Make it personal: a social explanation system applied to group recommendations

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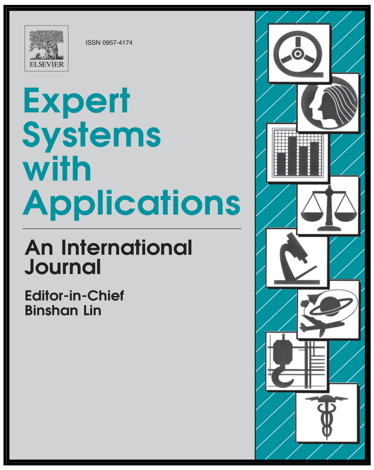

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Lara Quijano-Sanchez, Christian Sauer, Juan A. Recio-Garcia, Belen Diaz-Agudo

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Highlights

- We propose Personalized Social Individual Explanations for group recommenders.
- We propose both a Textual and a Graphical Social Explanation approach.
- We study the benefits of including explanations in group recommender systems.
- We study the benefits of including social components to these explanations.
- Results show a significant increase in users' intent to follow our recommendations.

Make it Personal: A Social Explanation System Applied to Group Recommendations

Lara Quijano-Sanchez*

UC3M-BS Institute of Financial Big Data
Universidad Carlos III de Madrid, Getafe, Spain

Christian Sauer

School of Computing and Engineering,
University of West London, London, United Kingdom

Juan A. Recio-Garcia, Belen Diaz-Agudo

Facultad de Informatica
Universidad Complutense de Madrid, Madrid, Spain.

Abstract

Recommender systems help users to identify which items from a variety of choices best match their needs and preferences. In this context, explanations act as complementary information that can help users to better comprehend the system's output and to encourage goals such as *trust*, *confidence* in decision-making or *utility*. **In this paper we propose a *Personalized Social Individual Explanation* approach (*PSIE*). Unlike other expert systems the *PSIE* proposal novelly includes explanations about the system's group recommendation and explanations about the group's social reality with the goal of inducing a positive reaction that leads to a better perception of the received group recommendations. Among other challenges, we uncover a special need to focus on "tactful" explanations when addressing users' personal relationships within a group and to focus on personalized reassuring explanations that encourage users to accept the presented recommendations. Besides, the resulting intelligent system significatively increases users' intent (*likelihood*) to follow the recommendations, users' *satisfaction* and the system's *efficiency* and *trustworthiness*.**

Keywords: Social Explanations, Group Recommenders, Personalization, Social Networks, Personality, Tie Strength

1. Introduction

Recommender systems (Ricci et al., 2015; Jameson and Smyth, 2007) are expert systems which support human decision-making. They commonly use real or inferred preferences to suggest to their users items that they might like to consume. Depending on the number of users that will employ the product, we can speak of individual recommenders (Ricci et al., 2015) or group recommenders (Jameson and Smyth, 2007). In this paper we focus on the latter, and, more specifically on how to improve user's acceptance of these systems' outcome.

In the literature, e.g. (Golbeck, 2006; Jamali and Ester, 2009; Massa and Avesani, 2007) it was shown that using Social Network information in addition to feedback data (e.g. ratings) can significantly improve group recommendations' accuracy. Besides, there is an agreement about the need to adapt group recommendation processes to group composition (Cantador and Castells, 2012; Salamó et al., 2012; Ricci et al., 2015). Recent work has focused on modelling users' social behaviour within a group to enhance the recommendation's outcome (Mccarthy et al., 2006; Salehi-Abari and Boutilier, 2015; Quijano-Sánchez et al., 2013). However, there is a lack of explanation methods for these so-

*Corresponding author

Email addresses: `laraquij@inst.uc3m.es` (Lara Quijano-Sanchez), `christian.sauer@uwl.ac.uk` (Christian Sauer), `jareciog@fdi.ucm.es` (Juan A. Recio-Garcia), `belend@ucm.es` (Belen Diaz-Agudo)

cial group recommendation results. Although some explanation components have been included in group recommender systems (Jameson, 2004; McCarthy et al., 2006; Boratto and Carta, 2011) none of them have focused on using the social reality within a group for explanation generation.

Explanations and recommender systems have frequently been considered as part of the studies developed in the area of knowledge-based systems (Lopez-Suarez and Kamel, 1994) where both of them can be used to support decision-making processes. It was found that explanations can help increase users' acceptance of the proposed recommendations, helping them make faster decisions, convincing them to buy the proposed items or even develop trust in the system as a whole (Herlocker et al., 2000). Besides, it has been acknowledged that for the users, many recommender systems function as black boxes, and therefore, do not provide transparency into how the recommendation process works and do not offer further information to go along with the recommendations. This situation can lead to the user being startled by a given recommendation, producing the need for an explanation (Herlocker et al., 2000). For instance, explanations are able to provide transparency by presenting the reasoning and data behind a recommendation. There are some individual explanation approaches (Christakis and Fowler, 2009; Guy et al., 2009), that provide the names of particular friends who liked the proposed item to induce a better acceptance of that specific item; especially if the chosen names refer to good friends, tapping into the idea that people we like are more likely to persuade us. We can consider this type of explanations to be *social*, as they induce a positive reaction by recalling social bonds.

To date, our main line of research has focused on improving current state-of-the art research on group recommenders through the inclusion of social factors in the generation of recommendations that satisfy a group of users with potentially competing interests. To do so, we have reviewed different ways of combining people's personal preferences and proposed an approach that takes into account the social reality within a group. **Quijano-Sánchez et al. (2013)'s *Social Recommendation Model* (SRM), defines a set of recommendation methods that include the analysis and use of several social factors such as the *personality* of group members, the *tie strength* between them and users' *satisfaction* with past recommendations.**

Departing from this starting point, this research takes a step forward and novelly translates the previously mentioned *social explanations* (Christakis and Fowler, 2009; Guy et al., 2009) to group recommender systems. This is done by including not only friend-related information, as the previous mentioned works propose, but also all the social information that the adopted system (SRM) is able to retrieve, that is: *personal ratings*, user's *personality*, *tie strength* between users and previous *satisfaction*. Hence, this paper's goal is to provide to each group member a *Personalized Social Individual Explanation* ($PSIE$) about the system's proposed group recommendation and, by doing so, to induce positive reactions that lead to a better perception of the received group recommendation and of the system in general.

Thus, this work aims to improve the performance of Quijano-Sánchez et al. (2013)'s system through the inclusion of $PSIE$. To do so, two different approaches are proposed, *Textual Social Explanations* (*TSE*) (Section 4.1) and *Graphical Social Explanations* (*GSE*) (Section 4.2). Then, the effects of including simple non-social explanations in group recommender systems, the effects of including just one social component to these group explanations and the effects of including all of SRM's social information to these explanations, that is, the complete $PSIE$ approach, are studied. To address these questions two experiments have been designed, for the textual approach (Section 5.2) and for the graphical approach (Section 5.3). By performing these experiments we evaluate which of the two presented approaches is preferable (Section 5.3).

Consequently, this research has the following main contributions:

1. Study of the benefits of including explanations in group recommender systems.
2. Study of the benefits of including a social component to explanations in group recommender systems.
3. Proposal of a *Personalized Social Individual Explanation* approach ($PSIE$):
   (a) Through a *Textual Social Explanation* approach (*TSE*).
   (b) Through a *Graphical Social Explanation* approach (*GSE*).

The remainder of this paper is structured as follows: In the next section we introduce some of the state-of-the-art research regarding explanations. In Section 3 we present the main theoretical concepts needed to develop this work. Section 4 presents our $PSIE$ proposal. In Section 5 we present experiments and results. Finally, Section 6 concludes the paper.

2. Related work

Jannach et al. (2011) affirm that explanations in recommender systems can be basically understood as some sort of communication between a selling agent (i.e. the recommender system) and a buying agent (i.e. the user). Research in explanations started with the premise that users would more likely trust a recommendation when they know the rationale behind it (Herlocker et al., 2000; Zanker and Ninaus, 2010; Lamche et al., 2014; Symeonidis et al., 2009). Explanation styles can be classified according to the underlying algorithm by which they are computed, e.g.:

- *Collaborative explanations* point out similar users that have also liked the recommended item. Amazon[1] is the most well-known example of collaborative-style explanations usage following an approach like: "Customers Who Bought This Item Also Bought". Another example is Herlocker et al. (2000), which evaluated 21 different explanation interfaces for the collaborative-filtering based "MovieLens" system, and found that when asking users about their *likelihood* to see a movie the most *persuasive* approach was to present a histogram with the ratings given by similar users.

