω, for example, for computational issues.

More in detail, for each User Agent UA_i we define a set Ω_i as the set of items ω_j for which we have an estimation of the individual utilities $U(a_i, \omega_j)$. Hence, if $\Omega_i = \Omega$ we have a **Complete Knowledge**. Otherwise, we have a situation of **Partial Knowledge**. In case of partial knowledge, the UA are requested to initially provide the evaluation of utility for b items that are the b best items for the corresponding agent. The number b is set as $20/g$, where $g = |G|$ is the number of users in the group G.

The MA asks to each UA_i his set Ω_i and the utilities associated to each item. Then, the MA construct the set $MD_G = \bigcup_{a_i \in G} \Omega_i$, that is the *Mediator Domain*. After, the MA asked to each UA_i the utilities for each item in MD_G for which it has not the estimation of the utility.

At this point the MA can construct a fist solution proposal. It firstly calculates a group utility $U_G \omega_j$ for each item $\omega_j \in MD_G$, as follows:

$$U_G(\omega_j) = \sum_{a_i \in G} \frac{U(a_i, \omega_j) \cdot p_j}{g} \tag{4.4}$$

where $g = |G|$. Such formula represents a weighted mean of the individual utilities. Here, the weight $p_j \in [0, 1]$ is a measure of the popularity of the item ω_j, hence, $p_j = 1$ if at the start of the process the MA have an estimation of the utility $U_(a_i, \omega_j)$ for all the $a_i \in G$.

The first proposal $P(0)$ hence is composed by selecting the K items with the highest group rank, so it is the solution that maximizes the Social Welfare (i.e., the weighted sum of the individual utilities). Once the first proposal is computed, the MA sends it to all UA_i that privately evaluate it according to their own utility function.

In case the proposal is rejected, the mediator receives a number of counteroffers, each one composed of a possible new set of K items from each user agent UA_i that rejected the proposal. If a counteroffer contains items that are not in the mediator domain MD_G, the MA adds such items to its domain and asks the user agents to provide an evaluation of the utility for them.

Then, the *MA* generates a new proposal on the new domain MD_G, by applying the same strategy used to build the first proposal. If the new proposal is different from the previous one, it is sent to the *UA*; otherwise, the mediator modifies it, according to the received counteroffers, by replacing the item that in its previous solution was discharged by the highest number of *UA* (when the counteroffers were generated) with the one that had the highest number of new occurrences in the generated counteroffers.

The User Agent Strategy

Each user agent UA_i evaluates the proposal sent by the mediator according to its behavior in conflict resolution. This behavior is assigned to the agent once the corresponding user filled the TKI questionnaire [47].

For each user agent UA_i, an individual *Optimal Value*, that is the value corresponding to the solution with the highest utility for it, and a *Reservation Value*, representing the minimum utility value up to which the user agent is willing to concede during the negotiation, are set. Given Ω_i the set if items for which we have an estimation of the utility of the user a_i, and Ω_i^K the set of K items with the highest utility for the user a_i, the optimal value at time $t = 0$ is given by:

$$OPT_i(0) = \sum_{\omega_j \in \Omega_i^K} \frac{\widetilde{U(a_i, \omega_j)}}{K} \tag{4.5}$$

where $\widetilde{U(a_i, \omega_j)}$ is the utility for user a_i of the item ω_j normalized in $[0,1]$. The reservation value is set to the half of $OPT_i(0)$ for all the user agents UA_i.

When the user agent receives an offer $P(t)$ from the mediator, at negotiation round t, it evaluates the utility of the received offer as follows:

$$U(a_i, P(t)) = \sum_{\omega_j \in P(t)} \frac{\widetilde{U(a_i, \omega_j)}}{K} \tag{4.6}$$

This value is compared with the agent utility value of the previous negotiation round $OPT_i(t-1)$. Now, there can be the following situations:

1. if $U(a_i, P(t)) \geq OPT_i(t-1)$, then the agent accepts the offer and sets $OPT_i(t) = U(a_i, P(t))$;
2. if $U(a_i, P(t)) \geq OPT_i(t-1) - \Delta_i(t)$, then the agent accepts the offer by conceding in its utility of a value smaller or equal of $\Delta_i(t)$, and it sets $OPT_i(t-1) = U(a_i, P(t))$;

3. in all the other cases, the agent rejects the offer, and it makes a counteroffer either by randomly conceding in utility ($OPT_i(t) = OPT_i(t-1) - \Delta_i(t)$) or by not conceding ($OPT_i(t) = OPT_i(t-1)$).

The utility concession value $\Delta_i(t)$, at time t, depends on the user profile in the conflict resolution style. In particular, in [52] the authors associated with each conflict resolution style of the TKI model different concession strategies depending on the negotiation round. Inspired by this work, we defined the agent concession strategies as follows:

- *Accommodating*, it is not assertive and cooperative, and it accommodates the objectives of the other group members, so helping them in finding a shared solution by conceding a constant utility value during all negotiation rounds, so being the most collaborative profile;
- *Competing*, it is assertive, and it prioritizes agent own objectives, by conceding low utility values at the beginning of the negotiation, while increasing the concession value at the end of negotiation to try to reach an agreement before a negotiation failure occurs;
- *Compromising*, it is a compromise between assertive and cooperative, and it tries to find a solution that accommodates the objectives of all involved parties, by conceding high utility values at the beginning and at the end of the negotiation, while conceding a constant utility value in the intermediate rounds;
- *Collaborative*, it is both assertive and cooperative, by trying to make all agents working together to find a common solution. In [52] it was showed that this behavioral style does not have a strong impact on the TKI model, hence, for this reason, it was decided to adopt constant concessions throughout the negotiation phase;
- *Avoiding*, it is a passive style of conflict resolution, meaning that the agent would not pursue a negotiation in the first place. So, in this work, we consider a smaller constant concession value.

For each profile, three concession steps are defined by the model proposed in [52]: initial, intermediate, and final concession. The corresponding concession values depend on the considered application domain. Here, the concession values for the different profiles were empirically derived from a set of experiments carried out adopting different conflict resolution strategies.

In case a user agent rejects a proposal, it has to generate a counteroffer whose utility value is calculated taking into account whether a concession takes place or not. Once fixed a utility value, there could be potentially many items combinations that result in having the same utility value. So, in order to compute a counteroffer, we defined two different heuristic strategies to reduce the search space, *Search in Domain* and *Reference Point*. Moreover, the mediator agent communicates to the user agents which strategy to use according to the negotiation state, i.e., the number of rounds, or the number of conflicts in the offers. The proposed mechanism allows to find a solution that is a compromise between a maximization of the Social Welfare (as evaluated by the mediator), and the individual user utilities. The two heuristics are detailed below:

- **Search in Domain**: With this heuristic, the user agent orders the items of the proposal $P(t)$ received by the mediator according to its own ranking, and it generates a counteroffer by modifying the proposal to obtain an admissible proposal (i.e., a proposal with the required utility) by making the less possible number of items substitutions searching in its private domain (the items for which it has an estimation of utility). However, in case the mediator domain is greater than a value τ, the mediator suggests a subset of items where a solution has to be found according to its own knowledge. The number of items τ can be derived from experiments carried out on the algorithm performances, and it strongly depends on the application domain.

- **Reference Point**: This strategy applies when there is only one agent conflicting with a given proposal that is admissible for the other members of the group. In such a case the mediator sends a proposal to that agent that represents a *reference point* for the agent to build a counteroffer. In fact, the agent tries to meet as much as possible the received proposal since it already satisfies the group. So the conflicting agent is required to adapt its objectives to the proposal satisfying the majority of the group.

Chapter 5

A Study of the Factors That Influence the Emotional Contagion

In this chapter, an analysis of the factors influencing the Emotional Contagion phenomenon in two-people sized groups is presented. Such analysis is performed through two experimental study conducted on the Amazon Mechanical Turk platform. In the first study, an analysis of the impact of the tie strength and the status of the relationship, intended as conflicting or peacefully relation, is realized. The second study explores the impact of the personality profile of the users, evaluated through the well-known Five Factor Model, to determine if traits related to prosocial and antisocial behaviours can be even related to positive and negative shifting of individual utilities.

5.1 First Experiment: The Role of Tie Strength and Conflicts

We conducted a first experiment, to determine if the tie strength and the presence of conflicts can influence on the direction and on the magnitude of the emotional contagion. The experiment is focused on two-sized group and is conducted with an online questionnaire, using the Amazon Mechanical Turk platform. Our objective is to evaluate if the tie strength have an impact with the Positive influence, that increases when the strength became stronger, and if the presence of conflict can lead to a Negative influence, mostly in case of weak ties.

Instructions

This experiment analyzes the influences of other people on your evaluation of joint activities.

You will be asked to imagine a person you know, with specific characteristics in their relationship between you. We are particularly focused on the strength of your relationship to the other person and the possibility of conflicts between you.

The strength of the relationship can be weak, intermediate or strong.

- Weak means that you occasionally contact or interact with this person.
- Intermediate indicates a person with whom you interact regularly.
- Strong means that you interact with this person every day, many times a day.

Regarding conflicts, we distinguish between:

- people that you like and with whom you are in a very peaceful relationship
- people you are indifferent about
- people with whom you are in a conflictual relationship with and you really dislike.

There will be 8 activities, named A, B, C, D, E, F, G and H. Initially, you will not know anything about these activities.

Fig. 5.1 Instruction view showed to the participants at the beginning of the questionnaire.

5.1.1 Description of the Experiment

In a first step we verified that the participants could understand the scenarios given in the experiment. Since the questionnaire is provided in English language, an English test was taken by each participant, and only those who passed the test was included. After that, we asked for personal information data, such as age and gender, for statistical purposes.

After that initial step, the questionnaire starts providing a detailed explanation of the experiment, focusing on the terminologies that will be used in the questions. The page is showed in figure 5.1.

As we can see, we explain that the ties strength of the relationship may be weak, intermediate or strong, as suggested in [43], using terms as follows:

- Weak: indicates a person with whom the participant has a weak relationship, with occasional interactions;
- Intermediate: is for a person with whom the participant has regular interactions;
- Strong: means that the interaction of the participant with this person occurs every day, many times a day, so their relationship can be defined as strong.

Regarding conflicts, we were inspired by [75] and decided to distinguish between:

- Like: People with whom the participants are in a peaceful relationship, namely, at this moment, they like them and they are on good terms;
- Indifferent: People with whom the participants are neither in a conflict nor in a peaceful relationship, and therefore, they are indifferent to them;
- Dislike: people with whom they are in a conflict situation, namely, at this moment, they dislike and with whom they are on bad terms.

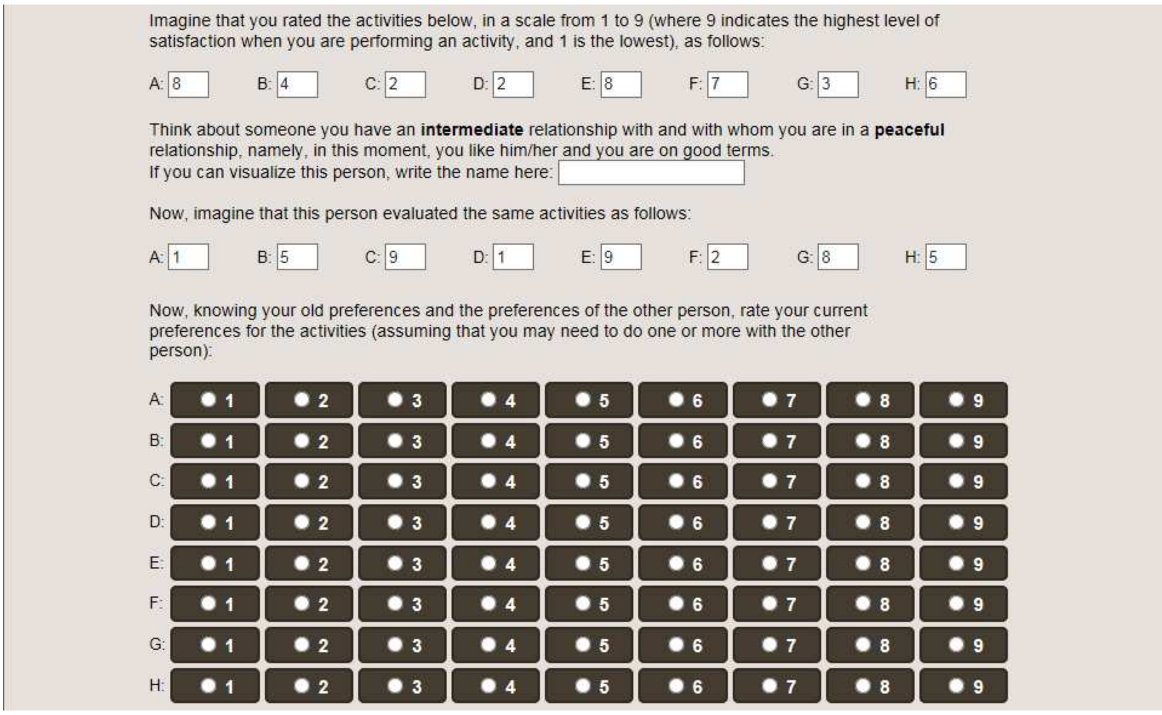


Fig. 5.2 Screenshot of the online questionnaire.

After this explanation, we presented the view shown in Figure 5.2. The view contains two evaluations for the same eight activities. We do not show any information about the activities, to avoid the participant's answers being influenced by this knowledge. The first set of evaluations is presented with the sentence:

"Imagine that you rated the activities below, on a scale from 1 to 9 (where 9 indicates the highest level of satisfaction when you are performing an activity, and 1 is the lowest), as follows:"

After that, a second set of evaluations, for the same activities, is presented. Here, we asked the participants to think about someone with whom they have a relationship with determinate characteristics, given by the possible combinations of the type of tie strength and conflicts explained before. More precisely, the sentences are the following:

- **Weak and Like**: *"Think about someone you have a **weak** relationship with and with whom you are in a **peaceful** relationship, namely, in this moment, you like him/her and you are on good terms*
- **Weak and Indifferent**: *"Think about someone you have a **weak** relationship with and with whom you are neither in a conflict nor in a peaceful relationship, therefore you are **indifferent** to him/her*

- **Weak and Dislike**: *"Think about someone you have a **weak** relationship with and with whom you are in **conflict**, namely, in this moment, you dislike him/her and you are on bad terms*
- **Intermediate and Like**: *"Think about someone you have an **intermediate** relationship with and with whom you are in a **peaceful** relationship, namely, in this moment, you like him/her and you are on good terms*
- **Intermediate and Indifferent**: *"Think about someone you have an **intermediate** relationship with and with whom you are neither in a conflict nor in a peaceful relationship, therefore you are **indifferent** to him/her*
- **Intermediate and Dislike**: *"Think about someone you have an **intermediate** relationship with and with whom you are in **conflict**, namely, in this moment, you dislike him/her and you are on bad terms*
- **Strong and Like**: *"Think about someone you have a **strong** relationship with and with whom you are in a **peaceful** relationship, namely, in this moment, you like him/her and you are on good terms*
- **Strong and Indifferent**: *"Think about someone you have a **strong** relationship with and with whom you are neither in a conflict nor in a peaceful relationship, therefore you are **indifferent** to him/her*
- **Strong and Dislike**: *"Think about someone you have a **strong** relationship with and with whom you are in **conflict**, namely, in this moment, you dislike him/her and you are on bad terms*

To help the participant to view the scenario as accurately as possible and to better identify herself into the proposed situation, we asked to write the name of the person that they are thinking about. Obviously, we do not store this information. Then, we ask the participants to imagine that the second evaluations have been provided by the person they are visualizing.

