A Chat-Based Group Recommender System for Tourism

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Abstract Group recommender systems aim at supporting a group of users in making decisions when considering a set of alternatives. State of the art solutions aggregate individual preferences acquired before the actual decision making process and suggest items that fit the aggregated model. In this paper, we illustrate a different approach, which is implemented in a system that records and uses the users' preferences expressed while the group discusses options. The system monitors users' interactions and offers appropriate directions and recommendations. The system runs on a smartphone and acts as a facilitator to guide and help the group members in coming up with an agreement and a final decision. In order to measure the effectiveness of the proposed technologies we have focussed on usability and perceived recommendation quality. In a controlled live user study, we have measured a high usability score, good user-perceived recommendation quality and choice satisfaction.

Keywords Group recommender systems · Group decision support · Travel recommender systems

1 Introduction

Recommender systems (RSs) are information search tools that alleviate information overload by straightforwardly suggesting items that are likely to suit users' needs and preferences (Ricci, Rokach, & Shapira, 2015). In many situations, the recommended items are consumed by groups of users (Jameson & Smyth, 2007). For instance, users may seek a restaurant for a group of friends or a vacation package for

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a whole family to experience together. These types of scenarios have led to the emerging field of Group Recommender Systems (GRSs).

Recommending items to a group has been regarded as complicated because of the existence of conflicting preferences between group members. To address this challenge, a large number of research studies on GRSs have focused on preference aggregation strategies, i.e., methods for merging individual preferences and identifying the "best" items for a group. According to Arrow's theorem, however, there is no single optimal method to aggregate individual preferences (voting system), hence many voting approaches have been proposed. Moreover, group members often change their mind, i.e., their preferences, while interacting with each other and with the system (Masthoff, 2015). A few studies in GRSs therefore have tried to model and use the interactions between users and system in order to support group members to reach a consensus. One technique that clearly exemplifies this direction is *critiquing* (McGinty & Reilly, 2011), which is implemented in naturalistic negotiations where users are enabled to respond to proposed items by providing feature-specific feedback. For example, the user's response "show me one like this, but cheaper" would be a directional critique on the "price" of the recommended item.

Actually, social scientists studying group dynamics have stressed the importance of various aspects and steps, of the full decision process adopted by a group, in determining the quality of the output decision (Forsyth, 2014). However, in the context of GRSs still little attention has been devoted to understand how the *process* of making choices in groups can be supported (Chen et al., 2013). In this context we note that a recent observational study on group decision processes has confirmed that group preferences are constructed *during* the process and further stressed that the research in GRSs needs to put more emphasis on the decision making process taking place in groups rather than on solving group recommendation problems in a mechanical way and focusing only on the preference aggregation (voting) step (Delic et al., 2016).

Motivated by these findings, in this paper, we introduce the interaction design of a mobile tourism application that supports a group decision making process. Places of interest items are typically experienced in groups and for selecting them we propose a new GRS that generates recommendations based on the ephemeral (group-dependent) preferences which are derived from the observation of users' interactions when they are in a group. More concretely, we make the following contributions:

- We have implemented a mobile GRS for the tourism domain. The system allows group members to take part in a group discussion, and supports various tasks that the members are likely to undertake during the decision process, such as, asking for information, making comparisons, or seeking a rationale for options.
- We introduce a model that, unlike previous approaches, which merely relies on individual long-term preferences, exploits the group-induced preferences that arise when users are members of the group by monitoring their actions during the group interaction. For that goal, we have designed a novel ranking and group recommendation techniques.

- We have conducted a user study to demonstrate the benefits of the proposed group recommender system and the empirical results show that it is usable and our model is able to enhance the perceived group recommendation quality and the group choice satisfaction.

The rest of the paper is structured as follows. Section 2 gives an overview of the related work. Section 3 introduces the proposed human-system interaction. The proposed model of providing group recommendations and ranking items is then presented in Sect. 4. Then, we describe the experimental evaluation in Sect. 5 and detail the obtained results in Sect. 6. Finally, in Sect. 7 we formulate our conclusions alongside the identified future work.