- *Content-based explanations* use descriptions of the items' properties. For example, Symeonidis et al. (2008) justify movie recommendations according to their inference of the users' favourite actor. Or, for a more domain independent approach, in Vig et al. (2009) the authors use tags to explain that the recommended item and the user's profile are semantically close.

Differently to this division by design principles, explanations can be discerned by the effects they have on users (Tintarev, 2007) (see Table 1). We have based our research in this categorization and focused on the effects of *PSIE* in the system's *persuasiveness*, *efficiency*, *trustworthiness* and users' *satisfaction* (see questions Q1-Q6 in Section 5). We have focused on these specific five goals and not in all existing objectives following Tintarev and Masthoff (2008)'s affirmation that: "It is important to identify these objectives/criteria as distinct, even if they may interact, or require certain trade-offs and to note that it would be hard to create explanations that do well on all potential objectives". For instance, in this same work (Tintarev and Masthoff, 2008), the authors found that while personalised explanations may lead to greater user *satisfaction*, they do not necessarily increase *effectiveness*.

Most of the objectives shown above in Table 1 are self-descriptive. However, in order to better understand

Table 1: Different existing explanation criteria Tintarev (2007).

Aim	Definition
Persuasiveness	To convince users to try or buy
Transparency	To explain how the system works
Trust	To increase users' confidence in the system
Satisfaction	To increase the ease of use or enjoyment
Effectiveness	To help users make good decisions
Efficiency	To help users make decisions faster
Scrutability	To allow users to tell the system it is wrong

them we now survey different ways in which explanations can be evaluated, how they differ with different explanation criteria and how, based on previous research (Gedikli et al., 2014), we evaluate each of the objectives that we have focused on:

- *Persuasiveness*, is mainly understood as the ability of an explanation to convince a user to accept or disregard certain items. It is commonly approximated by a measurement that determines to which extent a user's evaluation changes depending on the presence or absence of an explanation (Bilgic and Mooney, 2005). In our experimental study (Section 5), we use such a measure of *persuasiveness* and evaluate if users' *likelihood* to follow our recommendation is indeed increased by the presence of explanations.

- *Transparency* is related to the capability of a system to expose the reasoning behind a recommendation (Herlocker et al., 2000). It is considered to contribute to users' *trust* in the system. *Transparency* can be divided into two types: *objective transparency* and *user-perceived transparency*. The first one is used when the recommender reveals the actual mechanisms of the underlying algorithm. However, this may not be very intuitive as algorithms may be too complex. Therefore, the second type, *user-perceived transparency*, might be better as it is based on users' subjective opinion about how good the system is at explaining its recommendation logic[2]. In our experimental study we assess the effect that the presented *PSIE* have on users' *trust* in the system.

- User's overall *satisfaction* with a recommender system is assumed to be strongly related to the perceived quality of its recommendations and explanations (Cosley et al., 2003; Mccarthy et al., 2004). Therefore, *satisfaction* can be related to either *satisfaction* with the system as a whole, or user's perceived quality of the explanations themselves. One typical method of measuring it, is asking users directly if they liked the explanation and to which extent (Tintarev and Masthoff, 2008).

[1] www.amazon.com

[2] Reports have shown that *user-perceived* transparency can be high even if the explanation does not correspond to the underlying recommendation logic, see (Herlocker et al., 2000), which is also true for explaining semantic search results (Forcher et al., 2014).

In our case, we understand that user's *satisfaction* (and also *trust* in the system) is increased when receiving explanations if users' response to questionnaires (questions Q1-Q6 in Section 5) reflect their intent to continue using the system and their opinion of the proposed item is indeed increased when receiving explanations.

- *Effectiveness* can be defined as the ability of an explanation to help users make better decisions. It is commonly measured by determining the closeness between users' estimated quality or appropriateness of the recommended item and the actual quality or utility of that item (Bilgic and Mooney, 2005). For example, in Tintarev and Masthoff (2008) users firstly estimated the quality of a recommended item, and afterwards they consumed it and rated it again. We have not focused on this criteria as findings in Tintarev and Masthoff (2008) reflected that focusing on increasing *effectiveness* does not go well with focusing on increasing *satisfaction*, which is one of our main goals.

- Finally, an explanation is considered to be *efficient* when it helps the user to decide more quickly or when it helps to reduce the cognitive effort required in the decision-making process. It is normally measured as the time used to complete the same task with and without an explanation (Pu and Chen, 2007). To test *PSIE*'s effect on *efficiency*, we follow Gedikli et al. (2014) in our explanation evaluation, and ask users if the provided explanations accelerated their decision-making process.

3. Motivation

Group recommenders, often operate in leisure domains, where it is common for people to consume items in groups. The choice of a date movie, a family holiday destination, or a restaurant for a celebration meal all require the balancing of the preferences of multiple consumers. These systems commonly aggregate real or predicted ratings for group members (Jameson and Smyth, 2007; Baltrunas et al., 2010; Berkovsky and Freyne, 2010; Pessemier et al., 2013). The aggregation functions typically used are inspired by the social welfare functions developed by Social Choice Theory research (Masthoff and Gatt, 2006). For each group member, an individual recommender system predicts a set of ratings ($\hat{r}_{u,i} \in [0,5]$) for the candidate items i. Next, the group recommender aggregates the ratings: for each candidate item, it might take, for example, the average of group members' ratings, the minimum, or the maximum. Finally, it recommends the items with the highest aggregated ratings to the group. There are many domains where group recommendation techniques can be applied (Park et al., 2012). For example, the *Pocket Restaurant Finder* (McCarthy, 2002) application, which is a restaurant recommender that bases its strategy on users' locations and the culinary characteristics of the restaurant. Or, in the traveling domain, the system *e-Tourism* (Garcia et al., 2011), that helps groups of users with the generation of a personalised tourist plan.

As mentioned in the introduction section, some explanation components have been included in group recommender systems: *CATS* (McCarthy et al., 2006) allows a "critiquing" process between group members after a recommendation is made, making recommendations proactive. Also, *Travel Decision Forum* (Jameson, 2004) recaptures face-to-face interaction through animated characters that express the individual preferences of each group member. These studies have two limitations that we aim to address:

1) They measure users' general acceptance of their system but fail to study the impact that the inclusion of explanations has on users' perception of the presented group recommendations. Hence, this paper's first research hypothesis is that:

H1) "Adding explanations in group recommenders can enhance users' *likelihood* to follow the recommendations".

2) These studies (McCarthy et al., 2006; Jameson, 2004) only aim at explaining the individual preferences of each group member. This goes along with most existing group recommender systems, that regardless of their domain, ignore the social factors that influence real group decision-making (O'Connor et al., 2001; McCarthy, 2002). However, in the last few years, group recommendation techniques have been refined by modelling user's social behaviour within the group (Mccarthy et al., 2006; Salehi-Abari and Boutilier, 2015; Quijano-Sánchez et al., 2013). Although social explanations have been included for individual recommenders (Groh et al., 2012; Sharma and Cosley, 2013; Knijnenburg et al., 2012) there is a lack of explanation methods for these social group recommendation approaches. Thus, our second research hypothesis is that:

H2) "Adding a social component to explanations in group recommenders can enhance the impact that explanations have on users' *likelihood* to follow the recommendations".

To address the posed hypotheses our strategy involves the design of *Personalized Social Individual Explanations* (*PSIE*). Our proposal focuses on the improvement of users' perception of the system's presented recommendations –in terms of user's acceptance or *likelihood* to follow the recommendation,

users' *satisfaction* and the system's perceived *efficiency* and *trustworthiness*–.

In Quijano-Sánchez et al. (2013), it was proved that including factors that reflected users' *personality*, *tie strength* between group members and previous *satisfaction* with group decisions in traditional preference-aggregation recommendation-techniques improved the group recommendation outcome. Also, it was shown that the combination of these three factors was the key to this improvement. Having acknowledged this, in order to prove the aforementioned hypotheses the aim of the designed $PSIE$ is to reflect the reasoning implemented by a recommender that follows the *Social Recommendation Model* (SRM) implemented in Quijano-Sánchez et al. (2013). Hence, in this work, SRM is used as starting point and not other state-of-the-art approaches (Amer-Yahia et al., 2009; Masthoff, 2011) as it was already proved that SRM outperformed *non-social* approaches (Quijano-Sánchez et al., 2013). Also, for testing purposes, Quijano-Sánchez et al. (2014)'s *HappyMovie* application will be reused. This expert system is a Facebook[3] application that provides a recommendation for a group of people who wish to go to the cinema together and that implements SRM. From it, the values that correspond to the studied three social factors are obtained:

- *Personality* (p_u), that represents user u's predominant behavior according to her/his TKI personality evaluation (Thomas and Kilmann (1974)). It fits within a range of (0,1], 0 being the reflection of a very cooperative person and 1 the reflection of a very assertive one. This value is computed through a compulsory personality test in *HappyMovie*.