Finally, we ask the participants to rate their current preferences for the proposed activities, knowing their old preferences and the preferences of the other person and assuming that they have to do the activities with the other person. More accurately, the question that we present is the following:

Now, knowing your old preferences and the preferences of the other person, rate your current preferences for the activities (assuming that you may need to do one or more with the other person):

All the evaluations are requested on a scale between 1 and 9 included. Each participant was asked to perform the test three times, answering for only 3 different configurations out of the 9 possible combinations, keeping the tie strength the same but varying the conflict. This choice is made to guarantee that the test occupies only few minutes, since, as suggested in [30], questionnaires that take more than a few minutes to complete may produce a loss of concentration in participants. Hence, the designed questionnaire has been designed to require only 5 minutes to be completed.

Setting of Initial Evaluations

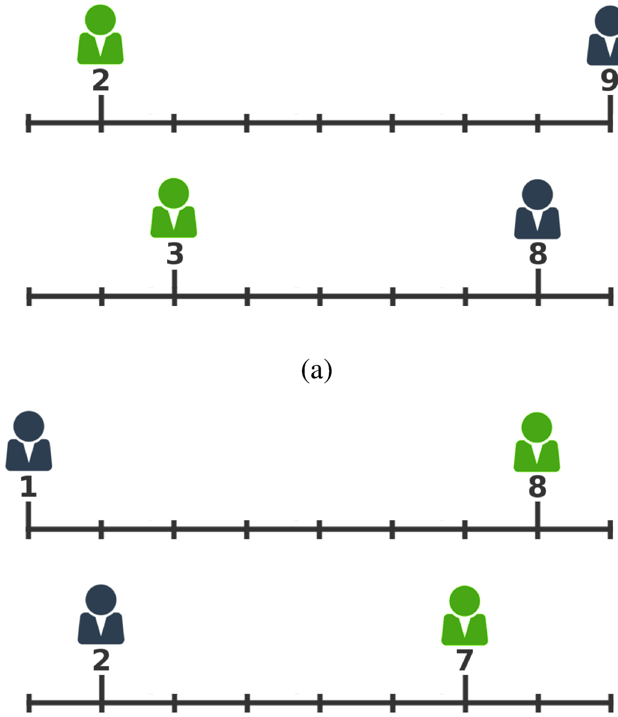
The two sets of initial evaluations have been designed in order to cover different situations. Namely, the differences between the participant's initial ratings and other person's ratings are set to present cases of agreement on the evaluation of the activity and cases of disagreement. Furthermore, the given ratings are set in order to have in half of the cases that the participant's rating is greater than the ranting by the other person, and in the other half of the cases, the opposite. Firstly, we are interested in the analysis of participant's behaviour for different initial differences, distinguish between *Large* and *Small* initial differences, and even between *Positive* and *Negative* differences. Large difference maps an initial disagreement between the two people, while a small difference indicates an initial agreement in the evaluations. On the other hand, a positive difference indicates that participant's initial rating is lower than the other person's one and, on the contrary, negative difference is the case of a participant's rating higher than the other person's one.

Focusing on the large initial difference, since we use a rating scale between 1 and 9, we can notice that such configurations give more chances to positive shifting, while negative shifting are very limited because the initial participant's rating is very near the boundaries of the scale. We decided to set four configurations with large difference, two positive and two negative, as showed in figure 5.3.

Regarding small initial differences, we have an initial agreement between people. Here, we have a very small possibility for positive shifting, since the initial ratings are very similar, with a difference of one value. Even in this case, we have four configurations, two positive and two negative 5.4.

5.1.2 Result Analysis

We recruit 60 participants, obtaining 180 answers. Since each answer contains 8 evaluations, we collected more than 1,400 evaluations. The participants were recruited through Amazon Mechanical Turk and paid $ 0.50 for the participation in the test. In Table 5.1, we report



(b)

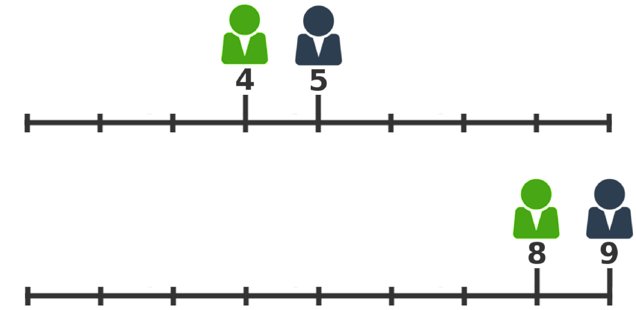
Fig. 5.3 Initial preferences for the participant (in green) and for the other person (in blue) for large initial difference configuration, for positive (a) and negative (b) initial difference.

Age Range	Number of Participants
16-25	8
26-40	33
41-65	17
Over 65	2

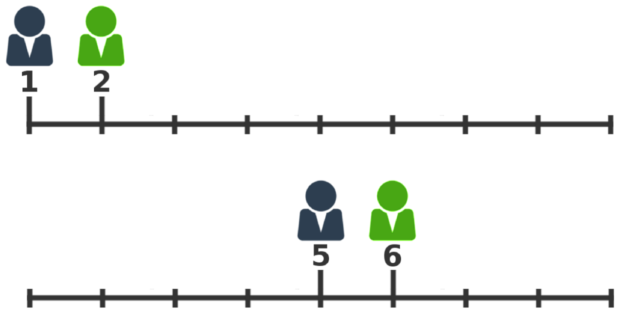
Table 5.1 Demographic data of the participants. The female/male ratio is about 50%

the statistical data on the participants on the study. Starting from the answers provided to the questionnaires, we evaluate the opinion shift by computing the variation between the new evaluations for the activities given by the participants in the test and the old evaluations, which had been shown to them at the start of the study. We consider as a positive shifting a change towards the rating of the second person, whom we asked them to imagine with determinate constraints on the relationship existing between them. A negative shift is in the opposite case (e.g., the rating variation value will have the negative sign).

Since our experiment was based on the combination of two factors, results of a two-way ANOVA analysis with the ties strength and conflicts as fixed factors and the rating variations



(a)



(b)

Fig. 5.4 Initial preferences for the participant (in green) and for the other person (in blue) for small initial difference configuration, for positive (a) and negative (b) initial difference.

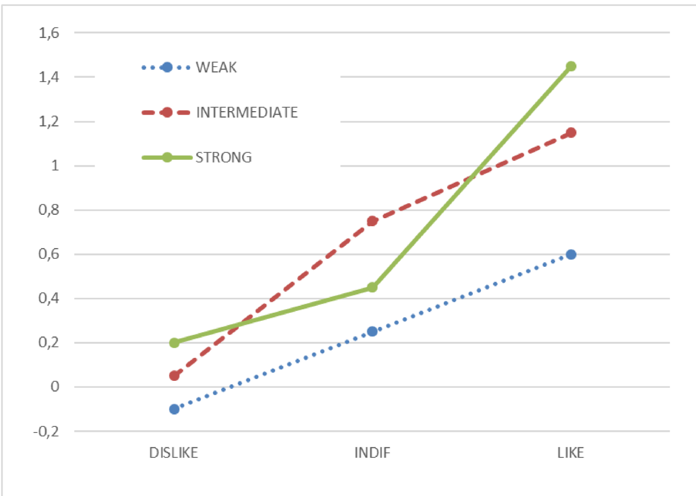


Fig. 5.5 Interaction graph of the ties strength over conflict

as the dependent variable are shown in Table 5.2. The interaction term is represented by the *conflict * ties* row in the table. Results show significant effects of tie strength and conflicts

Source	Sum Sq.	d.f.	Mean Sq.	F	p-value
conflict	269.504	2	134.752	40.274	0.000
ties	56.885	2	28.442	8.501	0.000
conflict * ties	31.263	4	7.816	2.336	0.054

Table 5.2 Table of ANOVA2 analysis.

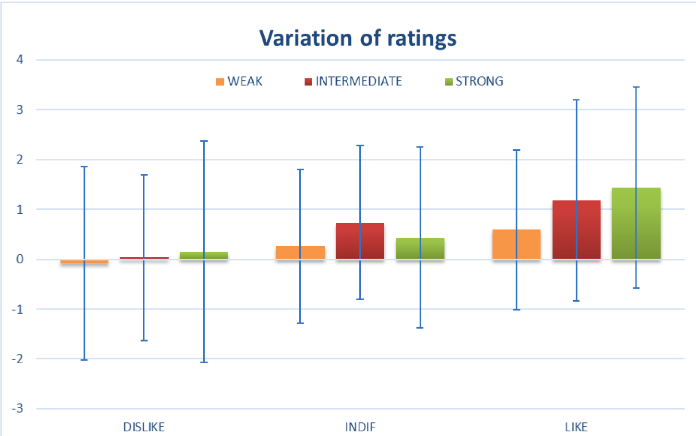


Fig. 5.6 Average values for the ratings variation.

and a trend towards an interaction effect between ties strength and conflict with $p = 0.054$, so it would require a successive analysis in order to understand the effects of such interaction. The interaction effect is also shown in Figure 5.5, where the possibility of a significant interaction exists because the lines are not parallel. It seems that the case of indifferent and intermediate is the one that would require a deeper analysis, while more defined (e.g., stronger) situation are following our expected trends. So for the other cases, where we have a probable ordinal interaction, we will discuss in the following the main effects.

Figure 5.6 shows the general trends, illustrating the average values and standard deviations of the rating variations, grouped with respect to the different parameters that we impose into the experiment. To ensure the significance of the data, we performed an *ANOVA* test that returned a p-value < 0.001, that indicates that obtained results are not due to the case.

As we can see, there is a general positive shifting in the case of good relationships, i.e. when the participant likes the other person, and, as we expected, this shifting increases when the strength of the ties became stronger. This behavior is in line with respect to the results in the literature. We can, also, notice that for indifferent people there are still a positive shifting, and so an influence on the rating variations, even if the amplitude is lower than in the previous case. Moreover, note that the combination of indifferent and intermediate is again the one with the unexpected behavior, since it is the one with the highest result in the

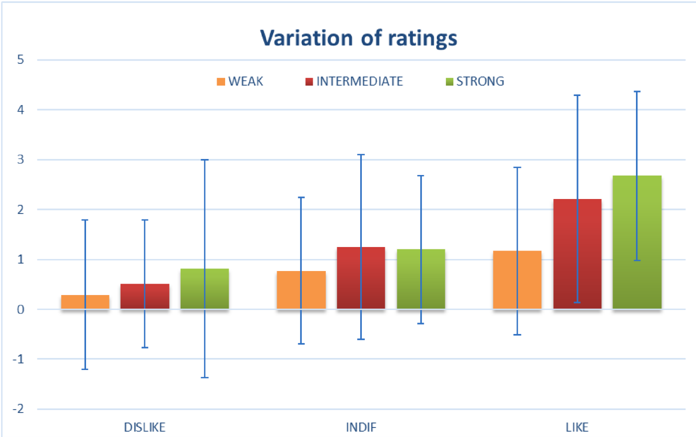


Fig. 5.7 Average values for the rating variations considering only the cases with a large initial difference between participant's ratings and other person's ratings.

group suggesting a sort of "social conformance behavior" that has to be further explored. The last evidence is that for disliked people, the average variations are very small, and, for weak ties, there is a small negative influence. However, a more accurate analysis must be performed.

Opinion Shift vs. Small/Large Differences in the Initial Ratings

In the first instance, we recall that the experiment settings were designed to present different situations, and we want to underline that initial differences between an individual's rating and those of the other person are equally divided into small and large differences. Hence, there are 50% of cases where the individuals are in a sort of initial agreement, and another 50% where the initial situation is a complete disagreement. Therefore, we are interested in analyzing the behaviors in these two situations.

Figure 5.7 shows the situation in case of large initial differences. This is the case in which there is a big initial disagreement, so the propensity to concede in utility can be analyzed in a more specific way. Since we are are considering half of the population at the time, we performed an *ANOVA* test to ensure the significance of the data. Also, in this case, the test returned a p-value < 0.001, hence the obtained results are not due to the case.

As the figure shows there is a general Positive shifting, stronger in the good relationships, but surprisingly also present in the conflict ones. Also, in this case, when the ties strength increases and becomes stronger, there is a general increase in the average Positive influence. Results confirmed the relationship between the peaceful relationships and the attitude to concede in utility, shifting evaluations towards the other person's evaluations. Moreover, in

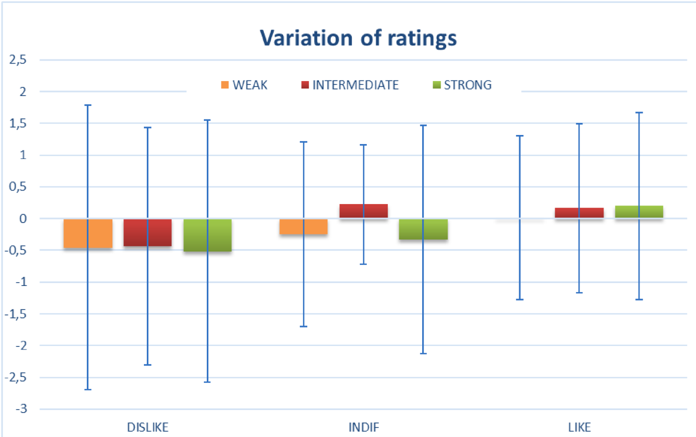


Fig. 5.8 Average values for the rating variations considering only the cases with small initial difference between participant's ratings and other person's ratings.

the case of a large initial difference in the ratings, there is always a propensity to concede towards the others that whose magnitude depends on the considered factors.

Finally, while, at the average, we have only positive opinion shifting, by looking at the values of the standard deviations in Figure 5.6, it suggests that there are cases, at least for the indifferent and disliked person, characterized by a Negative shifting. As you can see in the followings, Negative influence is much more evident in the case of small initial rating distances.

Figure 5.8 shows the trends for the configurations in which there is a small initial difference between evaluations, and, hence, there is an initial agreement between the participant in the study and the hypothetical other one. We can notice a substantial absence of shifting in the case of a good relationship, so we can observe that people that have similar ideas and like each other tend to keep the same position, and not change their evaluations.

Instead, in the indifferent and conflict relationships, we can notice a Negative influence. Even if the greatest proportion of people do not change their evaluations, there is a considerable proportion of participants that, starting from an agreement situation, decides to shift their evaluations in opposite direction with respect to the other person's evaluations, only because of the conflict. Hence, negative influence has more effect in the case of the user and the disliked person having the same initial ideas on rating, so to remark a difference between them.

Opinion Shift vs. Positive/Negative Initial Difference

Here, we analyze the trends in opinion shift in relation to the direction of the initial difference between the individual's ratings and those of the other person, that is positive if the other

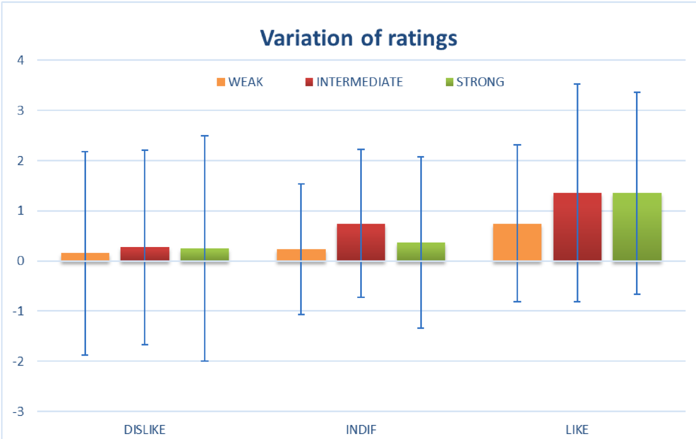


Fig. 5.9 Average values for the rating variations considering only questions with negative initial differences between participant's ratings and other person's ratings.

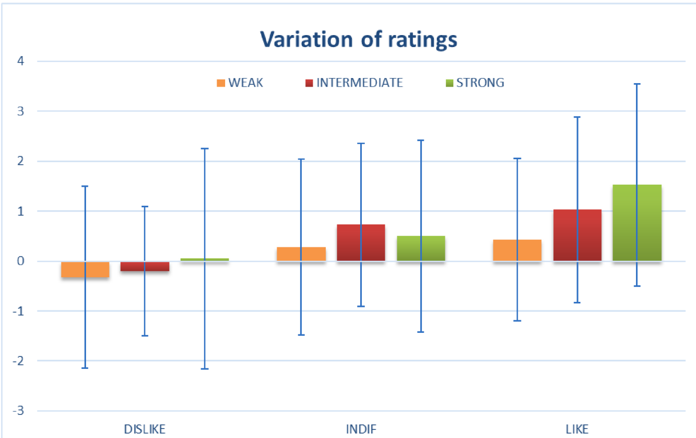


Fig. 5.10 Average values for the rating variations considering only questions with positive initial differences between participant's ratings and other person's ratings.

person's rating is greater than the individual's ones, and negative otherwise. We recall that also in this case, the experiment settings was designed to have 50% of cases with positive initial differences and another 50% where the initial differences were negative.

Figure 5.9 shows the averages values for negative initial differences. This is the case in which individuals' ratings are greater than those of the other person. As we can see, the trends indicate that in this situation the individual is more likely to move his/her initial opinion towards the other person's opinion. As in previous case, to ensure the significance of the data we performed an *ANOVA* test. In this case, the test returned a p-value $= 0.086$, hence difference are not significant. However, as we see in the Figure 5.9, the general trends of tie strength and status are similar, with greater Positive variations in strong and friendly relationships, and lower shifting for conflict and weak relationships.

In Figure 5.10, the trends for the case in which there are positive initial differences are shown. Recall that, in this case, the initial individual's ratings are lower than those of the other person. In this case, we can notice a small negative shifting in the conflict relationship. Data indicates a general trend in which people are more likely to change their opinion to a lower value: in the case of a conflicting relationship, if the individual's rating is higher, then the individual, on average, decides to have a small shift towards the other person's opinion, while, if the individual's rating is lower, the individual prefers to shift in the opposite direction.

Correlation Analysis

The previous results suggest an impact of the tie strength and the conflict on the opinion shift phenomenon. Here, we analyze the correlations between the new evaluations, considered dependent variable, and the old and the other evaluations, considered independent factors, for the different combinations of the tie strength and conflicts parameters.

First, we focus on the correlation between the shift $\Gamma(a_i, \omega_j)$, here computed as the difference between the new evaluation $U^{new}(a_i, \omega_j)$ of the user a_i with respect to the item ω_j and the old evaluation, that is the starting utility $U(a_i, \omega_j)$, and the initial difference $\Delta(a_i, a_k, \omega_j)$, computed as the difference between the old evaluation $U(a_i, \omega_j)$ and the other person's evaluation $U(a_k, \omega_j)$. More formally, we define:

$$\Gamma(a_i, \omega_j) = U^{new}(a_i, \omega_j) - U(a_i, \omega_j) \tag{5.1}$$

$$\Delta(a_i, a_k, \omega_j) = U(a_k, \omega_j) - U(a_i, \omega_j) \tag{5.2}$$

Here, we consider as $U^{new}(a_i, \omega_j)$ the new evaluation given by the participant, $U(a_i, \omega_j)$ is the initial evaluation given by the setting of the experiment, and $U(a_k, \omega_j)$ is the other person's evaluation. The Pearson correlation between Γ and Δ has a value of 0.439, with a $p-value < 0.001$, that indicates a statistically significant general positive correlation. We even analyze the correlations splitting the data in relation to the different configurations of tie strength and conflicts in the relationship. The results are summarized in table 5.3 and even reported in figure 5.11.

We can see that the correlations are statistically significant for most cases, except for the case of conflicts (Dislike in the table). The correlation increases when the tie strength became higher. The same thing happen when the status of the relationship became more peaceful. Hence, we could assume that the initial difference can be used as a predictor for the shift in such cases.

Tie Strength	Conflict	F	p-value	
Weak	Dislike	0,127	0,102	
Weak	Indif	0,326	0,000	**
Weak	Like	0,494	0,000	**
Interm	Dislike	0,201	0,011	*
Interm	Indif	0,538	0,000	**
Interm	Like	0,683	0,000	**
Strong	Dislike	0,288	0,000	**
Strong	Indif	0,430	0,000	**
Strong	Like	0,769	0,000	**

Table 5.3 Pearson Correlation between the shift, computed as defined in equation 5.1, and the initial difference, defined in the equation 5.2.

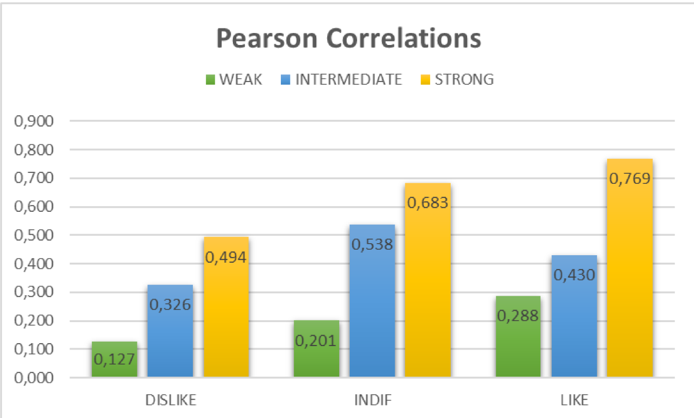


Fig. 5.11 Pearson Correlation between the shift, computed as defined in equation 5.1, and the initial difference, defined in the equation 5.2.

We evaluate even the correlation between the initial evaluation and the new evaluation. In this case, we have a general positive correlation, with an F value of 0.657, and the $p-value < 0.001$ confirm a statistical significance. Once again, we perform an analysis of correlations in the different cases of tie strength and status of the relationship. The results are reported in table 5.4 and in figure 5.12.

We have a $p-value < 0.001$ in all the cases that indicate a statistical significance of all the correlations. In general, we have positive correlations that decrease in the case of peaceful relationship (Like in the table). In this case, a high correlation can indicate a lower or a constant variation, but if we consider the previous results we could conclude that in the cases with lower correlation we have a higher shift. However, as expected, we can use the old evaluation as predictor for the new.

Tie Strength	Conflict	F	p-value	
Weak	Dislike	0,723	0,000	**
Weak	Indif	0,767	0,000	**
Weak	Like	0,717	0,000	**
Interm	Dislike	0,756	0,000	**
Interm	Indif	0,731	0,000	**
Interm	Like	0,501	0,000	**
Strong	Dislike	0,604	0,000	**
Strong	Indif	0,675	0,000	**
Strong	Like	0,411	0,000	**

Table 5.4 Pearson Correlation between the new evaluation and the old evaluation.

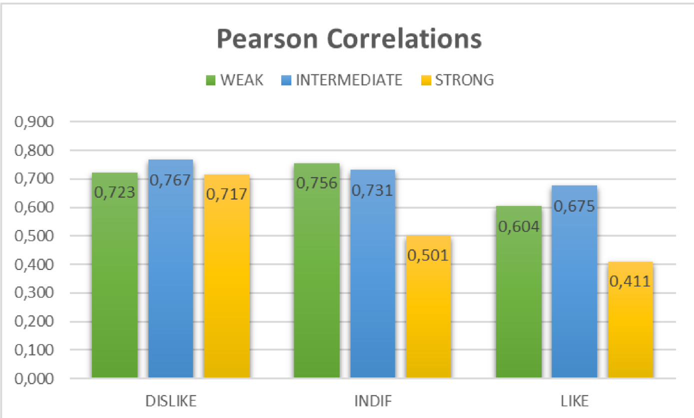


Fig. 5.12 Pearson Correlation between the new evaluation and the old evaluation.

Multiple Regression Analysis

Starting from the previous results we decide to perform a Multiple Regression Analysis trying to predict $U^{new}(a_i,\omega_j)$ from the predictors $U(a_i,\omega_j)$ and $U(a_k,\omega_j)$. Hence, the regression line will have the form specified in equation 5.3.

$$U^{new}(a_i,\omega_j) = \alpha + \beta_2 * U(a_i,\omega_j) + \beta_2 * U(a_k,\omega_j) \tag{5.3}$$

In the general case, the variables statistically significantly predicted new utility, with a value $F(2,1437) = 590.367$ and a $p-value < 0.0005$. The statistic $R^2 = 0.451$ indicates a good explanation of the dependent variable, but other factors can be considered to fully describe the phenomenon. However, both the variables considered added statistically significantly to the prediction, with $p < 0.05$. Hence, the general form of the equation is:

$$U^{new}(a_i,\omega_j) = 1.140 + 0.653 * U(a_i,\omega_j) + 0.103 * U(a_k,\omega_j) \tag{5.4}$$

As expected, in the general case the old evaluation factor has the biggest impact on the new evaluation, but in the previous section we showed that the phenomenon has different patterns in relation to the state of the relationship, so we can deepen the analysis performing different regressions considering the different configurations of tie strength and conflict. The results of this analysis are reported in table 5.5.

Tie Strength	Conflict	α	β_1	β_2	R^2	Sig.	
Weak	Dislike	1.630 **	0.719 **	-0.088 **	0.535	0.000	**
Weak	Indif	1.183 **	0.737 **	0.031	0.590	0.000	**
Weak	Like	0.785	0.686 **	0.124 **	0.546	0.000	**
Interm	Dislike	1.535 **	0.705 **	-0.060	0.578	0.000	**
Interm	Indif	0.438	0.733 **	0.177 **	0.595	0.000	**
Interm	Like	0.481	0.555 **	0.316 **	0.443	0.000	**
Strong	Dislike	1.750 **	0.628 **	0.003	0.365	0.000	**
Strong	Indif	1.530 **	0.635 **	0.072	0.466	0.000	**
Strong	Like	0.962 *	0.460 **	0.370 **	0.468	0.000	**

Table 5.5 Results of the Multiple Regression Analysis for the different configurations of Tie Stregth and Conflict. The regression coefficients are intended for a regression line of the form specified in equation 5.3.

All the models have a statistical significance (with a $p-value < 0.0005$), and, in average, a good explanation of the dependent variable, as indicated in the R^2 column. We have better values for the rows that have Weak and Intermediate tie strength, that could have a more linear pattern. As we can see from the coefficient, the old evaluation factor has a great impact in such cases, while in the rows with a peaceful status we have an increasing impact of the other evaluation factor, and even in the case of Intermediate tie strength and Indifferent status we have a bigger impact of the other evaluation factor.

5.1.3 Discussion

The analysis provided on the opinion variations shows an impact of tie strength on positive influence, that increases according to the strength of the relationship if this is in a friendly status, and, to a lesser degree, also in a conflicting status. Also, there is evidence that negative shifting can occur in the case of a conflicting relationship. There is a clear difference in the opinion shift if we analyze results in relation to the initial difference between an individual's ratings and others' ratings; in case of initial disagreement, opinion tends to shift positively, with more marked variations in case of strong and peaceful relationship, and lower for conflicting and weak ties. On the contrary, if we start with an agreement, the variation is close to zero in a strong and friendly relationship, while a negative shift is shown in conflicting ties. The analysis of the variations in relation to the direction of the initial difference between ratings shows that participants are more likely to shift their ratings towards the other person's ratings if they start from a higher evaluation, and, on the contrary, they move ratings in the opposite direction when they start from a lower rating and there is a conflict.

Finally, the correlation analysis confirm that the old evaluations and the other evaluations are strictly correlated with the new evaluation, hence is it possible to apply a model like that defined in equation 4.1. Furthermore, the correlations varying in relation to the strength and the status of the relationship. This suggests that we can use different parameters for the model in relation to the state of the relationship.

5.2 Second Experiment: The Role of Personality

We conduct a second experiment to explore the impact of personality traits in the emotional contagion. As in the previous test, we focus on two-sized groups. Our hypothesis is that positive influence is related to personality traits generally associated with pro-social behaviour, and, on the contrary, personality traits that may cause antisocial behaviours are related to negative influence. Even this experiment is conducted using an online questionnaire on the Amazon Mechanical Turk platform.

5.2.1 Description of the Experiment

The methodology used is similar to the one used in the previous test, hence, we refer to the section 5.1.1 for the details. Here, we specify the differences. The first one is that we perform a personality test before performing the questionnaire. The second one is about the initial evaluations used.