- *Tie strength* ($t_{u,v}$) that fits within a range of (0,1], 0 being the reflection of a person someone is not close to and 1 the reflection of a person someone is very close to. This value is computed as in (Quijano-Sánchez et al., 2014), by automatically extracting features that act as predictors of tie strength in both users u's and v's Facebook profiles.

- *Satisfaction* (s_u), that fits within a range of [0,1], where a user who is extremely dissatisfied with previous group decisions will have it close to 0 and a user who is extremely satisfied with previous group decisions will have this value close to 1. This value is computed by directly asking users their initial state and updated each time users report feedback through *HappyMovie*.

Observing Facebook, which is where *HappyMovie* is embedded (Quijano-Sánchez et al., 2014), we can see that most of the items have information about how many users, and more specifically how many of a person's own friends, have *liked* an item. $PSIE$**'s main strategy relies on the concept of social proof**, which affirms that people follow other people's behavior feeling that others have reasons for this behaviour (Cialdini and Trost, 1998). Explanations based on the behaviour of other users are often used to support recommendations from recommender systems embedded in Social Networks (e.g. "Jaime, Claire and 3 more friends like this"). Examples of this are: Groh et al. (2012) that presented a study that outlined the "extensive need" for explanation in social recommenders, Sharma and Cosley (2013) that proposed the use of social information as an explanation itself, or Knijnenburg et al. (2012) that concluded that social recommender users were more satisfied with the system when having more "inspectability" and control of it. **These approaches have again two limitations that we aim to address:**

1) Their strategy is limited to explaining individual recommendations. As opposed to their approaches, this paper novelly presents a proposal to extending *social explanations* to group recommenders. This new perspective, shown in Sections 4.1.5 and 4.2, faces new challenges such as a special need to design "tactful" explanations when addressing users' personal relationships within a group.

2) These studies (Groh et al., 2012; Sharma and Cosley, 2013; Knijnenburg et al., 2012; Cialdini and Trost, 1998) only involve the inclusion of one social component, related mainly to *tie strength*. However, as we have mentioned before, *HappyMovie* –the system that we use as baseline for the explanation generation– takes into account two additional factors: *personality* and *satisfaction*. Thus, in this research we aim at studying the impact that each of the social factors involved in the social group recommendation has on the composed explanations by designing different systems that take into account each of them separately (Sections 4.1.1 to 4.1.3) and a complete system that analyses all of them (Sections 4.1.5 and 4.2). This study leads to the formulation of a third hypothesis:

H3) "Including all of the social components, that the expert system can retrieve, in the generated explanations can improve the system's performance

[3] www.facebook.com

against just adding one social component".

In summary, to the best of our knowledge this is the first work to present a social explanation approach in group recommenders and to study the relevance of each of the factors involved. It is important to note that the $PSIE$ approach has been designed to explicitly explain the recommendations generated by the *HappyMovie* system and the three social factors that it analyses. Thus, although the experiment results obtained in Section 5 prove our hypotheses and provide promising results we encourage other researchers to pursue further investigations with different expert systems and social factors in this subject matter. Having reviewed the existing work on explanations, group recommendations and our previous contributions we now introduce the $PSIE$ approach.

4. Personalized Social Individual Explanations

We understand *explanation* as in the Oxford Dictionary definition: "give a reason or justification for". In our case, explanations aim to justify the recommendation of an item for the group's welfare. We appeal to users' sense of justice and social bonds to help them comprehend why the recommender has presented a specific item as the best option for the group. **Our hypotheses aim to demonstrate that, by helping users understand the system's recommendation through a set of explanations, the system's *persuasiveness* is increased. Furthermore, the hypotheses aim to prove that, by appealing to users' sense of justice and social bonds, the system's *efficiency* and users' *trust* and *satisfaction* with the system is improved. To do so, we present users a $PSIE$ of how the system's three estimated social factors plus users' individual predicted ratings have affected the group recommender's proposal.**

In the literature, when designing explanations, there are two main approaches based on how to present them (Herlocker et al., 2000): 1) showing an explicative text giving a reason or justification for (Zanker and Ninaus, 2010; Tintarev and Masthoff, 2012) or 2) using images to enhance the credibility of information (Sharma and Cosley, 2013; Fogg et al., 2001; Nguyen and Masthoff, 2008; Forcher et al., 2014). To prove this research's hypotheses we have designed $PSIE$ for these two different approaches: the first one is based on textual templates formed by prefixed sentences introduced at the end of each recommendation when certain situations occur; we will refer to this approach as *Textual Social Explanations* –*TSE*– (Section 4.1). The second one is based on a social graph that represents the explanation itself; we will refer to this approach as *Graphical Social Explanations* –*GSE*– (Section 4.2). The goal of designing these two alternatives is to moderate the impact that the concrete presentation (textual or graphical) of the designed $PSIE$ has on the research outcome and hence provide more generalizable conclusions.

4.1. Textual social explanations

TSE explain the recommender's aggregation strategy by analyzing the inter-dependencies between the group's social factors and presenting them in a text. **This approach's aim is to find patterns** that characterize social situations that need to be explained. An example of a social situation inside a group is a case in which a close friend v of a user u requesting an explanation, really wants to see a movie i and the user u may be tempted to see it. However, the user's willingness to see this movie might vary depending on: her/his personality, the more cooperative s/he is (low p_u) the more likely s/he will be to follow the recommendation. Or, depending on past events, the more unsatisfied s/he is with past recommendations (low s_u) the less willing s/he will be to cooperate. To represent each social situation we initially propose to associate each possible factor combination to a textual template. Note that textual templates have been previously used in individual explanations (Lamche et al., 2014) but never in social and/or group explanations as in our case.

Analysing the social reality in a group and using it for explanation generation is very complex and not easily solved. Firstly, because it is not clear how to find patterns between situations to characterize dependencies between all social factors in groups of different sizes; and secondly, because the complexity and network structure of social relations inside a group produces a combinatorial explosion of the number of social situations that require different, prepared or "canned", textual explanations. Next, we exemplify the lingering combinatorial explosion problem by presenting examples of possible social factors' values permutations composing all the possible social situations that can occur in our system and would require a unique prepared explanation:

4.1.1. *The personality factor* (p_u)

Even if we assume that each user is "only" classified in one of three categories: high (assertive), low (cooperative) or medium (reserved), for a given active group

G_a, being $|G_a| = n$ there are already 3^n possible personality combinations (variations with repetition of 3 elements taken n by n). An example of *TSE* regarding personality is the case where user u, who is receiving the explanation, has a low personality value ($p_u < 0.4$) and a low estimated rating ($\hat{r}_{u,i} < 3$) for the selected item, whereas the rest of the group have higher personality values and higher estimated ratings. In that particular case, a possible good explanation in terms of increasing user u's acceptance of the group's recommendation (a *persuasive* explanation) would be: "*Although we have detected that your preference for this item is not very high, your friends X and Y really like it. Besides, we have detected that they usually don't give in*". An explanation system based only on this factor would have the goal to recall to a greater comprehension when facing users with assertive personalities.

4.1.2. *The tie strength factor* ($t_{u,v}$)

Let us assume again that we introduce "only" three categories: high, low or medium. For a given active group G_a, being $|G_a| = n$ there are already again $3^{n*(n-1)}$ possible tie strength combinations, as tie strength is a directed value and therefore $t_{u,v} \neq t_{v,u}$. An example of *TSE* regarding the tie strength factor is the case where user u, receiving the explanation, has a low estimated rating for the recommended item but s/he is really close to a member of the group that has a high estimated rating for the recommended item. In that particular case, a possible good explanation in terms of increasing user u's acceptance of the group's choice could be: "*Although we have detected that your preference for this item is not very high, your close friend X (who you highly trust) thinks it is a very good choice.*". An explanation system based only on this factor would have the goal to recall a desire to please and/or follow close friends' opinions.

4.1.3. *The satisfaction factor* (s_u)

Again, this factor could also be divided into three categories: high, low or medium. For a given active group G_a, being $|G_a| = n$ there are again 3^n possible satisfaction combinations. An example of *TSE* regarding satisfaction is the case where user u, receiving the explanation, has a very high satisfaction value compared to the rest of the group members. In that particular case, a possible good explanation in terms of increasing user u's acceptance of the group's recommendation could be: "*Last time users X and Y gave in with the selected choice, it would be fair if this time they were given some kind of priority*". An explanation system based only on this factor would have the goal to recall to users' sense of justice and equality.