Personality Slider Test

To determine the Big Five personality traits of the participant in the experiment, the *Personality Slider* method [72] have been chosen. In this way, we can obtain the five factors in a really small amount of time. In fact, the personality slider method only requires five evaluations, one for each personality trait. In each one two stories are showed to participants, describing two people that are low or high for that trait. An example is showed in figure 5.13. Participants are asked to set the slider between the two stories, getting it closer to the person they are most like. For each personality trait, the story related are specified above:

- **Agreeableness**

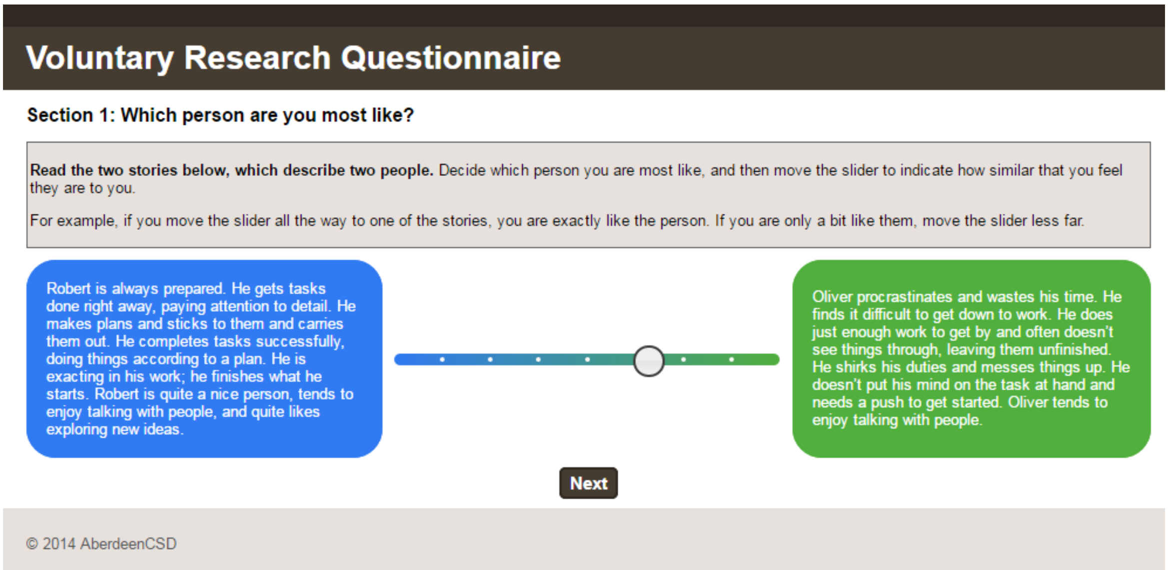


Fig. 5.13 Screenshot of one of the five questions of the personality test.

- Low: *"Mary has a sharp tongue and cuts others to pieces. She suspects hidden motives in people. She holds grudges and gets back at others. She insults and contradicts people, believing she is better than them. She makes demands on others, and is out for her own personal gain. Mary tends to be calm and quite likes exploring new ideas."*
- High: *"Charlie has a good word for everyone, believing that they have good intentions. He respects others and accepts people as they are. He makes people feel at ease. He is concerned about others, and trusts what they say. He sympathizes with others' feelings, and treats everyone equally. He is easy to satisfy. Charlie tends to be quite anxious."*

• **Conscientiousness**

- Low: *"Oliver procrastinates and wastes his time. He finds it difficult to get down to work. He does just enough work to get by and often doesn't see things through, leaving them unfinished. He shirks his duties and messes things up. He doesn't put his mind on the task at hand and needs a push to get started. Oliver tends to enjoy talking with people."*
- High: *"Jennifer is always prepared. She gets tasks done right away, paying attention to detail. She makes plans and sticks to them and carries them out. She completes tasks successfully, doing things according to a plan. She is exacting in*

his work; she finishes what she starts. Jennifer is quite a nice person, tends to enjoy talking with people, and quite likes exploring new ideas."

- **Neuroticism**
  - Low: *"Susan often feels sad, and dislikes the way she is. She is often down in the dumps and suffers from frequent mood swings. She is often filled with doubts about things and is easily threatened. She gets stressed out easily, fearing the worst. She panics easily and worries about things. Susan is quite a nice person who tends to enjoy talking to people and tends to do her work."*
  - High: *"Helen seldom feels sad and is comfortable with herself. She rarely gets irritated, is not easily bothered by things and she is relaxed most of the time. She is not easily frustrated and seldom gets angry with herself. She remains calm under pressure and rarely loses her composure."*
- **Extraversion**
  - Low: *"David has little to say to others, preferring to stay in the background. He would describe his life experiences as somewhat dull. He doesn't like drawing attention to himself, and doesn't talk a lot. He avoids contact with others and is hard to get to know. He retreats from others, finding it difficult to approach them. He keeps people at a distance. David is quite a nice person."*
  - High: *"Alexander feels comfortable around people and makes friends easily. He is skilled in handling social situations, and is the life and soul of the party. He knows how to start conversations and easily captivates his audience. He warms up quickly to others, and likes talking to a lot of different people at parties. He doesn't mind being the centre of attention and cheers people up."*
- **Openess to Experience**
  - Low: *"Steven is not interested in abstract ideas, as he has difficulty understanding them. He does not like art, and dislikes going to art galleries. He avoids philosophical discussions. He tends to vote for conservative political candidates. He does not like poetry and rarely looks for a deeper meaning in things. He believes that too much tax money goes to supporting artists. He is not interested in theoretical discussions. Steven is quite a nice person, and tends to enjoy talking with people."*

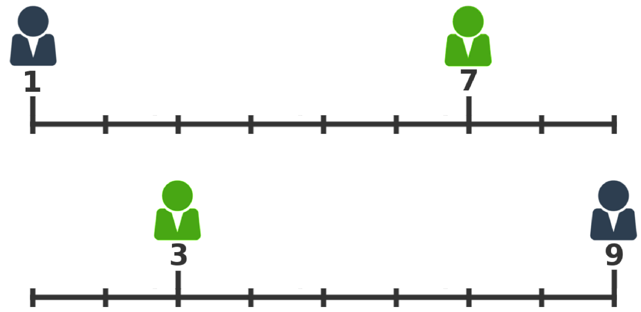


Fig. 5.14 Initial preferences for the participant (in green) and for the other person (in blue) for large initial difference configuration.

– High: *"Claire believes in the importance of art and has a vivid imagination. She tends to vote for liberal political candidates. She enjoys hearing new ideas and thinking about things. She enjoys wild flights of fantasy, getting excited by new ideas."*

At the end of the personality test a value for each trait between 18 and 162 is determined. These values are stored in an anonymous database.

Setting of Initial Evaluations

As in the previous experiment, in order to analyze different interesting scenarios, we set the initial evaluations to cover different situations. These initial ratings obviously influence the answers since they impose constraints on the possible variations, and have to be considerate in the analysis of the results. Firstly, we are interested in the analysis of participant's behaviour for different initial differences, distinguish between *Large* and *Small* initial differences, and even between *Positive* and *Negative* differences, as in the precedent test.

Focusing on the large initial difference, since we use a rating scale between 1 and 9, we can notice that such configurations give more chances to positive shifting, while negative shifting are very limited because the initial participant's rating is very near the boundaries of the scale. Anyway, we decided to set two configurations with large difference, one positive and one negative, giving some possibility of negative influence by setting participant's initial rating to value not too close to the boundaries, as showed in figure 5.14.

Regarding small initial differences, we have an initial agreement between people. Here, we have a very small possibility for positive shifting, since the initial ratings are very similar, with a difference of one value. In this case, we decide to set three possible scenario, since the agreement could be on low, intermediate or high values. To map this three configurations

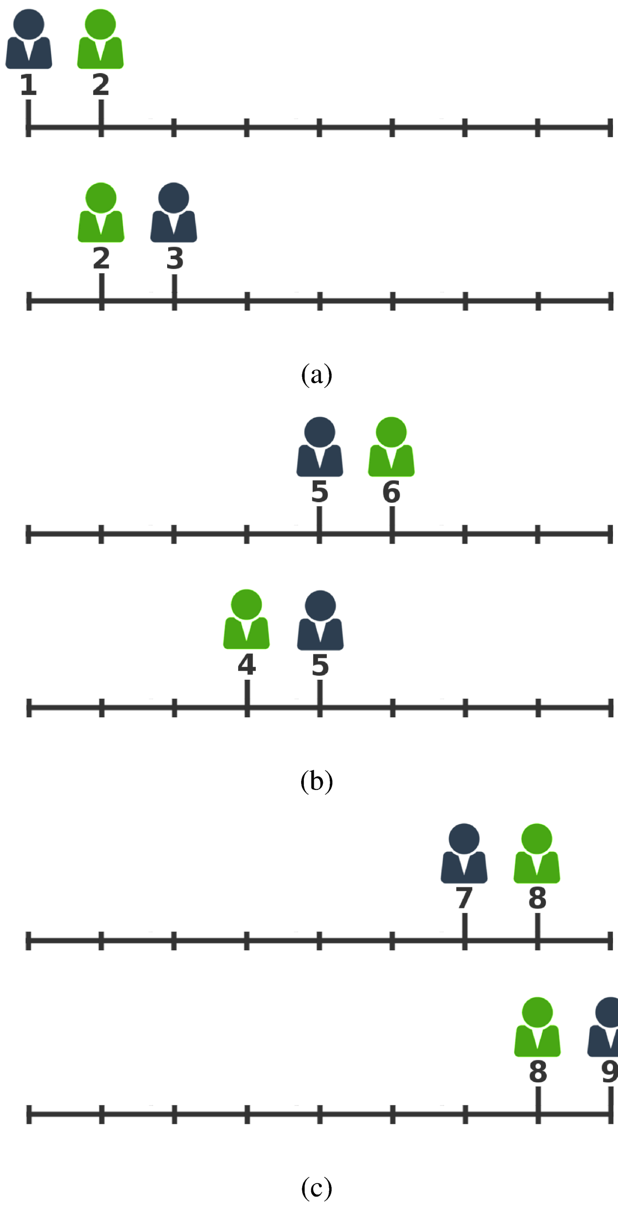


Fig. 5.15 Initial preferences for the participant (in green) and for the other person (in blue) for small initial difference configuration, with agreement on low (a), intermediate (b) and high (c) values.

and even have the same number of positive and negative initial difference, we use six configurations as showed in figure 5.15.

Age Range	Number of Participants
16-25	19
26-40	56
41-65	40
Over 65	5

Table 5.6 Demographic data of the 120 participants, 57 female and 62 male (1 person preferred not to give this information).

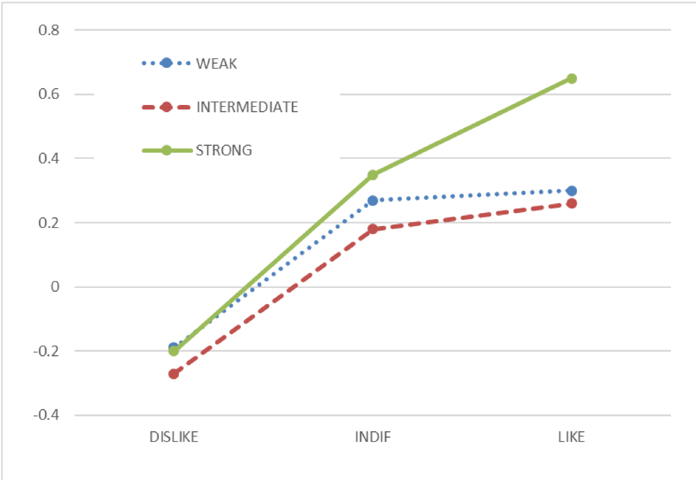


Fig. 5.16 Interaction graph of the ties strength over conflict.

5.2.2 First Analysis: Validation of Previous Results

Since the setting of the experiment is very close to the previous one, except for the personality evaluation, we can perform an analysis similar to that we perform for the first experiment, in way to validate the results evidenced. Hence, we first present such analysis.

We recruit 120 participants, obtaining 360 answers. We collected more than 2,880 evaluations, since each answer contains 8 evaluations. Also, in this case, the participants were recruited through Amazon Mechanical Turk and paid $ 0.50 for the participation in the test. In Table 5.6, we report the statistical data on the participants on the study. Again, we evaluate the opinion shift by computing the variation between the new evaluations for the activities given by the participants in the test and the old evaluations, which had been shown to them at the start of the study, considering as a positive shifting a change towards the rating of the second person, whom we asked them to imagine with determinate constraints on the relationship existing between them. A negative shift is in the opposite case (e.g., the rating variation value will have the negative sign).

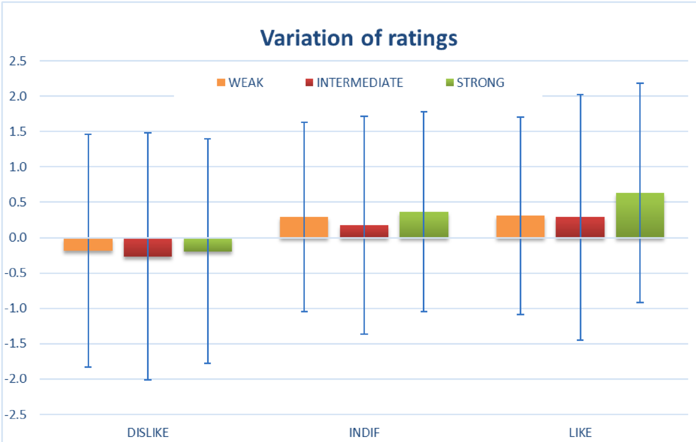


Fig. 5.17 Average values for the ratings variation.

As first analysis we perform a two-way ANOVA. Here, the ties strength and conflicts are the fixed factors and the rating variations is the dependent variable. Results are shown in Table 5.7. The interaction term is represented by the *conflict * ties* row in the table. Even in this case, results show significant effects of tie strength and conflicts. However, differently from previous test, the interaction effect between ties strength and conflict seems not significant, with$p = 0.341$. Even the interaction graph in figure in Figure 5.5 seems to confirm this, since the lines do not intersect, although they are not parallel. Hence, in this case, we should have an ordinal interaction.

Source	Sum Sq.	d.f.	Mean Sq.	F	p-value
conflict	209.03	2	104.515	43.124	0.000
tie	20.33	2	10.165	4.194	0.015
conflict * tie	10.951	4	2.738	1.13	0.341

Table 5.7 Table of ANOVA2 analysis.

Figure 5.17 shows the general trends of shifting, illustrating the average values and standard deviations of the rating variations with respect to the different parameters that we impose into the experiment. The *ANOVA* test returned a $p = 0.054$, that indicates that obtained results are quite close to be significant. We can see a trend similar to that showed in the previous test. Here, we can notice a negative shift in the case of conflicting relationships, and, as in the previous case, a more negative shift for the intermediate and indifferent relationships, with respect to the weak.

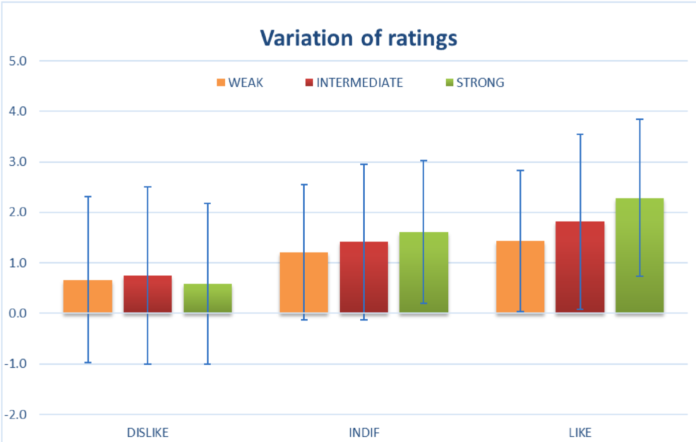


Fig. 5.18 Average values for the rating variations considering only the cases with a large initial difference between participant's ratings and other person's ratings.

Opinion Shift vs. Small/Large Differences in the Initial Ratings

Before analyzing the results grouped with respect to the size of the difference between the initial ratings, we recall that in the configurations of this experiment we have more cases for the small difference and less for the configuration with a large initial difference. Hence, there are 75% of cases where the individuals are in a sort of initial agreement, and another 25% where the initial situation is a complete disagreement. Therefore, we are interested in analyzing the behaviors in these two situations. It is our idea that this difference can provide most information since in this case we can cover more situation of agreement and have a better result.

Figure 5.18 shows the situation in case of large initial differences. The scenario is very similar to that in the previous test, with a general Positive shifting, stronger in the good relationships, but also present in the conflict ones. As in previous test, when the ties strength increases and becomes stronger, there is a general increase in the average Positive influence. We performed an *ANOVA* test to ensure the significance of the data returning a $p = 0.053$, as in the general case. Hence, we can confirm that in the case of a large initial difference in the ratings, there is always a propensity to concede towards the others that whose magnitude depends on the considered factors.

In the figure 5.19 the trends for the configurations with a small initial difference between evaluations are showed. We can see that there are not shifting in peacefully relationship and, instead, a negative shifting in conflictual situations. Furthermore, all the configurations with intermediate tie strength. The *ANOVA* test return a $p = 0.004$, hence the data are significant. These results are complying with the results of the previous test, even if there is some difference because there is a general absence of positive shifting. This could depend on

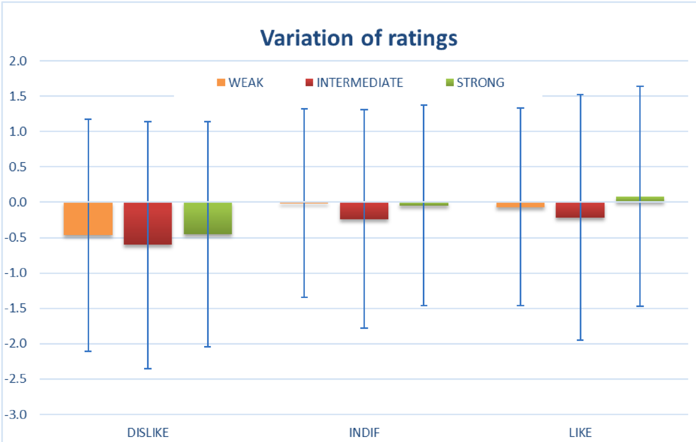


Fig. 5.19 Average values for the rating variations considering only the cases with small initial difference between participant's ratings and other person's ratings.

our choices for the initial evaluations that permit to better describe the small initial difference scenario. It is confirmed that for many participants, starting from an agreement situation, shifts their evaluations in opposite direction with respect to the other person's evaluations, only because of the conflict, and that the negative influence has more effect in the case of the user and the disliked person having the same initial ideas on rating.

Opinion Shift vs. Positive/Negative Initial Difference

We continue analyzing the trends in relation to the direction of the initial difference between the individual's ratings and those of the other person. In this case, the experiment settings was designed to have 50% of cases with positive initial differences and another 50% where the initial differences were negative.

Figure 5.20 shows the averages values for negative initial differences. Differently from the previous test, we can notice a negative shifting for conflicting situations, while a general positive shifting trend is in the other cases. *ANOVA* test return a $p - value = 0.010$, hence difference are significant.

In Figure 5.21, the trends for the case in which there are positive initial differences are shown. In this case, the initial individual's ratings are lower than those of the other person. In this case, the trends are similar to that of the previous test, with low negative shifting in the case of conflicting situations and positive shifting in the others. In this case, the ANOVA test returned a $p = 0.479$, hence difference are not significant. However, as we see in the Figure 5.20, the general trends of tie strength and status are similar to the case of negative initial difference.

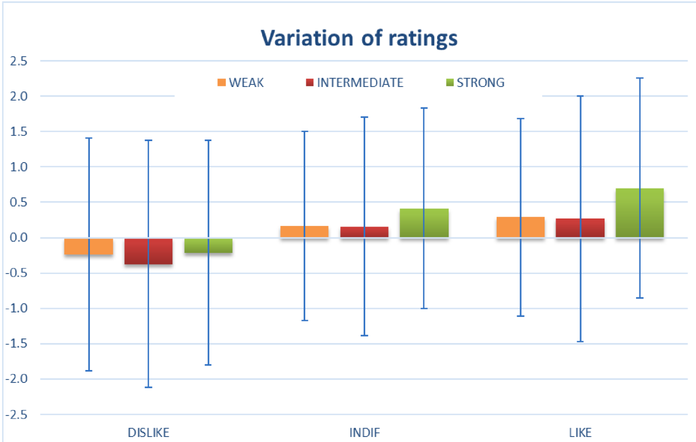


Fig. 5.20 Average values for the rating variations considering only questions with negative initial differences between participant's ratings and other person's ratings.

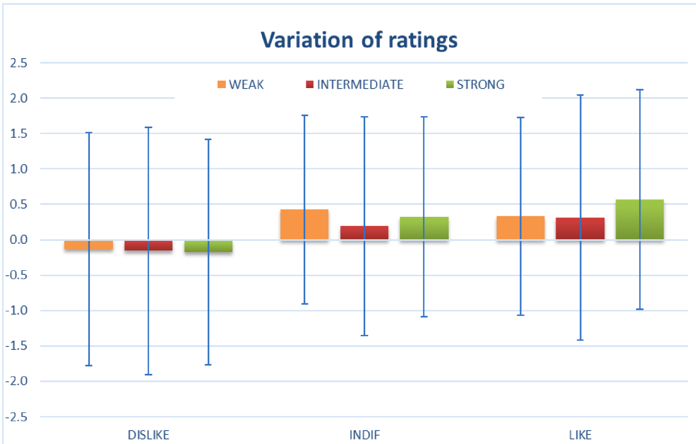


Fig. 5.21 Average values for the rating variations considering only questions with positive initial differences between participant's ratings and other person's ratings.

Correlation Analysis

These results confirm a general impact of the tie strength and the conflict, hence, we continue analyzing the correlations between the new, the old and the other evaluations. The new evaluations are considered dependent factor, while the old and the other are considered independent factors. We compute the Pearson correlation between the shift, computed as defined in equation 5.1, and the initial difference, computed as in the equation 5.2, obtaining a value of 0.381, with a $p-value < 0.001$, that indicates a statistically significant general positive correlation. We even analyze the correlations splitting the data in relation to the different configurations of tie strength and conflicts in the relationship. The results are summarized in table 5.8 and even reported in figure 5.22.

Tie Strength	Conflict	F	p-value	
Weak	Dislike	0.192	0.001	**
Weak	Indif	0.428	0.000	**
Weak	Like	0.474	0.000	**
Interm	Dislike	0.189	0.001	**
Interm	Indif	0.416	0.000	**
Interm	Like	0.475	0.000	**
Strong	Dislike	0.161	0.004	**
Strong	Indif	0.521	0.000	**
Strong	Like	0.660	0.000	**

Table 5.8 Pearson Correlation between the shift, computed as defined in equation 5.1, and the initial difference, defined in the equation 5.2.

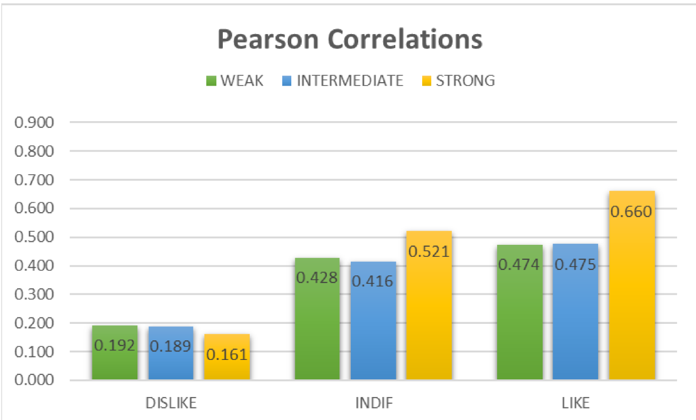


Fig. 5.22 Pearson Correlation between the shift, computed as defined in equation 5.1, and the initial difference, defined in the equation 5.2.

We can see that the correlations are statistically significant for all the cases, with correlations that increase when the tie strength became higher. The same thing happen when the status of the relationship became more peaceful. Hence, this confirm that the initial difference can be used as a predictor for the shift, and this result is the same of the previous experiment.

Then, an evaluation of the correlation between the initial evaluation old and the new evaluation new is performed. In this case, we have a general positive correlation, with an F value of 0.722, and a $p-value < 0.001$ that confirm a statistical significance. Once again, we perform an analysis of correlations in the different cases of tie strength and status of the relationship. The results are reported in table 5.9 and in figure 5.23.

We have a $p-value < 0.001$ in all the cases, that indicate a statistical significance of all the correlations. In general, we have positive correlations, with very small variations

Tie Strength	Conflict	F	p-value	
Weak	Dislike	0.684	0.000	**
Weak	Indif	0.815	0.000	**
Weak	Like	0.774	0.000	**
Interm	Dislike	0.643	0.000	**
Interm	Indif	0.719	0.000	**
Interm	Like	0.675	0.000	**
Strong	Dislike	0.675	0.000	**
Strong	Indif	0.721	0.000	**
Strong	Like	0.771	0.000	**

Table 5.9 Pearson Correlation between the new evaluation and the old evaluation.

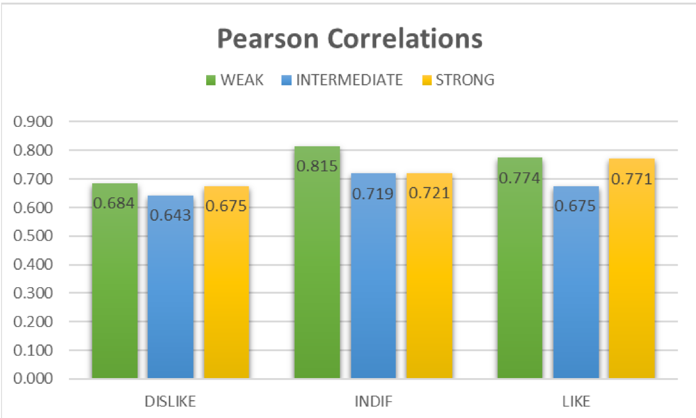


Fig. 5.23 Pearson Correlation between the new evaluation and the old evaluation.

between the different cases. Differently from the previous test, where a decreasing trend in correlations were showed. Here, we interpret this result as a consequence of the larger amount of small initial difference cases, where there are lower shifting. However, as expected, the results confirm that we can use the old evaluation as predictor for the new, as obtained for the previous test.

Multiple Regression Analysis

The Multiple Regression Analysis is performed to predict new evaluation using the old and the other evaluations as predictors. The regression line will have the form specified in equation 5.3. In the general case, the variables statistically significantly predicted the new evaluation, with a value $F(2,4489.950) = 1784.026$ and a $p - value < 0.0001$. The statistics $R^2 = 0.554$ indicates a good explanation of the dependent variable, better than in

Tie Strength	Conflict	α	β_1	β_2	R^2	Sig.	
Weak	Dislike	1.294 **	0.692 **	0.024	0.469	0.000	**
Weak	Indif	0.340	0.741 **	0.170 **	0.704	0.000	**
Weak	Like	0.671 **	0.671 **	0.199 **	0.655	0.000	**
Interm	Dislike	1.555 **	0.644 **	0.006	0.413	0.000	**
Interm	Indif	1.058 **	0.613 **	0.157 **	0.555	0.000	**
Interm	Like	1.097 **	0.557 **	0.212 **	0.522	0.000	**
Strong	Dislike	1.156 **	0.733 **	0.008	0.520	0.000	**
Strong	Indif	0.667 **	0.655 **	0.228	0.669	0.000	**
Strong	Like	0.578 **	0.546 **	0.349 **	0.675	0.000	**

Table 5.10 Results of the Multiple Regression Analysis for the different configurations of Tie Stregth and Conflict. The regression coefficients are intended for a regression line of the form specified in equation 5.3.

the previous experiment. Both the considered variables added statistically significantly to the prediction, with $p < 0.0001$, and the general form of the equation is:

$$U^{new}(a_i, \omega_j) = 0.935 + 0.650 * U(a_i, \omega_j) + 0.150 * U(a_k, \omega_j) \tag{5.5}$$

As we can see, the parameters are very close to that of the previous experiment, confirming that the old evaluation factor has the biggest impact on the new evaluation in the general case. However, we perform a deeper analysis for the different configurations of tie strength and status of the relationship. Results are reported in table 5.10.

As in the previous test, all the models have a statistical significance (with a $p-value < 0.0001$). In average, we have a good explanation of the dependent variable, as by the R^2 values. Analyzing the coefficient, we can notice that the impact of the old evaluation factor is higher in almost all the cases, while in the rows with an intermediate or peaceful status we have an increasing impact of the other evaluation factor.

5.2.3 Exploring Personality Traits Influence

Finally, we perform an analysis to explore the relations between personality traits and Emotional Contagion. The Big Five Personality traits have been divided into two categories (Low and High). Hence, we want to analyze if there are any difference in the behaviour of the subject in relation to low and high level of the traits. We start reporting the number of participants for each level of each trait of personality 5.11.

As we can see, while some of the traits is well balanced, there are traits, like the Agreeableness and the Conscentiousness, with a great imbalance towards the high level.

Trait	Low	High
Neuroticism	46	74
Extraversion	66	54
Openness to Experience	26	94
Agreeableness	18	102
Conscentiousness	19	101

Table 5.11 Number of participants for each level of each trait of personality.