4.1.4. *The individual estimation* ($\hat{r}_{u,i}$)

Could also be divided into three categories: good, bad or medium. For a given active group G_a, being $|G_a| = n$ there are again 3^n possible individual estimation combinations. An example of *TSE* regarding the individual estimations, is the case where user u receiving the explanation, has a low estimation value for the recommended item and the rest of the group members have higher estimation values. In that particular case, a possible good explanation in terms of increasing user u's acceptance of the group's choice could be "*Although we believe that your preference for this item is not very high, we have predicted that X and Y would really enjoy it.*"[4]. An explanation system based only on this factor would have the goal to present other friends' preferences.

4.1.5. *PSIE* ***proposal***

An initial approach to provide explanations could be using text templates associated **to each of the system's factors** and all the situations that might exist when combining them. A major problem however, is the large amount of templates needed to cover each possible configuration. **For example, in our particular case (*HappyMovie*),** the smallest group configuration, $|G_a| = 2$, would have to contemplate $3^2 * 3^2 * 3^2 * 3^2 = 6561$ different group situations. Obviously, it is impossible to design templates for each situation when considering all these permutations. However, we must note that some situations can be grouped or clustered, a fact we have based our solution on.

The knowledge acquisition bottleneck associated with the problem of gathering useful, complete, canned explanation texts, initially suggested approaching it with a lazy method such as case-based reasoning (Chazara et al., 2016), where explanations are learned through the system's use. However, challenges like the *cold-start problem* may have arisen should we have opted to follow that approach. Another possible approach to tackle the problem is the knowledge-based reasoning framework for generating explanations presented by Zanker and Ninaus (2010), where authors employed a predicate-based finite state automata meant for composing flexible explanations from canned text. Following the initial idea of *Zanker and Ninaus's framework for knowledgeable explanations* we have composed explanations from canned text segments within a predefined ruled-based explanation model. **However, *Zanker and***

[4]There is a huge body of work on explaining individual recommendations (Herlocker et al., 2000; Tintarev, 2007). Hence, their explanation is not the focus of this paper.

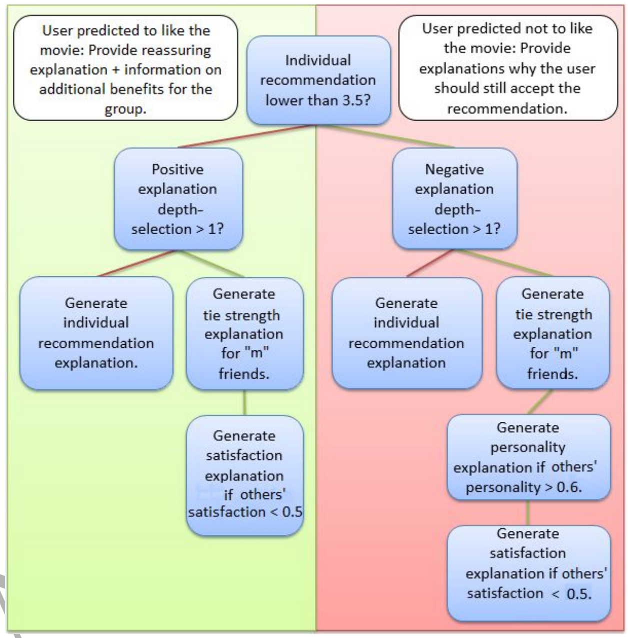
***Ninaus's* approach does not suit this paper's goal entirely, as we aim to provide explanations to groups rather than to individuals and we also aim to add a social component to them (hypotheses 1 & 2)**. Therefore, we have picked up the idea of using text segments but we have also introduced the possibility to select the detail or "depth" of a composed explanation, ranging from an individual explanation for a single user to explanations including all members of a group of any given size. We have further used fine-grained text segments of sub-sentence resolution and introduced direct user addressing and word variances for a more personal and affective style of explanations. **This is done as the** $PSIE$ **approach is** intended to be personalised, meaning that each user will receive a different explanation of the group recommendation presented by the system.

This is motivated by Tintarev and Masthoff (2012), where authors stated that personalised explanations, although no more effective, were usually more satisfying, and Sharma and Cosley (2013) where the authors also observed that people have quite different strategies for making sense of explanations, suggesting that personalising explanations might have real value. More important still, and with the goal of producing *persuasive* explanations **that increase users' *likelihood* to follow the presented recommendations**, our approach classifies the generated explanations into: *positive* explanations, that merely need to inform the user that the presented recommendation is one s/he may like, pointing out additional group benefits. And *negative* explanations, that need to back up a recommendation the user may dislike but which might be highly appreciated by the group as a whole.

The choice of focusing on personalization against a more traditional approach of a general group explanation is motivated by the following issues:

- Induce positive and "tactful" explanations. Presenting all users' personalities, mutual tie strengths and satisfactions in a single recommendation could lead to offended users reading between lines examples such as "my opinion was taken into account less due to my personality" or "someone does not trust me".
- As a consequence, this could also give rise to serious privacy issues.
- It allows for decision-tree pruning and removal of undesirable explanations.
- It results in shorter explanations, tackling the problem of providing an unappealing chunk of text with excessive information.

Figure 1: Our approach to composing explanations. Where: depth-selection refers to the selected explanation depth (i.e. number of close friends to be taken into account in the explanation) and both satisfaction and personality explanations refer to the "m" closest friends that meet the indicated thresholds and that have individual predicted ratings > 3.5.



Hence, we focus on giving a personal motivation/reason to accept the recommendation. We have developed a decision tree model, steering the composition of an explanation (see Figure 1), where we combine the knowledge extracted by having *HappyMovie* embedded in Facebook (user names, group structure and the actual computed values for the social factors), the knowledge generated by the individual and group recommendations, and a number of additional knowledge artifacts: i.e., canned explanation text segments, sub-methods to find and sort users by *tie strength*, *satisfaction* and *personality*, and sub-methods to create word variances in the explanation segments.

As described previously our approach aims at circumventing the combinatorial explosion problem. For this reason, even for our modular explanation composition approach, we initially aimed to prune the tree of possible explanations. The goal of this process is to create a minimal representation of the space of possible explanations, in the form of a decision tree (see Figure 1). An opportunity to simplify the decision structure shown in Figure 1, for example, arose from the fact that, **as pointed out in Section 3**, when explaining social situations to a group of users it is important to spare users' feelings. Therefore, as we have said before, we must avoid situations with explanations of the kind: "*Your opinion was not taken into account because your personality is weak*" or "*Your opinion was not taken into account because X does not trust you*" because they can create conflict and discomfort between users. **Bearing this in mind and focusing only on reassuring explanations that encourage users to accept the presented recommendations**, our *PSIE* proposal does not include personality explanations in positive explanations, does not explain conflict scenarios as the ones described above and includes certain rules, like if a user's *tie strength* value with a friend is below 0.4, we just subtly don't call them a "close friend" anymore but only "friend". Reasoning about the possible explanations in the described way, we found the following opportunities to prune the decision tree, removing a number of irrelevant or undesirable explanations:

- We focus on user centric explanations, thus excluding all explanations regarding other intra-group member relations. That is, other than between the user asking for an explanation and the other group members.
- Focusing on the user asking for an explanation, we only base our explanation on that particular user's tie strength map, excluding the tie strength relationships between other group members.
- For explanations based on groups of four or more users we provide detailed explanations for the first three closest friends of the user requesting the explanation. The explanations concerning the remaining friends are summarised. Summarising is implemented by deriving the mean values for all the remaining group members after detailed explanations for the three closest friends of the user who has requested the explanation, have already been given.
- We only create personality based explanations (Section 4.1.1) for negative explanations that are backing up a recommendation the user might not like but that is beneficial for the group.
- We only provide satisfaction based explanations (Section 4.1.3) if the *satisfaction* of at least one friend is lower than 0.5.

These simplifying measures have proven efficient and not damaging to the system's ability to generate rich and personalised explanations, as we will next show in our experimental evaluation (Section 5). However, we are aware of the limitation of only testing this particular approach and not other ruled-based combinations, work that we leave for the future. After the simplification we have derived an overall decision tree, as shown in Figure 1, that guides our explanation composition.