Here, we have to report some consideration. This scenario should indicate that the great part of our participant are highly conscentious and with a great agreeableness. Hence, we can speculate that the population of workers on Amazon Mechanical Turk (AMT) mainly is composed of such subjects. Another possible explanation is that by accident we selected only this kind of personalities. A third hypothesis, that is the most likely in our view, is that, even if the participation in this test on the AMT platform is totally anonymous, people do not want to appear as egoistic or, in general, as bad people. This aspect must be highlighted and more deeply analyzed because it could have an implication on the studies conducted through the platform. However, we start analyzing the average values of the shifting for the different levels of each trait. Such difference are showed in table 5.12.

	Low	High	Sig.	
Neuroticism	0.170 ± 1.407	0.140 ± 1.771	0.601	
Extraversion	0.080 ± 1.801	0.170 ± 1.539	0.241	
Openness to Experience	0.310 ± 1.490	0.130 ± 1.597	0.025	*
Agreeableness	0.190 ± 1.627	0.140 ± 1.553	0.470	
Conscentiousness	0.040 ± 1.767	0.190 ± 1.525	0.030	*

Table 5.12 Average values of the shift in relation to the different level of each of the Big Five personality traits.

As we can see, only few data are statistically significant, according to the "Sig." column reporting the p-values. However, there is not any level characterized by a negative average shifting. When the Openess to Experience increases then the shift tends to decrease. On the contrary, when the Conscentiousness decreases, we have a decreasing shifting that become very close to zero. These relations are in line with the results in the Psychological field. Furthermore, the average values seem to indicate a positive relation between Extraversion and shifting.

We also perform a Pearson Correlation analysis between each trait and the shift. As we can see in table 5.13, such correlations are quite near zero. In our opinion this result could depend by the impact on the shift of the other factors, that are not included in this analysis.

	Pearson	Sig.	
Neuroticism	-0.066	0.000	**
Extraversion	-0.023	0.221	
Openness to Experience	-0.039	0.034	*
Agreeableness	0.010	0.603	
Conscentiousness	-0.068	0.000	**

Table 5.13 My caption

Source	Sum Sq.	d.f.	Mean Sq.	F	p-value	
Cons	34.630	1	104.515	14.232	0.000	**
Cons * Extr	13.239	1	10.165	5.441	0.020	*
Cons * Agre	10.534	1	10.534	4.329	0.038	**
Cons * Neur	38.281	1	38.281	15.733	0.000	**
Neur * Open	20.379	1	20.379	8.375	0.004	**
Cons * Extr * Agre	28.240	1	28.240	11.600	0.001	**
Extr * Agre * Neur	40.865	1	40.865	16.794	0.000	**
Cons * Agre * Neur	20.505	1	20.505	8.427	0.004	**

Table 5.14 Table of ANOVA analysis.

We have seen in the previous sections that the tie strength and the conflict have a big impact on the phenomenon. Furthermore, we should consider the possibility that the phenomenon is not directly related to each trait, but it is related to an interaction between two or more traits. To analyze such aspect an ANOVA analysis has been performed, and the significant interactions are reported in table 5.14.

The analysis presents a significant effect of the Conscentiousness trait over the shift, but even many significant interactions. The Conscentiousness interacts with the Extraversion, the Agreeableness and Neuroticism, that has even an interaction with the Openness. Furthermore, we have interactions between 3 traits, in particular, the first one is between Conscentiousness, Extraversion and Agreeableness, the second one between Extraversion, Agreeableness and Neuroticism and the last one between Conscentiousness, Agreeableness and Neuroticism. Hence these interactions should be considered in the design of the general model in future experiments.

Finally, we performed a multiple regression analysis dividing the dataset into two sets for each trait, according to the level Low or High, with respect to the regression line defined in 5.3. Hence, we want to analyze if there are any difference between the two levels of each trait in the impact, as predictors of the new evaluation, of the old evaluation and even of the other evaluation. The table 5.15 report such results.

Factor	Level	α	β_1	β_2	R^2	Sig.	
Extraversion	Low	0.761 **	0.701 **	0.137 **	0.635	0.000	**
	High	1.148 **	0.587 **	0.166 **	0.465	0.000	**
Agreeableness	Low	1.492 **	0.535 **	0.145 **	0.646	0.000	**
	High	0.837 **	0.670 **	0.151 **	0.761	0.000	**
Conscentiousness	Low	0.663 **	0.651 **	0.208 **	0.616	0.000	**
	High	0.986 **	0.650 **	0.139 **	0.543	0.000	**
Neuroticism	Low	1.074 **	0.616 **	0.158 **	0.524	0.000	**
	High	0.849 **	0.671 **	0.145 **	0.572	0.000	**
Openness to Experience	Low	1.363 **	0.597 **	0.114 **	0.455	0.000	**
	High	0.817 **	0.664 **	0.160 **	0.583	0.000	**

Table 5.15 Results of the Multiple Regression Analysis grouped for Low and High levels of the Big 5 personality traits. The regression coefficients are intended for a regression line of the form specified in equation 5.3.

We can see that all the models have a statistical significance (with a $p-value < 0.0001$) with a good explanation of the dependent variable, as by the R^2 values. Regarding the Extraversion factor, we can see that when the trait is High we have an increase of the β_2 parameter, while the β_1 decrease. Hence, the importance of the other evaluation become more strong when the Extraversion increases. A different situation is showed by the Agreeableness, where we have a decreasing of the β_2 factor, even if the β_1 even decrease. Here, we suppose that the analysis is too influenced by the limited number of individuals with Low Agreeableness, that determines a difficulty in rightly represent the trait. The same thing happens for the Conscentiousness factor, where the coefficients do not substantially change. Regarding the Neuroticism trait, we have a small increasing in the β_1, while the β_2 coefficient decrease.

5.2.4 Discussion

The analysis of this second experiment confirm, in general, the results of the first test, showing an impact of tie strength on positive influence, and an impact of conflict on negative influence. Results even confirm a difference in the opinion shift analyzing the results in relation to the initial difference between an individual's ratings and others' ratings, showing a positive shift in case of initial disagreement, and, on the contrary, negative shift for conflicting ties if we start with an agreement. Besides, the analysis of the variations in relation to the direction of the initial difference between ratings do not show great differences, hence the higher inclination to shift positively when the individual starts from a higher evaluation seems not confirmed.

However, the correlation and multiple regression analysis confirm that the old and the other person's evaluation can be used as predictor of the new evaluation. Furthermore, we derive that is it possible to define a variation of the *Interdepentent Preferences* model using different parameters in relation to the tie strength, the status of the relation and the users' personality.

5.3 Conclusion

In this chapter, two experimental study have been analyzed, with the aim to analyze the Emotional Contagion phenomenon and the impact of the tie strength and of the status, peaceful or conflicting, of the relation between them. Hence, we explored the impact of the personality profile of the users, trying to underline if the big five personality traits related to prosocial and antisocial behaviours are even related to positive and negative shifting of individual utilities.

From the analysis carried out in the first experiment, we can conclude that ties strength and conflicts are important factors to determine how opinions shift when people know the evaluations of other people which whom they must perform some activities, and these results can be used in the definition of a general model for the adaptation of users' satisfaction to group context. Furthermore, we derive that such factors can be used to apply different model for each configuration depending from the old evaluation of the individuals and the others. The second user study confirm such results, highlighting that the configurations with indifferent status and intermediate tie strength should be deeper analyzed.

Furthermore, the second study shows a positive relation between Extraversion and positive shifting and even confirm a positive relation between Neuroticism and negative shifting. Unfortunately, the little number of participants with Low levels of Agreeableness and Conscentiousness does not permit fully analyze this phenomenon, and some future experiments will be required in way to derive the ORP models to be used for the framework.

Chapter 6

Evaluation of the Aggregation Strategies

In this chapter the aggregation strategies introduced in section 4.2 is presented, in way to determine if the proposed approaches can provide an increasing in the performance of a GRS. Firstly, we analyze the two weighted social choice functions, performing two user study in a touristic domain. Here, we compare the performances of our algorithm with respect to two basic strategies used as baseline even asking to the users to evaluate the recommendations provided by the system. Then, we evaluate the negotiation approach based on the conflict resolution styles in terms of the accepted recommendations generated.

6.1 Evaluation of the two Weighted Social Choice Functions

In section 4.2.1 two weighted social choice functions have been defined, that use a dominance ranking between the group's members as weight in the aggregation process. Here, an evaluation of the approaches is presented. To evaluate the proposed functions, we had to address the problem that, as seen in section 2.4 there is no dataset that can be used for the evaluation. In fact, our strategies would require a dataset containing information about users interactions on a social network, information on the preferences of individual users, and information on the final choices of the groups, in order to apply the proposed techniques and compare the obtained results. A dataset like this does not exist, so we decided to conduce two pilot studies with real users. We decide to focus on travel domain, involving the participants in the task of planning a trip in a city. In the first study, the aim is to evaluate the benefits of the introduction of the dominance values as weights in the proposed functions. In the second one, we focus on the users' satisfaction with respect to the recommendations proposed by the system.

6.1.1 A User Study With Binary Decisions

In the first case study, we evaluated the behavior of 14 groups composed, in the average, of 3.36 close friends. 46 users took part in the experimentation (26 men and 20 women). The average age was 27.3 with a graduate education. Regarding the estimation of individual utilities, to avoid that some wrong estimation given by an individual RS can negatively influence the performance of the aggregation functions, we decide to ask an evaluation of the item directly to the users. In this way we have a more accurate result, but we have to restrict the number of items in the system, in order to require a small amount of time for the evaluation by the participant in the test. In this first test, such evaluations are simple choice on a set of item. Since we decide to focus on the travel domain, the items of the system are activities to perform and restaurants in a city. The task required is the planning of a one-day visit.

Description of the Experiment

At the beginning, each user was asked to register on a specific web site using the credentials of *facebook.com*. Once registered, they were asked to imagine to plan a one-day visit in a specific city and to select three activities (from a checklist of ten items) and two restaurants (from a check list of eight) for the day. Since, in this first test, we do not want the users to be involved in strategic reasoning, we did not ask the users to express numerical ratings for the selected choices in this first setting. Hence, we will assign $U(a_i, \omega_x) = 1$ if the user a_i selects the item ω_x and $U(a_i, \omega_x) = 0$ otherwise. A screen-shot of the interface used to select the activities to perform is shown in Figure 6.1. In a second phase, the group was asked to discuss face-to-face, in order to obtain a shared and unique decision for the group. This final decision corresponds to the set $\succ_{GT}$ used to evaluate our functions.

Result Analysis

In order to evaluate our results, we apply our aggregation strategies and compare the results with the real choices of the group. Regarding the fairness strategy, we adapted it to binary selections. Since a single vote is associated with each item (0 or 1), at each iteration a user (selected according to his/her dominance value in a descending order) proposes its first K choices (with $K = 3$). For each of the K proposals the votes made by the other users are summed, and the choice with the higher sum is selected. Note that if K is equal to the number of possible outcomes (as in this case), an activity, selected by all the member of the group, will be selected in the final decision. Finally, in order to evaluate the impact of the users'

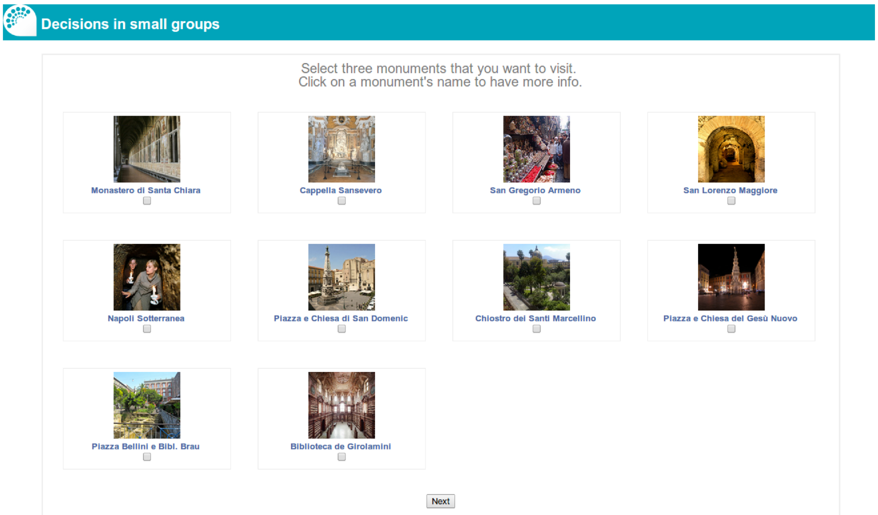


Fig. 6.1 A screen-shot of the web page used to select the activities to perform.

dominance, we also implemented a standard fairness version with a random users ordering ($U_G^{st.fair}$).

Regarding, instead, the second strategy, with binary choices the evaluation of dissimilarity does not have a relevant impact on the final decision. Hence, the weights associated to Eq. 4.3 are $\alpha = 1$ and $\beta = 0$. As in the previous case, we also implemented the standard version of a simple averaging function ($U_G^{st.avg}$).

We evaluated the similarity of the recommendation provided using the weighted version of our functions and the corresponding standard implementations with respect to the group's ground truth. The final choice of the used approaches are denoted as: $\succ_{fair}$ for our fairness function; $\succ_{avg}$ for our average satisfaction function; $\succ_{st.fair}$ for the standard fairness; $\succ_{st.avg}$ for the standard average satisfaction. The groups' ground truth is referred as $\succ_{GT}$.

Similarity %	$\succ_{st.fair}$	$\succ_{fair}$	$\succ_{st.avg}$	$\succ_{avg}$
$\succ_{GT}$	61 ± 20	66 ± 18	64 ± 16	74 ± 12

Table 6.1 Rate of similairty for $\succ_{st.fair}$, $\succ_{fair}$, $\succ_{st.avg}$ and $\succ_{avg}$ with respect to $\succ_{GT}$.

Aggregated results are reported in Table 6.1. With respect to their standard implementations, functions that take into account social relationships perform slightly better (66% w.r.t 61% for fairness, and 74% w.r.t. 64% for average). A bigger improvement was noted for the weighted average strategy that, on the average, performs better than the weighted fairness strategy, often guessing 4 on 5 activities. In many cases the responses of both strategies were the same, and there is only one case in which the fairness strategy performs better than the average. Fairness strategy, in this simple binary case, with no information about rankings, suffers more of random choices made by the function in the case of activities with the same final score.

6.1.2 A User Study with Rankings

In this second case study, we evaluated the behavior of 17 new groups of friends composed, in the average, of 3.1 people. 53 users took part in the experimentation (26 men and 27 women). The average age was 26.8 with a graduate education. Differently from previous case, we asked the real users to give an estimation of the utilities necessary to our approaches, providing an explicit rating for each item. Also in this case, the items are in a touristic domain. The overall process is detailed in the next section.