The thresholds we use to restrict the explanation generation are as follows:

- We only consider strong *personality* users to be those who have a *personality* value (p_u) higher than 0.6. This follows TKI's (Thomas and Kilmann, 1974) *assertive* personality threshold.
- We further only consider a group member to be dissatisfied if her/his *satisfaction* value (s_u) is below 0.5. This value represents the mid-point of the s_u measurement scale.
- Negative explanations are composed when the requesting user (u_r) has an individual predicted rating ($\hat{r}_{u_r,i}$) lower than 3.5 (out of 5).
- Positive explanations are composed when the requesting user (u_r) has a $\hat{r}_{u_r,i}$ equal or higher than 3.5. This threshold has been set to 3.5, which is higher than $\hat{r}_{u,i}$ measurement scale mid-point, in order to make sure that if we refer to an item "liked" by the user, the user really considers that s/he likes the item and it is not only just "ok" for her/him.
- Explanations explicitly mentioning a "close friend" are only generated when user's u tie strength value ($t_{u,v}$) in group member v is higher than 0.4, otherwise the explanation only mentions v as "friend". This threshold has been established after analysing users' tie strength distribution where the normality curve is right-tailed and does not match the exact measurement scale mid-point (0.5).

For each partial explanation, based on *tie strength*, *personality* and *satisfaction* values, we determine the "m" *closest*, highest *personality*, lowest *satisfaction* group members. By choosing an "m" (by default $m = 3$) the system can generate explanations of various "depths". The following is an automatically generated explanation (*depth*=3) composed by our system: "*Hi there Jaime, we have predicted that you will be just basically okay with this movie. However, we have detected that your friend Claire, who you are really close to and trust, will love it. Moreover, your other close friend Peter will be okay with this movie recommendation as well, so it should be okay. Additionally, your friend Mary* *would enjoy the film we suggest, so it might be good for you too. You should also see that Claire really craves to see this film and we reckon that she won't be talked out of it easily. On top of this, we have also predicted that your resolute friend Peter will enjoy our suggestion, so you won't talk him out of it easily. What's more, your friend Peter, who is not very satisfied with this group's decisions so far, would get a satisfaction boost, as we believe he would like the movie we recommend.*". The example is generated from the following computed group configuration: *Requesting-user* u_r: $p_{u_r} = 0.55$, $\hat{r}_{u_r,i} = 3.0$, $s_{u_r} = 0.9$, $t_{u_r,f_1} = 0.8987$, $t_{u_r,f_2} = 0.7627$ and $t_{u_r,f_3} = 0.6084$. *Friend* f_1: $p_{f_1} = 0.85$, $\hat{r}_{f_1,i} = 5.0$, $s_{f_1} = 1.0$. *Friend* f_2: $p_{f_2} = 0.8$, $\hat{r}_{f_2,i} = 4.0$, $s_{f_2} = 0.2$. *Friend* f_3: $p_{f_3} = 0.3$, $\hat{r}_{f_3,i} = 3.5$, $s_{f_3} = 0.7$.

Next we detail the concrete algorithm that our $PSIE$ for the TSE proposal follows.

4.1.6. $PSIE$ algorithm

As stated before, our $PSIE$ approach for the TSE proposal (see Algorithm 1) is able to give two kinds of group explanations to a requesting user, u_r. The first kind are negative group explanations (see Algorithm 2), i.e. when the user is likely not happy with the recommendation and needs to be persuaded to follow it, as the group overall likes the recommendation. And, the second kind are positive group explanations (see Algorithm 3), i.e. when the explanation is basically backing up the group recommendation and thus can be seen as a kind of reinforcement and clarification of the recommendation for the group. If the group only consists of the requesting user we provide a simple explanation based on $\hat{r}_{u_r,i}$. If there are more than two users (u_r and at least one other user u) in the group G, our $PSIE$ approach provides a group recommendation explanation to u_r following the next algorithm scheme:

Algorithm 1 $PSIE$ Algorithm

Input: Group G consisting of the requesting user u_r and other group members $(u_1, .., u_m)$, depth m, $\hat{r}_{u,i}$ (for each user in G), s_u (for each user in G), p_u (for each user in G), $t_{u_r,u}$ (for u_r and each other user in G)

Output: $PSIE_{u_r}$

Generate an opening sentence (see Table A.4 for example wordings) :

$PSIE_{u_r}$ = OpeningExplanation(u_r){ **return** wordVariance("introHi",T)+ name+wordVariance("introWord",F)}
if ($\hat{r}_{u_r,i} < 3.5$) **then**
  $PSIE_{u_r}+=$ CreateNegativeExplanation(G,m,$\hat{r}_{u,i}$,s_u,p_u,$t_{u_r,u}$)
else if ($\hat{r}_{u_r,i} \geq 3.5$) **then**
  $PSIE_{u_r}+=$ CreatePositiveExplanation(G,m,$\hat{r}_{u,i}$,s_u,p_u,$t_{u_r,u}$)
end if
return $PSIE_{u_r}$

Note that:

- For the sake of clarity we just outline the main methods of our algorithm and present a table that exemplifies their behaviour, see Appendix A.
- Presented tables (see Appendix A) represent examples of "canned" text segments that for each option are randomly picked to provide richer explanations.
- u is a tuple that contains both the name and the gender of each group member. This information is extracted directly from users' profiles in Facebook –the Social Network where our application is implemented– and helps explanations to have a more personal and affective style.
- For the sake of brevity we do not mention the included "canned" text endings and beginnings of each sentence (see Table A.4 for example wordings). Inserted with $PSIE_{u_r}+ = wordVariance(category, StartsWithCapital(T/F))$. These segments are divided in different categories to be used depending on their goal: "butInfo", "addInfo", "plusToThis", etc. Inside each category the different existing options are picked at random to generate richer explanations. Furthermore, depending on the order of the sentence (the first and only sentence of a method, the first and more to come, the second sentence, etc) we compose differently these segments.

Algorithm 2 CreateNegativeExplanation Method

Input: Group G consisting of the requesting user u_r and other group members $(u_1, .., u_m)$, depth m, $\hat{r}_{u,i}$ (for each user in G), s_u (for each user in G), p_u (for each user in G), $t_{u_r,u}$ (for u_r and each other user in G)

Output: $PSIE_{u_r}$

Generate an opening sentence based on $\hat{r}_{u_r,i}$ (see Table A.5 for example wordings) :

$PSIE_{u_r} + =$ OpeningNegativeExplanation($\hat{r}_{u_r,i}$)

Create explanation sentences based on m u_r's most trusted friends who like the group recommendation i (see Table A.6 for example wordings)

Compute $TG = u \in G \mid \hat{r}_{u,i} \geq 3.5$

Sort TG by descending order of tie strength ($t_{u_r,u}$)

for ($u \in TG[1..m]$) **do**

  $PSIE_{u_r} + =$ CreateTrusteeExplanation($\hat{r}_{u,i}$,$t_{u_r,u}$,negative)

end for

Create explanation sentences based on m users with highest p_u who like the group recommendation i (see Table A.7 for example wordings)

Compute $PG = u \in G \mid p_u > 0.6$ & $\hat{r}_{u,i} \geq 3.5$

Sort PG by descending order of personality (p_u)

for ($u \in PG[1..m]$) **do**

  $PSIE_{u_r} + =$ CreateStrongPersonalityExplanation($\hat{r}_{u,i}$,p_u)

end for

Create explanation sentences based on m users with highest s_u gain if u_r accepts the group recommendation i (see Table A.8 for example wordings)

if ($\exists\, u \in G \mid s_u < 0.5$) **then**

  Compute $SG = u \in G \mid \hat{s}_u(t_1) - s_u(t_0) > 0$ & $\hat{r}_{u,i} \geq 3.5$

  Sort SG by ascending order of satisfaction (s_u)

  for ($u \in SG[1..m]$) **do**

    $PSIE_{u_r} + =$ CreateSatisfactionExplanation($\hat{r}_{u,i}$,s_u,negative)

  end for

end if

return $PSIE_{u_r}$

Note that there are some methods that both the "*CreateNegativeExplanation*" and "*CreatePositiveExplanation*" methods contain (*CreateTrusteeExplanation* and *CreateSatisfactionExplanation*) with a difference in the "tone" parameter (positive or negative). This parameter serves as condition to compose the ending a beginning segments of each sentence (see Table A.4). Thus, in these methods the "tone" parameter allows us to generate different types of sentences (persuasive or reassuring) given the same social parameters. E.g., for high $\hat{r}_{u,i}$ and high $t_{u_r,u}$ we could generate: "However, we have detected that Jaime, who you trust the most, will highly enjoy this recommendation and you can normally rely on him" for negative explanations and "Additionally, Jaime, who you trust the most, would really love this movie, so why not give it a try" for positive explanations.

Algorithm 3 CreatePositiveExplanation Method

Input: Group G consisting of the requesting user u_r and other group members $(u_1, .., u_m)$, depth m, $\hat{r}_{u,i}$ (for each user in G), s_u (for each user in G), p_u (for each user in G), $t_{u_r,u}$ (for u_r and each other user in G)

Output: $PSIE_{u_r}$

Generate an opening sentence based on $\hat{r}_{u_r,i}$ (see Table A.5 for example wordings) :

$PSIE_{u_r} + =$ OpeningPositiveExplanation($\hat{r}_{u_r,i}$)

Create explanation sentences based on m u_r's most trusted friends who like the group recommendation i (see Table A.6 for example wordings)

Compute $TG = u \in G \mid \hat{r}_{u,i} \geq 3.5$

Sort TG by descending order of tie strength ($t_{u_r,u}$)

for ($u \in TG[1..m]$) **do**

  $PSIE_{u_r} + =$ CreateTrusteeExplanation($\hat{r}_{u,i}$,$t_{u_r,u}$,positive)

end for

Create explanation sentences based on m users with highest s_u gain if u_r accepts the group recommendation i (see Table A.8 for example wordings)

if ($\exists\, u \in G \mid s_u < 0.5$) **then**

  Compute $SG = u \in G \mid \hat{s}_u(t_1) - s_u(t_0) > 0$ & $\hat{r}_{u,i} \geq 3.5$

  Sort SG by ascending order of satisfaction (s_u)

  for ($u \in SG[1..m]$) **do**

    $PSIE_{u_r} + =$ CreateSatisfactionExplanation($\hat{r}_{u,i}$,s_u,positive)

  end for

end if

return $PSIE_{u_r}$

The next section presents a second approach of $PSIE$ where instead of presenting explanations through a text, TSE, we present them through a social graph, GSE.

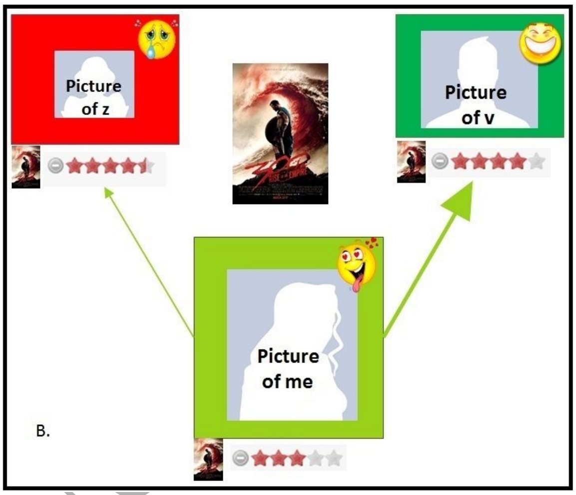
4.2. Graphical social explanations

GSE explain the recommendation strategy by presenting the inter-dependencies between the group's social factors in a graph (see Figure 2, B). To visualize information incorporated in explanations, a number of visualization techniques have been used such as tables, images, diagrams, etc. (Forcher et al., 2014). In the literature, it has been argued that the use of images (Nguyen and Masthoff, 2008) can have a persuasive effect on users. Following this idea, we have designed a *graphical* alternative to our *textual* explanations approach. In our *GSE*, instead of presenting an explanatory text, we have focused on presenting the concrete computed measures for the different factors involved in the group recommendation. This choice is backed up by other work that captured users' tendency to request additional information in explanations in terms of how much the system perceived each measure (Hingston and Kay, 2006). Furthermore the literature also supports the necessity of increasing explanations' informativeness by showing users information about the computed similarity measures, either by translating similarity metrics into legible indicators or by using representative examples of items liked (Sharma and Cosley, 2013). We study the impact of these suggestions in *PSIE* (Note that the *GSE* are always accompanied with a key map that explains the meaning of the graph representation):

- **When explaining the recommended item:** We show a picture of the recommended item following studies like Fogg et al. (2001) where it was found that while photos increased credibility, names had no significant effect on how people perceived items. Or Sharma and Cosley (2013), where the authors reported that explanations combined with technical information about the recommended item, like presenting movie posters where leading actors can be seen, increased the acceptance of recommendations.
- **When analysing users' personality:** The size of each node (Facebooks' picture profile) denotes user's personality value p_u, where bigger sizes correspond to higher p_u's.
- **When analysing tie strength between group members:** Each edge is formed by a directed vector where the arrow's size represents the tie strength value ($t_{u,v}$) between the two nodes (user u pointing at v). We believe that viewing a representation of the existing tie strength towards each friend can be a good endorsement for the recommendation and the system in general as other works like Sharma and Cosley (2013) have reported that "good friends are seen as more influential and informative than others".
- **When analysing individual estimations.** We show a 5-star Likert scale that represents users' predicted rating for the given recommendation $\hat{r}_{u,i}$. With it, users are able to analyse their preferences in contrast to other group members' preferences and, for example, be more willing to accept the recommendation if they see that a close friend (large arrow) likes (has a lot of stars) the recommended item.
- **When analysing users' satisfaction with past recommendations:** Each node is framed with a color+size graduated frame that shows each user's satisfaction value s_u (when s_u is close to 0 the frame is redder and wider, whereas when it is close to 1 it is greener and narrower). We try to reinforce *persuasiveness* by showing users' prior satisfaction levels, hence making a call to users' sense of justice and equality within a group. Besides, to make it more visual, we show an emoticon (crying, sad, neutral, happy or in love) to illustrate satisfaction levels.

Figure 2: A. Textual Social Explanations (top) B. Graphical Social Explanations (bottom).

A. *"Although we have predicted that your preference for this particular item is not very high, your friend V, who you highly trust, thinks that it is a very good option. Besides, Z really wants this item to be chosen, and remember that last time he was the one who gave in ."*



Note that for the GSE approach we again focus on user centric explanations, that exclude explanations regarding other intra-group member relations and thus aim to induce positive and "tactful" explanations.

5. Experimental Evaluation

To validate this paper's posed hypotheses (Section 3), we have performed two randomized experiments (Diez et al., 2013) that, in general allow us to study causal connections between providing explanations and improving users' reactions and in particular, allow us to address each of the stated research questions. The first experiment (Section 5.2) uses the *TSE* approach and the second one (Section 5.3) uses both the *TSE* and the *GSE* approaches. The overall experiment procedure has two major steps:

1. **Randomly divide the population into different treatment groups that receive: no explanations, non-social explanations and different variations of the $PSIE$ proposal.**
2. **Study the differences in participants' answers to a questionnaire. As introduced in Section 2, these questions allow us to assess the effects of $PSIE$ in the system's *persuasiveness*, *efficiency*, *trustworthiness* and users' *satisfaction*.**

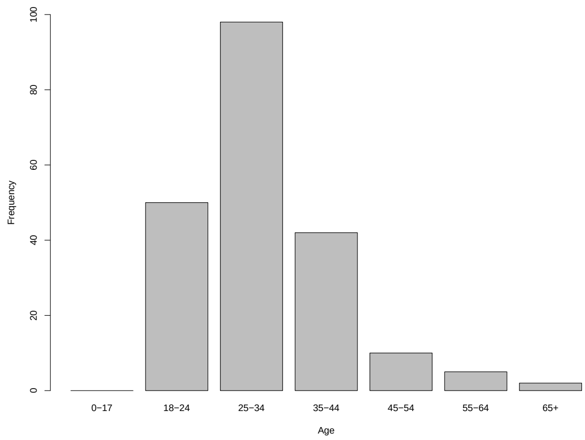
Participants's answers in the different treatment groups allow us to:

- **Experiment 1: Study the effects of including simple non-social explanations in group recommender systems against including no explanations at all (H1).**
- **Experiment 1: Study the effects of including just one social component to these group explanations (H2).**
- **Experiment 1: Study the effects of including the complete $PSIE$ approach (that contains the 3 studied social factors) to these group explanations (H3).**
- **Experiment 2: Validate the results by verifying again the hypotheses using the two presented approaches, *TSE* and *GSE*, and testing which one is preferable.**

5.1. Dataset description

For the study, participants of various age ranges, educational background and occupation have been looked for. Participants were initially recruited among the staff and student population of the Universidad Carlos III de Madrid using poster boards and mailing lists. Subsequently, we extended the call for participation through chain messages posted via Facebook walls. The final sample is a self-selected and voluntary group of 207 Facebook users where 46% of participants are female and 54% are male. Regarding the collected data: respondents belong to two different countries: Spain (201) and UK (6). Regarding the age distribution, Figure 3 shows that it presents similar characteristics to SN users' distribution presented in other studies[5]: skewed to the right and with the mode located at the interval 25-34.