Description of the Experiment

This experiment was divided into two phases. In the first, as in the previous user study, each person was asked to register on a specific web site using the credentials of *facebook.com*. Once registered, he/she was asked to imagine planning a one-day visit in a specific city, but this time also to provide ratings (from one to five stars) to the ten proposed activities for the day and to the eight restaurants. Each rate corresponds to how likely it would be for the user to visit such place (or to eat in). The interface for the rating process is shown in Figure 6.2. For each activity/restaurant, a picture and a short description was provided to the users, plus a link to *tripadvisor.com* that provides additional information and a way to evaluate the popularity of the item. Once that all the member of a group completed this first phase, we separately invited each member to login again and to complete the process by evaluating the proposed recommendations. Since the first phase was more time-consuming with respect to the previous user study, in the second phase users were only asked to evaluate the proposed results.

In the fairness strategy the users were selected according to their dominance values in a descending order, with $K = 3$. On the contrary, regarding the average strategy, the weights associated to Equation 4.3 were $\alpha = 0.8$ and $\beta = 0.2$ as suggested in [38].

Users were presented with both the recommendation provided by using the two functions (as in the previous case the top five activities were recommended). Moreover, the associated ratings for the proposed activities provided by all the members of the group in the first phase were shown. A screenshot of this interface is shown in Figure 6.3.

Finally, each user was requested to answer the following questions:

1. Which of the two proposed itineraries do you prefer? [None/First/Second/Both]

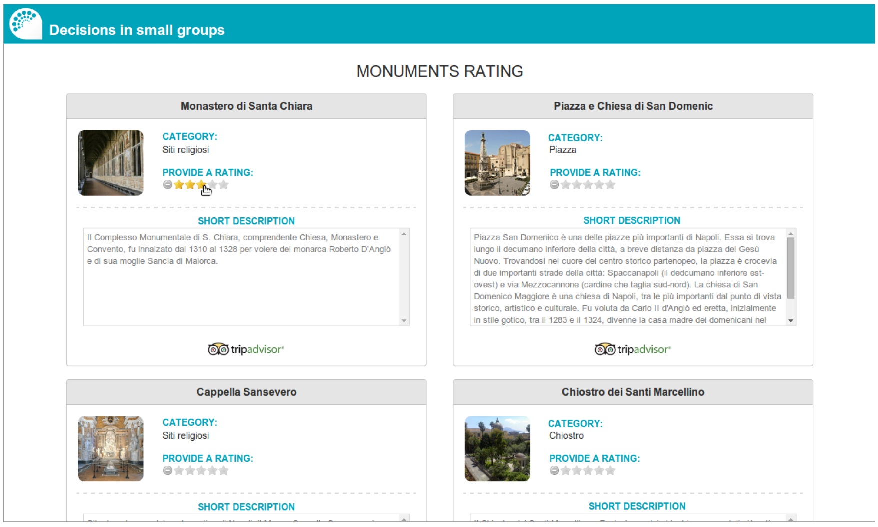


Fig. 6.2 The rating page where participants were asked to rate activities.

2. How do you rate the first itinerary? [1 to 5]
3. How do you rate the second itinerary? [1 to 5]
4. How much have you been influenced in the evaluations by the knowledge of your friends' ratings? [1 to 5]

Result Analysis

Accept. %	$\succ_{fair}$	$\succ_{avg}$	$\succ_{fair} + \succ_{avg}$
average	66 ± 32	62 ± 30	81 ± 20

Table 6.2 Acceptance rate for the $\succ_{fair}$, $\succ_{avg}$ and globally $\succ_{fair} + \succ_{avg}$.

Users' rates	$\succ_{fair}$	$\succ_{avg}$	$friends$
average	4.3 ± 0.6	4.2 ± 0.5	2.6 ± 0.6

Table 6.3 Average ratings for the $\succ_{fair}$, $\succ_{avg}$ and for the evaluation of the friends' influence.

In the average, the two used strategies differ one from the other for two choices, with some cases in which they provided the same results. In Table 6.2, we reported the acceptance rate mean percentage. In the average, two out of three members of each group accepted the proposed solution evaluated by the fairness strategy, while for the average strategy the value is a little bit smaller. Considering both the proposed options the system had an acceptance rate of 81%. Moreover, considering directly all the users involved in the test, and not averaging

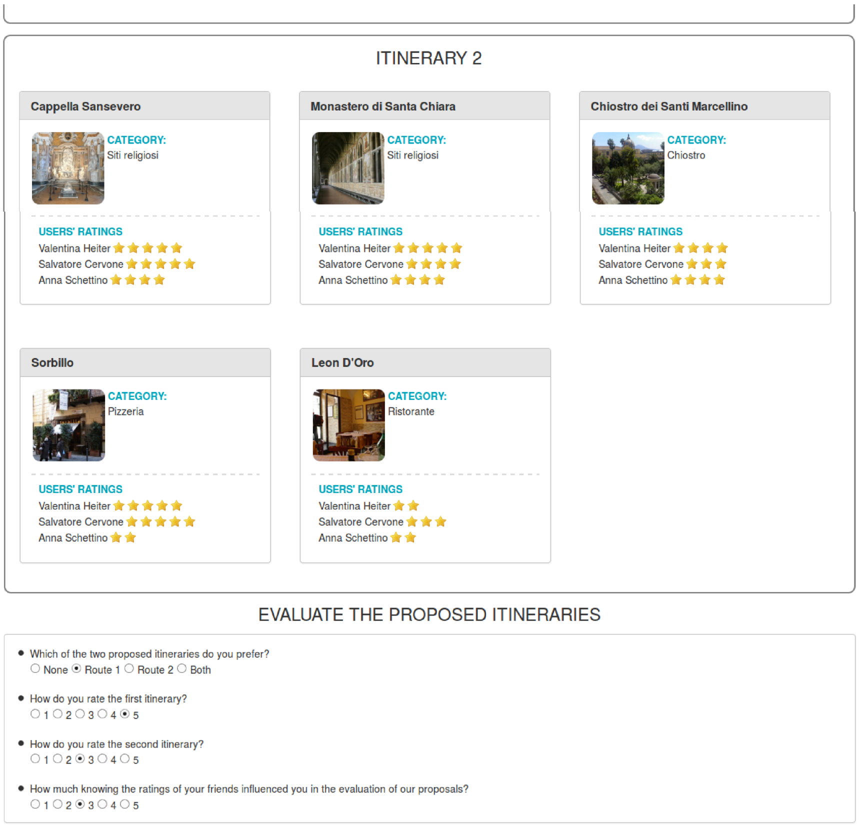


Fig. 6.3 Web interface for accepting/rejecting results.

on groups, 49 people out of 53 (i.e., 93% of the users) accepted at least one of the proposed itinerary.

In Table 6.3, we reported the mean values for the users' ratings of the $\succ_{fair}$ proposed itinerary (i.e., question number 2), and $\succ_{avg}$ proposed itinerary (i.e., question number 3). Both the proposed results got, on average, a good appreciation by the users (more than 4 stars). Moreover, we evaluated the Pearson correlation index ρ between such ratings and the acceptance rates of the proposed strategies. As we expected, there is a strong correlation between the acceptance rate of the proposed strategies and their evaluations made by the users. The obtained value for $\succ_{fair}$ is $\rho = 0.67$ (with a significance $p = 0.003$), while for $\succ_{avg}$ is $\rho = 0.77$ (with $p = 0.0003$).

Surprisingly, the average evaluation of the impact of the friends' opinions on the evaluation of results ($friends$ in Table 6.3) is 2.6. We imagine that such value is an effect of the testing procedure that ends with a private evaluation of the proposed solutions for the group.

6.1.3 Discussion

From these first analysis we can observe that our dominance weighted functions show encouraging results; in the first user study with binary selections, a bigger improvement was noted for the average satisfaction function, while the fairness seems to suffer more of random choices. On the contrary, in the second one, which involved item ranking, fairness strategy has a bigger acceptance rate and appreciation evaluation. A more deep analysis is necessary, involving greater number of users and possibly items to choice in the pilot studies, to evaluate the scalability of the approach.

6.2 Evaluation of the Negotiation approach based on Conflict Resolution Styles

In this section an evaluation of the negotiation based approach, presented in section 4.2.2, is proposed. In order to evaluate the performances in terms of the accepted recommendations generated, a first preliminary analysis was carried out on simulated data, i.e. assigning random rating values to the items extracted from the social network *Foursquare*. Two types of simulations were carried out in the cases of mediator *complete* and *partial knowledge* of items utilities. Successively, the same experiments were executed in a pilot case study, where a group of real end users were asked to provide real data. Final users interact with a Group Decision Support System based on our negotiation approach. Users are involved only in providing their utilities on items (to obtain reliable data), and in the final decision approval.

We decided not to rely on any recommendation algorithm to estimate individual utilities, but to have the users explicitly expressing them. Whenever a user accesses the system, he/she is able to rate as many items as he/she wants. This allows guaranteeing the quality, the attainability, and accuracy of the system data. A user $a_i \in G$ assigns a value $U_{a_i,\omega_j} \in \{1,2,3,4,5\}$ to an item $\omega \in \Omega$. In principle, in order for the mediator to search for a solution, each group member a_i should evaluate all the items that have been evaluated by the other members, but not by him/herself. This configuration is denoted as *Complete Knowledge*) and allows finding optimal solutions. However, this process would potentially require each user to be involved in a long process to provide all the needed information, so an upper bound to the number of items to be rated can be set, in the *Partial Knowledge* configuration. Subsequently, whenever the mediator requires additional information to proceed, additional ratings could be requested to the users. Of course, in the partial knowledge case, it is not guaranteed to find an optimal solution. If all the allowed negotiation rounds take place without reaching an agreement, the process ends by proposing a solution to the end user that

	Initial Rounds	Intermediate Rounds	Final Rounds
Accomodating	0.08	0.08	0.08
Competiting	0.01	0.025	0.05
Compromising	0.06	0.025	0.06
Collaborative	0.07	0.07	0.07
Avoiding	0.01	0.01	0.01

Table 6.4 Concession strategies and Δ values.

maximize the Social Welfare in the mediator current domain. After using the system, users filled a questionnaire concerning both the goodness of the recommendations provided by the system, and its usability.

Regarding the User Agent Strategy, the used concession values, depending from the conflict resolution style and the phase of the negotiation, are reported in Table 6.4.

6.2.1 Complete Knowledge

First, the performances of the heuristics for the generation of counteroffers, the *Search in Domain* and the *Reference Point*, were evaluated together with the negotiation success rate when the mediator has a *complete knowledge*, i.e. in the case it knows all the rating for all the POI in the dataset. The generated recommendations were evaluated in the different experimental setting by varying the number m of items, from 20 to 1000, the group size g from 3 to 5 members, and the number K of items in the solution from 1 to 5. The size of a group is kept within the chosen range because the focus of the present work is to test decision-making mechanisms for small groups that rely on mechanisms (e.g., interpersonal relationships and mutual influences) that are different with respect to the ones adopted for larger groups [50]. The group size determines the significant number of POI in the solution in the case of simulated experiments. In fact, from a preliminary experimental analysis, we derived that for cases with $K > g$ a solution is always found, so we set $K \leq g$.

Each algorithm is executed 100 times for each possible configuration, and for each execution, the users' behaviors, i.e. their conflict resolution styles, are randomly generated. The maximum number of allowed negotiation rounds was empirically set to 30.

The success rate for the first heuristic is 99%, against 77% of the second one. In Figure 6.4(a), the average number of rounds to reach an agreement is plotted, varying the number of available POI, and discharging the cases of negotiation failures. As shown in Figure 6.4(a), the Reference Point heuristic requires a greater number of rounds to reach an agreement with respect to the Search in Domain case, reaching similar performances when the number

(a) Average number of rounds to reach an agreement.

(b) Average execution time to reach an agreement.

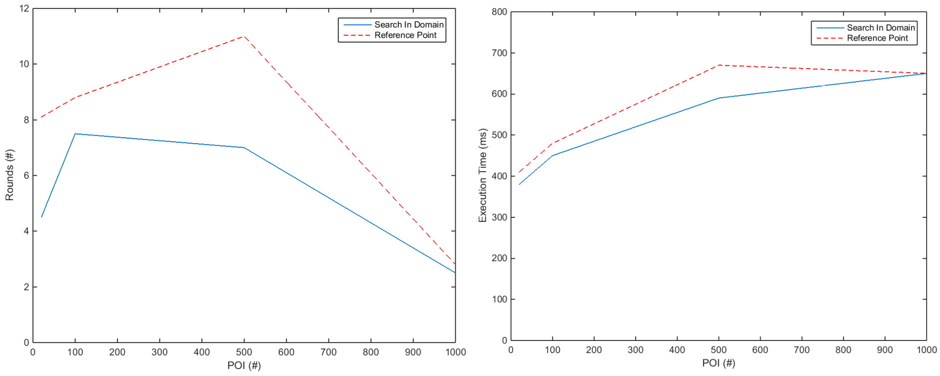


Fig. 6.4 Results in case of complete knowledge.

of items is greater than 1000. Therefore, the Reference Point does not represent a feasible solution for sets of items that vary from 20 to 1000, by making more complicated for user agent to build counteroffers, so leading to failures in the negotiation process.

Moreover, notice that by increasing the number of items up to 500, the number of rounds necessary to reach an agreement increases, as expected, because of the increased dimension of the solution search space. On the contrary, by further increasing the number of items, the number of rounds to reach an agreement decreases because the chances to generate acceptable counteroffers increase, so potentially reducing the number of conflicts.

The execution time of the Reference Point algorithm is slightly greater than the Search in Domain one, as reported in Figure 6.4(b). Moreover, the trend of execution time differs from the one of negotiation rounds. While, for a number of items greater than 500, the number of rounds to reach an agreement starts to decrease, the average execution time increases. In this case, in fact, it is the time required to compute a counteroffer that impacts more on the execution time.

We also evaluated the performances of the two heuristics by varying the size of the group from 3 to 5 members. The success rate is very high, ranging from the 100%, for groups of 3, to 98% for groups of 5, in the case of complete knowledge for the mediator. As we expected, when the number of agents increases, the number of negotiation rounds necessary to reach a shared solution increases, reaching the value 7 when the number of items varies from 250 to 500 (see Figure 6.5(a)). Again, when the number of items is more than 500, fewer negotiation rounds are necessary to find a solution (3 rounds). As showed in Figure 6.5(b), when the number of items and the number of agents increase, the execution time of both algorithms also increases, even though the execution time is more dependent on the number of items than the number of agents.

(a) Average number of rounds to reach an agreement.

(b) Average execution time to reach an agreement.