Figure 3: Dataset Age Histogram



The experimental design has been structured as follows: We first ask participants to provide demographic information about themselves and their experience with recommender systems (such as Amazon, Filmaffinity, HappyMovie, etc.) in order to later study if there is any correlation between this fact and the given answers. Note that the later on performed statistical analysis[6] has reported that there is no correlation between experience with recommender systems and participants' answers. Next, the system is introduced and the actual two experiments are carried out as explained in the following two subsections.

5.2. Experiment 1: $PSIE$ Validation

We have recruited 38 groups of friends that usually go to the movies together (124 participants; 10 groups of 2, 12 groups of 3, 12 groups of 4 and 4 groups of 5). Next, we have created a group recommendation event

[5] See http://royal.pingdom.com/2012/08/21/report-social-network-demographics-in-2012/, last access on January 26, 2017.

[6] We have performed a multi-level analysis comparison using a multiple linear regression model.

for each group in *HappyMovie*. The following steps are asked to be performed individually by each participant and are independent for each group member. Participants are asked to: (1) Access Facebook. (2) Enter *HappyMovie*[7]. (3) Answer *HappyMovie*'s personality test (predicts p_u). (4) Answer a movie's preference test (provides $r_{u,j} \in [0,5], with\ j$=items in the test)[8]. (5) Check the provided group recommendation. (6) Answer the following questions (with a 5-star Likert scale):

- **Q1** Rate your *likelihood* to follow the recommendation.
- **Q2** Do you find *HappyMovie* useful?
- **Q3** Would it speed up the group decision process?
- **Q4** Would you use it again?
- **Q5** Are you satisfied with the recommendation?
- **Q6** Do you believe it balances group members' interests?

As presented in Sections 2 and 3, with these questions we aim to check if TSE increased *HappyMovie*'s *persuasiveness* (Q1), *usability* (Q2), *efficiency* (Q3), *trustworthiness* (Q4), *individual satisfaction* (Q5) and *group satisfaction* (Q6). Regarding the formulated hypotheses: we want to test if a simple non-social explanation (as in Section 4.1.4) achieves these goals (H1), or, if one social component is needed to provide good explanations (as in Sections 4.1.1, 4.1.2 or 4.1.3) (H2), or, if only the full TSE proposal (Section 4.1.5) achieves these goals, and hence the three studied social factors are crucial in $PSIE$ (H3). To do so we randomly assign participants to one of these groups[9]:

- **G1** The user sees no explanation.
- **G2** The user sees a non-social explanation.
- **G3** The user sees a personality explanation.

[7]A detailed explanation about how *HappyMovie* works can be found in Quijano-Sánchez et al. (2014).

[8]$t_{u,v}$ and s_u are predicted as explained in Section 3 and $\hat{r}_{u,i}, with\ i$=cinemas' current movie listing are predicted by means of an individual recommender (da Silva et al., 2016).

[9]This means that users in the same group can be presented with different explanation options as the whole process is random. This makes no difference in users' answers as participants access *HappyMovie* individually and are not aware of what possible options exist or what is being shown to the other participants. That is, there is no leakage between treatments.

Table 2: Experiment I questions' average ratings and average (of all questions) standard deviation for randomly assigned groups. Differences between groups G1-G6 have been proven to be statistically significant save for differences between those marked with (*).

	Q1	Q2	Q3	Q4	Q5	Q6	$\overline{s_G}$
G1 (n=21)	3.381	3.214	3.429	3.262	3.262	3.429	0.766
G2 (n=20)	3.8	3.65	3.825	3.775	3.675	3.875	0.592
G3 (n=18)	4.25 (*)	4.111 (*)	4.361 (*)	4.194 (*)	4.028 (*)	4.389 (*)	0.500
G4 (n=22)	4.227 (*)	4.091 (*)	4.227 (*)	4.182 (*)	4.136 (*)	4.318 (*)	0.533
G5 (n=20)	4.225 (*)	4.05 (*)	4.3 (*)	4.175 (*)	4.1 (*)	4.275 (*)	0.531
G6 (n=23)	4.696	4.522	4.739	4.63	4.348 (*)	4.804	0.371

- **G4** The user sees a tie strength explanation.
- **G5** The user sees a satisfaction explanation.
- **G6** The user sees a complete $PSIE$ explanation.

Results (see Table 2) show that on average answers to all questions are higher in G2-G6 than in G1 and the difference is statistically significant (performing a Kruskal-Wallis H Test and pairwise Wilcoxon tests obtaining p-values < 0.05). This result allows us to validate H1 and to conclude the need of including explanations in group recommenders, fact observed by other researchers (Jameson, 2004; McCarthy et al., 2006). Besides, answers to all questions are higher in G3-G6 than in G2 and the difference is again statistically significant. This result allows us to validate H2 and to conclude the need of including a social component in group explanations, a fact also observed by other researchers in individual recommenders (Groh et al., 2012; Sharma and Cosley, 2013; Knijnenburg et al., 2012) but never applied for group recommenders. Furthermore, answers to all questions are higher in G6 than in G3-G5 and the difference is also statistically significant. This result allows us to validate H3 and to conclude that the more social information we include in the explanation the better and that it is the combination of the three studied social factors the option that ensures an optimal user response. Differences in answers to questions in G3-G5, although mostly higher in G3, are not statistically significant. Note that adding social factors minimized answers' fluctuations, as we can see in the last column of Table 2, where the standard deviation in users' answers decreases when adding social information. Future research should investigate in more detail which social factor actually enhances each different characteristic of the system (Q1-Q6). Also, permutations of two social factors in comparison with G6's results require further investigation in the future as it could clarify whether the size of explanations is a key aspect in users' reactions and which explanation size is most effective.

Next, we validate the previously obtained results by verifying hypotheses 1 & 2 this time using the second presented approach, *GSE*. Also, we test whether *TSE* or *GSE* are preferable. Note that this comparison has already been carried out for individual recommenders (Al-Taie and Kadry, 2014; Tintarev, 2007), but never for social recommenders, group recommenders or both as in our case.

5.3. *Experiment 2:* TSE *vs.* GSE

To test which proposed approach, *GSE* or *TSE*, is better we have asked to 30 groups of friends (83 participants; 11 groups of 2, 15 groups of 3 and 4 groups of 4) to follow the same instructions as the experiments carried out in the previous section. Note that these users are different from the ones in the previous experiment. Differently from the previous experiment we have randomly assigned participants to one of these groups:

- **GI** The user sees no explanation.
- **GII** The user sees a *TSE* as explained in Section 4.1.5.
- **GIII** The user sees a *GSE* as explained in Section 4.2.
- **GIV** The user sees a simple graph with all nodes equally connected and below each node a 5-star Likert scale that represents users' predicted rating.

Table 3 summarizes the results obtained in this experiment. In it, we can see that on average users' acceptance is higher in GII followed by GIII and GIV, than in GI, group that received no explanations at all. The difference in the results has proven to be statistically significant again shown by running a Kruskal-Wallis H Test and pairwise Wilcoxon tests and obtaining p-values < 0.05 for all results' combinations save for the tests between GII and GIII where the difference between results is not statistically significant. These are not surprising results as they go along with Al-Taie and Kadry (2014) and Tintarev (2007) findings that concluded that "users don't have a clear preference for *textual* or *graphical* explanations". However, they are new in the context of group and social explanation research. **Due to these results, the significant difference between GI and the rest of the groups, we can again verify H1 and confirm that by introducing explanations users' perception of the received group recommendations is increased. The significant difference between GIV and, GII and GIII lets us further verify H2 and conclude that introducing a social component induces a positive and significant impact in users' *likelihood* to follow recommendations, hence increasing the system's *persuasiveness*, *trustworthiness*, *usability* and *efficiency*.** Furthermore, by proving in both experiments that the social component of explanations is significant we are able to verify our general $PSIE$ proposal and moderate the impact that our concrete wording or presentation in *TSE* or *GSE* respectively can have on the results.

Table 3: Experiment II questions' average ratings and average (of all questions) standard deviation for randomly assigned groups. Differences between groups GI-GIV have been proven to be statistically significant save for differences between those marked with (*).

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	$\overline{s_G}$
G1 (n=22)	3.273	3.023	3.318	3.068	3.159	3.318	0.722
GII (n=20)	4.7 (*)	4.55 (*)	4.75 (*)	4.625 (*)	4.3 (*)	4.775 (*)	0.328
GIII (n=21)	4.452 (*)	4.333 (*)	4.619 (*)	4.452 (*)	4.167(*)	4.476 (*)	0.499
GIV (n=20)	3.725	3.575	3.75	3.7	3.6	3.8	0.672

5.4. *Discussion*

In the above experiments, different explanation systems are considered: no explanations, non-social explanations and different variations of the $PSIE$ proposal. After the encouraging results of the aforementioned experiments that allow us to validate this paper's research hypotheses there are three key issues to consider with regards to the inclusion of explanations in group recommender systems:

- **Adding explanations in group recommenders enhances users' *likelihood* to follow the recommendations.**
- **Adding a social component to explanations in group recommenders enhances the impact that explanations have on users' *likelihood* to follow the recommendations.**
- **Including all of the social components, that the expert system can retrieve, in the generated explanations can improve the system's performance against just adding one social component.**

However, there are a couple of research issues that must be noted and need to be considered in the future:

- **Based on the results of experiment 1: significant differences in participants' answers belonging to G6 compared to the rest of the treatment groups. Further research should study if it is possible that part of the success of G6 may be due to the size of the explanation, rather than**

the combination of different types of explanations.

- **Based on the results of experiment 1: non significant differences in participants' answers belonging to G3, G4 and G5. Further research should look deeper into this matter and study the relevance of each social factor on each system's property.**
- **Based on the results of experiment 1 and 2: validation of this research's posed hypotheses. Note that the $PSIE$ proposal has been designed to explicitly explain the recommendations generated by the *HappyMovie* system and the three social factors that it analyses. Thus, although the experiment results prove this paper's hypotheses we encourage future investigations to delve further in this subject matter with different expert systems and social factors.**

6. Conclusions

In this paper we have introduced a *Personalized Social Individual Explanation* ($PSIE$) approach where we present group recommenders' users an explanation of why the system assumes that the recommended item is the best option for the group. **The presented research illustrates a novel way of reflecting group dynamics as opposed to other works (McCarthy et al., 2006; Jameson, 2004) that limit the explanation of a group recommendation to the trivial process of justifying the selected aggregation technique. This new perspective enables the study of explanations related to user's social behaviour within the group. Social explanations have been previously included for individual recommenders (Groh et al., 2012; Sharma and Cosley, 2013; Knijnenburg et al., 2012) but, to the best of the authors' knowledge, never for group recommenders. In particular the proposed approach focuses on explaining the recommendation process followed by the *HappyMovie* system (Quijano-Sánchez et al., 2014), that consists of the evaluation of different social factors (user's *personality*, *tie strength* between users and previous *satisfaction*) on top of the typical nonsocial aggregation techniques. Thus, enriching the presented explanation with the groups' social behaviour.**

When introducing our $PSIE$ approach a lot of challenges have arisen due to the inclusion of recommendations' social aspects –related to the explanation of human behaviour in groups–. **One example for this complexity is the use of factors such as *personality* and *tie strength*. Based on these factors, a special consideration for "tactful" explanations must be taken into account. Thus,** we have aimed to avoid explanations that might damage friendships, by telling users that someone in the group does not trust them, or offend users, by telling them that their preferences are taken into account less, due to their personality. These insights have led us to build a personalized individual explanation system instead of the more traditional approach of a general group explanation.

From the viewpoint of whether adding explanations to group recommenders results in a better perception of the system's output, experiments' results after testing the impact of $PSIE$ in a real-world environment have shown that not only adding an explanation is a key issue to consider but also that, adding a social component to explanations enhances the impact that explanations have on users' *likelihood* to follow the recommendations and consequently increases the system's *persuasiveness*, *efficiency*, *trustworthiness*, and *usability*. And that also, the more social factors that are included in the explanation the better perception of the received group recommendation.

Note that, although explaining group recommendations to groups may seem an intuitive idea, little research has been done to establish the effects of such group explanations and on how to engineer explanations systematically. To the best of our knowledge, this is the first work that formally proposes social explanations for group recommender systems. Further, our approach is also the first one that proposes to automatically generate $PSIE$ by explaining social factors involved in decision-making processes.

Based on the encouraging results from this paper's experiments we deem our new approach most obviously applicable in social media-based marketing. Our proposal significantly facilitates the unlocking of the immense potential presented by groups of users in social networks, being seen as a new form of customers. By deliberately placing the relations and dynamics inherent in any group at the core of our method we are now able to interact with groups in a similar intrinsic level as traditional marketing and CRM (Customer Relationship Management) interacted with individuals as customers. Beyond the facilitating of marketing and CRM to groups as a new form of customers we see further implications of our approach in areas such as managing project-team cooperation systems. By adjusting the studied social factors to a work environment, for example taking into account individual workloads, individ-

ual skill portfolios or individual experience of team members, our approach could be used to allocate work packages and provide explanations on why a team is assigned with a specific task.

Appendix A.

Table A.4: Sample phrases to generate endings and beginnings of sentences.

Key	Example phrases used (selection)
“butInfo”	“..Still,..”,“..Having said that,..”,“..Despite that,..”
“addInfo”	“..Additionally,..”,“..Furthermore,..”,“..Besides,..”
“plusToThis”	“..As an additional factor, we have also predicted that..”, “..On top of this, we have also predicted that..”
“introWord”	“..We have predicted that..”,“..We believe that..”
“considerWord”	“You may also consider..”,“You may also take into account..”
“stubbornWord”	“..resolute..”,“..adamant..”,“..wilful..”
“comeOn”	“..so why not give it a chance..”, “...so it may be fun for you too.”
“introHi”	“Hi there,..”,“Thanks for asking,..”, “Hello,..”, “As you wonder,..”
“item”	“..this recommendation..”,“..this movie.”,“..our suggestion..”
“trustPositiveEnd”	“..too..”,“..also..”,“..as well..”
“trustNegativeEnd”	“..so you may find something new..” “..and you can normally rely on..”

Table A.5: Sample phrases to generate opening sentence.

$\hat{r}_{u_r,i}$	Example phrases used (selection)
Very weak individual recommendation $\hat{r}_{u_r,i}$ <= 1.5	“..you are likely to detest..” “..you are likely to not really enjoy..”
Weak individual recommendation $\hat{r}_{u_r,i}$ <= 2.5	“..you probably will not really like..” “..you will not be really happy with..”
Indifferent individual recommendation $\hat{r}_{u_r,i}$ < 3.5	“..you will be somewhat okay with..” “..you will be just basically okay with..”
Medium individual recommendation $\hat{r}_{u_r,i}$ >= 3.5	“..you will like..” “..you will enjoy..”
Strong individual recommendation $\hat{r}_{u_r,i}$ < 4.5	“..you will highly enjoy..” “..you will be really happy with..”
Very strong individual recommendation $\hat{r}_{u_r,i}$ >= 4.5	“..you will love..” “..you will cherish..”

Table A.6: Sample phrases to generate explanations based on trusted friends who like the recommended item.

$\hat{r}_{u,i}$, $t_{u_r,u}$ (selection)	Example phrases used (selection)
High $\hat{r}_{u,i}$ (> 4.5) First in TG	“..your friend..” +name+ “,..who you trust most, will love..”
Elevated $\hat{r}_{u,i}$ (> 4.0) Elevated $t_{u_r,u}$ (> 0.4)	“..your trusted friend..” +name+ “,..will highly enjoy..”
Indifferent $\hat{r}_{u,i}$ (>= 3.5) Indifferent $t_{u_r,u}$ (<= 0.4)	“..your friend..” +name+ “,..will be okay with..”

Table A.7: Sample phrases to generate explanations based on users with high personality value who like the recommended item.

$\hat{r}_{u,i}$, p_u > 0.6 (selection)	Example phrases used (selection)
High $\hat{r}_{u,i}$ (> 4.5)	“..”+name+“..really wants to see..” “..and won’t be talked out of it easily..”
Elevated $\hat{r}_{u,i}$ (> 4.0)	“..”+name+“..wishes to see..” “..and will be hard to persuade otherwise..”
Indifferent $\hat{r}_{u,i}$ (>= 3.5)	“..”+name+“..will like to see..” “..so almost no chance that..”+“..can be talked out of it.”

Table A.8: Sample phrases to generate explanations based on the satisfaction other group members would gain if the requesting user accepts the recommended item.

$\hat{r}_{u,i}$, s_u (selection)	Example phrases used (selection)
High $\hat{r}_{u,i}$ (> 4.5) Low s_u (< 0.5)	“..”+name+“..who is not very satisfied with..” “..this group’s decisions so far,..” “..would get a satisfaction boost, as we believe that..” “..would really love..”
Elevated $\hat{r}_{u,i}$ (> 4.0) Low s_u (< 0.5)	“your other disappointed friend,”+name+ “..who is not very satisfied with this group’s past decisions,..” “..would be really happy and satisfied with..”
Indifferent $\hat{r}_{u,i}$ (>= 3.5) Indifferent s_u (>= 0.5)	“..”+name+ “..would be quite satisfied with..”

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