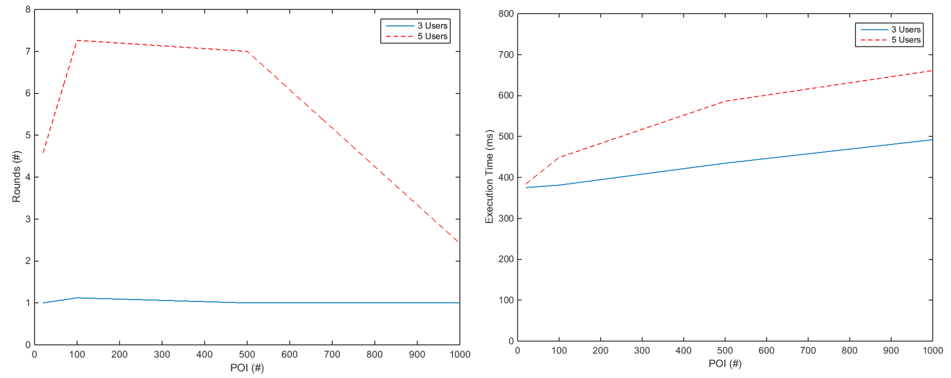


Fig. 6.5 Results in case of complete knowledge w.r.t. the number of users.

(a) Average number of rounds to reach an agreement.

(b) Average execution time to reach an agreement.

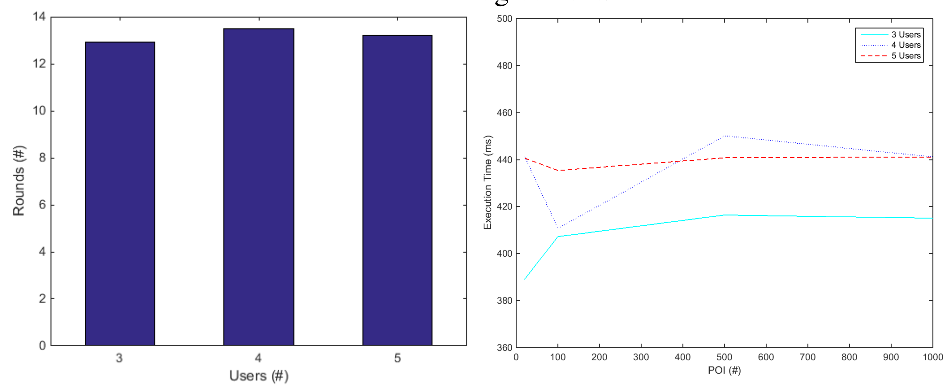


Fig. 6.6 Results in case of partial knowledge.

6.2.2 Partial Knowledge

In the second set of experiments the performance of the whole system using both heuristics, the Search in Domain one in the first rounds, and the Reference Point one in case of few conflicts, is analyzed with datasets varying from 20 to 1000 items, the number of group's members varying from 3 to 5, and solutions with a number of items varying from 1 to 4. The algorithm is executed 10 times for each setting, with a maximum number of 30 negotiation rounds. Also in this case, for each execution, the users' behaviors are randomly generated.

The success rate of the heuristics decreases by increasing the number of agents (98% with 3 agents, 92% with 4 agents, and 85% with 5 agents). The success rate in the case of partial knowledge is lower than the one obtained in the case of complete knowledge (from 99% to 91%), and the highest number of negotiation failures occurs in the case of a solution

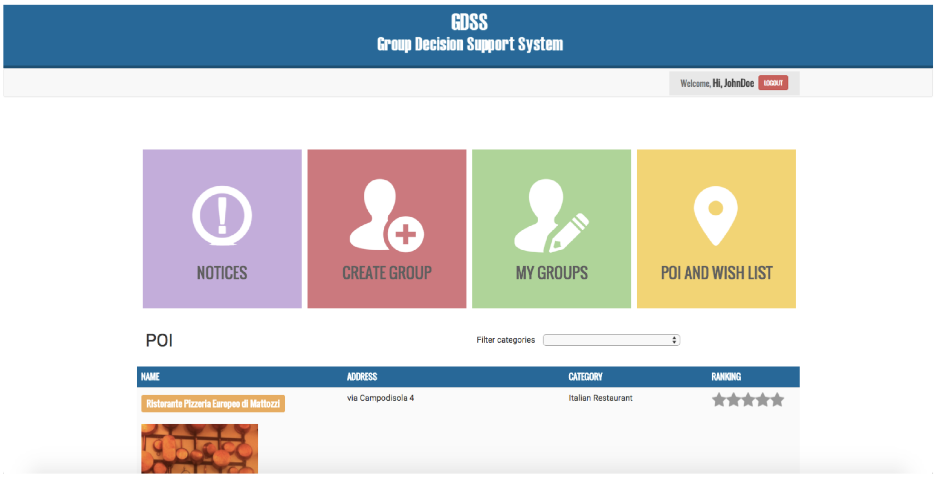


Fig. 6.7 The web application user interface.

with 1 POI. As shown in Figure 6.6(a), the average number of rounds necessary to find an agreement increases by increasing the number of agents (12.9 rounds with 3 agents and 13.5 rounds with 4 agents). Instead, for negotiations with 5 agents, the average number of rounds decreases (13.2 rounds) due to the highest number of negotiation failures. Accordingly, the negotiations among 4 agents require more rounds to find a solution, while the negotiations with 5 agents fail (when the algorithm fails, the number of rounds employed is not included in the computation of the average number of rounds).

The execution time of the negotiation algorithm, showed in Figure 6.6(b), is lower than in the previous case since the combined use of the Reference Point and the Search in Domain heuristics improve the system performances when the number of POI is greater than 500.

6.2.3 User Case Study

In the last experiment, the system is evaluated in a realistic case study, with a group of users having to choose a set of restaurants with respect to the preferences of each group's member. The realized system is composed of a Web Application, showed in Figure 6.7, and of an Automatic Negotiation Module, that represents the core of the system. The Web Application allows the users to interact with the system compiling the TKI questionnaire, providing the ratings for the POI, and indicating the group's composition. The Automatic Negotiation Module is developed using the Jade framework [12].

We conducted the study on 10 groups, composed of 2 or 3 users. For each group, the required solution is composed of a number of restaurants varying from 1 and 3. The maximum number of rounds for each negotiation is set to 30. The used dataset contains 521 items of the city of Naples, obtained using the Foursquare API. After using the system,

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Q1	0%	13%	0%	56%	31%
Q2	0%	0%	0%	69%	31%
Q3	0%	6%	6%	75%	13%
Q4	6%	19%	44%	31%	0%
Q5	0%	0%	0%	100%	0%
Q6	0%	0%	0%	31%	69%
Q7	0%	19%	25%	50%	6%

Table 6.5 Percentage of answers for each question.

we propose to each user a questionnaire containing 9 questions which aims to obtain an evaluation of the goodness of the recommendation and of the usability of the system. The questionnaire is composed of two sets of statements that the users are asked to rate with a score ranging from 1 to 5 (respectively, strongly disagree, disagree, neutral, agree, strongly agree). The first set concerns the evaluation of the user interaction with the system, while the second one concerns the evaluation of the quality of the proposed recommendations.

- System-User Interaction:

  Q1 The system is easy to use;

  Q2 Specific expertise is not required to use the system;

  Q3 The system does not require several user interaction steps;

  Q4 The number of required ratings is fair;

- Recommendations evaluation:

  Q5 The system produced a recommendation;

  Q6 The system produced a satisfying recommendation;

  Q7 The system allowed discovering new POI.

The users' answers percentages reported in Table 6.5 show that the system is user-friendly, rapid, easy to use and effortless. Conflicting opinions concern the number of ratings required by the system to end users (Q4).

Regarding, the evaluation of the recommendations, we initially observe that the agents always find an agreement without the necessity to use the majority voting criterion. The evaluations assigned by the users to the provided recommendations show a great satisfaction, with the 70% of the users strongly satisfied, and the remainder 30% simply satisfied. In addition, the users positively replied to the question regarding if the system helped them in discovering new items.

6.2.4 Discussion

The results show that the system, that models users' behavior in a conflict situation through the well-known Thomas Kilmann Instrument, provides high success rate in finding a solution with a number of negotiation rounds lower than 30, both in the case of complete knowledge and of partial knowledge. The user case study reported satisfying results in terms of the negotiation success rate, and of the quality of the recommendations provided. These results are promising and even suggests that such system can be a useful approach to increase the performances of a GRS. To extend this analysis, it can be possible to evaluate if there are any difference in the performances when the individual utilities are estimated through an individual RS. Even a comparison of the negotiation approach with other classical approaches can be useful, to understand if such strategies is more suitable for determinate kind of groups. A possibility is to apply this approach to conflicting groups.

6.3 Conclusion

The analysis carried out on the aggregation strategies defined in this thesis present very interesting and encouraging results. Firstly, we showed that the two dominance weighted social choice functions provide an improvement on the goodness of the recommendations provided. We can notice that in case of binary selection the greater improvement is related to the weighted average strategy, while the weighted fairness performs better in the test with items ranking. Even the results on the user's acceptance of the recommendations and on their satisfaction about them evidence very good results. However, both the approach must be analyzed with a larger number of items and users, in way to analyze the scalability of the two strategies.

Regarding the negotiation based approach, we have a high success rate in finding a solution with a number of negotiation rounds lower than 30, both in the case of complete knowledge and of partial knowledge. Furthermore, the user case study reported satisfying results in terms of the negotiation success rate, and of the quality of the recommendations provided. Hence, even in this case, we have promising results indicating that such system can be a useful approach to increase the performances of a GRS.

The next step is to understand if there are substantial difference in the performance on a specific group applying both the weighted social choice functions and the negotiation approach, in way to determine if there are kinds of group on which a determinate strategy performs better. A possibility is to apply this approach to conflicting groups and use the social choice functions on more cohesive and similar groups.

Chapter 7

Conclusion

The problem to provide a shared solution that can be a good recommendation for a group of people can be a challenging problem, because the users' interests can be conflicting, and it can be difficult meeting all users' tastes. The Group Recommendation Systems (GRSs) have the objective to solve such problem, helping groups of users in a group decision-making process providing suggestions that can be of interest for all the group's members. In this context, approaches taken from Economics and Multi-Agent Systems (MAS) fields are usually used, to merge the individual recommendation obtained by an individual Recommendation System (RS) for each user in the group, end obtain a shared solution for the group. Unfortunately, the results presented in the literature showed that there is no strategy can be defined as the "best", but different approaches are better suited in different scenarios, depending from the characteristics of the specific group. Besides, traditionally MAS techniques do not seem to capture all the features of real-world scenarios. Hence, it appears necessary that GRSs need to capture both preferences of the group members but also these key factors in the group decision process [38] taking into account the type of control in the group decision-making process [46]. On the basis of these considerations some advanced approaches try to integrate information from the social relationships among group members with the classical MAS techniques and so to derive new strategies more applicable to the considered settings.

Another important aspect to be considered is that, as showed from Economics studies on Other-Regarding Preferences (ORP) and from Psychological studies on the Emotional Contagion, people tend to influence each other, hence the utility of each person related to a particular item can change with respect to the utilities of the individuals which whom he/she has to use the item. Hence, in GRS it is necessary to consider this influence in the process of generation of the group's recommendations.

In this context, the work presented in this Ph.D. thesis trying to address the problem of GRSs defining a two-step architecture, composed by an adaptation module that, using an

ORP model, try to adapt the individual utilities estimated by an individual RS to the specific context of the group in which the item will be used, and a merging module that aggregate such adapted utilities with advanced aggregation strategies that considers social aspects in the merging of such utilities.

Hence, we presented two study performed to explore the factors that should be considered in the adaptation step and, in particular, a first study analyze the impact of tie strength and the status of the relationship in two-sized groups, while a second study focuses on the impact of the personality of the individual trying to derive a relation between big five personality traits and the variation of the utility.

Furthermore, we define two different approach for the aggregation step. The first one is based on weighted social choice functions. Here, a dominance ranking, derived from the interaction between users on a social network, is used as weight in two classical aggregation strategies, a weighted average strategy and a fairness strategy. The second approach is a negotiation based strategy, where the agents acting in the negotiation on behalf of group's members have a behaviour that depends on the Conflict Resolution Style of the corresponding user.

The analysis performed show very interesting results. First, the analysis of the factor influencing the emotional contagion phenomenon shows clearly that the tie strength and the status of the relationships has an impact on the phenomenon, in fact we register a positive variation that increase when the tie strength tends to be strong, and, also, the possibility of negative variations when the relationship became conflicting. Also, the size of the initial difference between the utility of the individual and the utility of the other person has an influence on the phenomenon since we registered more marked variations in case of initial large difference. Furthermore, the analysis on the personality factors shows some interesting results, showing a positive relation between Extraversion and positive shifting and even confirming a positive relation between Neuroticism and negative shifting. Unfortunately, the little number of participants with Low levels of Agreeableness and Conscentiousness does not permit fully analyze this phenomenon, and some future experiments will be required in way to derive the ORP models to be used for the framework.

Regarding, instead, the aggregation strategies defined, the analysis carried out present very interesting and encouraging results. Firstly, we showed that the two dominance weighted social choice functions provide an improvement on the goodness of the recommendations provided. We can notice that in case of binary selection the greater improvement is related to the weighted average strategy, while the weighted fairness performs better in the test with items ranking. Even the results on the user's acceptance of the recommendations and on their satisfaction about them evidence very good results. However, both the approach must be analyzed with a larger number of items and users, in way to analyze the scalability of the two strategies. Regarding the negotiation based approach, we have a high success rate in finding a solution with a number of negotiation rounds lower than 30, both in the case of complete knowledge and of partial knowledge. Furthermore, the user case study reported satisfying results in terms of the negotiation success rate, and of the quality of the recommendations provided. Hence, even in this case, we have promising results indicating that such system can be a useful approach to increase the performances of a GRS.

7.1 Open Problems and Future Works

As evidenced from our results, there are promising results, but many aspects should be analyzed in future works. Firstly, regarding the study of the Emotional Contagion, a further analysis on the personality traits can be useful to confirm the result evidenced in this work, and even to better analyze the influence of the Agreeableness and the Conscientiousness traits. In particular the Agreeableness factor, according to [45], should have an impact both for prosocial and antisocial behaviour and, hence, can be an important factor in our model of utilities adaptation. Furthermore, the definition and the evaluation of the ORP model performing this adaptation is necessary. Finally, a study on other aspects that can have an influence on the phenomenon like, for example, the nature of the items and the relative cost, in terms of time or money spent for it, could be useful to better explain the phenomenon.

On the other hand, regarding the merging strategies, as evidenced in the analysis, regarding the two weighted social choice functions, a larger evaluation, comprising more users and more items, is necessary to evaluate the scalability of the approaches. Furthermore, it will be interesting to investigate other social factors that could be integrated in the functions to provide more accurate recommendations. Regarding, on the contrary, the negotiation based approach, it could be useful to compare it with other approaches, using different negotiation protocols or other completely different strategies, in way to determine the type of groups for which this approach performs better. Our final objective is to define several aggregation strategies and determine, at run time, on the base of the characteristics of the specific group, the best strategy to use to generate the recommendations.

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