2 Related Work

Group recommendation techniques fall into two general approaches: aggregate profiles and aggregate recommendations. The former merges existing item ratings of group members to create a single group profile to which conventional recommendation techniques can be applied. The latter generates individual recommendation lists for each member and then combines those lists to form a single one for the group (Jameson & Smyth, 2007). However, it is still not clear which approach should be preferred. The choice depends on the domain, the data and the precise task. For instance, in a food recommendation scenario, Berkovsky and Freyne (2010) compare these two strategies, and show that the former marginally outperforms the latter. More in general, how to optimally aggregate (either preferences or recommendations) is a well-researched topic. Masthoff (2015) gives an overview of different aggregation strategies for reaching group decisions such as *Average*, *Least Misery* or *Most Pleasure*. In Baltrunas, Makcinskas, and Ricci (2010), the authors took a further step by investigating the performance of different rank aggregation strategies for generating group recommendations from individual recommendations by using simulated data of user groups. Recently, a group decision support environment *Choicla* has been developed. It allows the flexible definition of decision functionality in a domain-independent setting (Stettinger, Felfernig, Leitner, Reiterer, & Jeran, 2015). *Choicla* implements basic aggregation heuristics mentioned above as well as Multi Attribute Utility Theory (MAUT) that helps to rank the items in the result sets.

The research in travel recommender systems for groups has made several contributions. Specifically, *Intrigue* (Ardissono, Goy, Petrone, Segnan, & Torasso, 2003) is a tool helping tour guides in designing tours for heterogeneous tourist groups such as families with children and elderly, which include relatively homogeneous subgroups (e.g. children). The group model, which aggregates user preferences, is a weighted average of the subgroup models, which are weighted according to the importance of the subgroups. Moving into the direction of supporting users-to-users and users-to-system interactions, *Travel Decision Forum* allows users to interact with embodied conversational agents representing group members to reach an accepted group preference (Jameson, 2004). In *Collaborative Advisory Travel System,* critiquing is used for allowing each group member to send a "critique" to the other members, thereby sharing thoughts about a specific option (McCarthy, McGinty, Smyth, & Salamó, 2006). In line with this research direction, Guzzi, Ricci, and Burke (2011) introduced interactive multi-party critiquing, an extension of the critiquing concept to a computer-mediated conversation between two group members, and the authors implemented it in a mobile phone application for group recommendation of restaurants called *Where2eat.*

However, as we notice, in traditional critique-based techniques, users are expected to explicitly point out the critiqued features, i.e., identifying the features that they like or dislike. This requires considerable user efforts and is especially hard for those who are not able to clearly differentiate the importance of such features. In contrast, our proposed technique derives preferences solely from user evaluations for items and then infers which item features are important to users by comparing the item the user liked and disliked. Thus, in this paper, we propose an approach that constructs the user and group profiles by observing a series of user interactions during the group discussion. Our system supports a real-time recommendation functionality based on the user-system interactions, so that the group has the possibility to interact and explore different alternatives that can be seen as compromises for the group.

3 Application Scenario

The rationale of the interaction design of the proposed system comes from studies on the functional theory of group decision making which suggest that groups, when facing decision tasks, are actually engaged in a four stages process: *Orientation–Discussion–Decision–Implementation* (Forsyth, 2014). Furthermore, decision makers often seek and construct reasons in order to resolve the conflicts and justify their choices when they are faced with the need to choose (Shafir, Simonson, & Tversky, 1993). In the scope of this paper, we primarily concentrate on the discussion stage which is regarded as the most vital part of the decision making process. According to Forsyth (2014), it is the information processing hub on which users typically rely to arrive at the final decision. More concretely, we address the issue of how to support the group discussion by providing a chat environment that is believed to be convenient and comfortable for group members to express their thoughts and to interact with each other as well as with the system. From the system perspective, through chat logs composed of exchanged messages and actions, the interactions between users can be tracked, and used for inferring information about the changing users' preferences.

For these reasons, we have designed and implemented a GRS with a chat-based interface called STSGroup (South Tyrol Suggests for Group). STSGroup is an Android-based mobile application that extends to groups STS

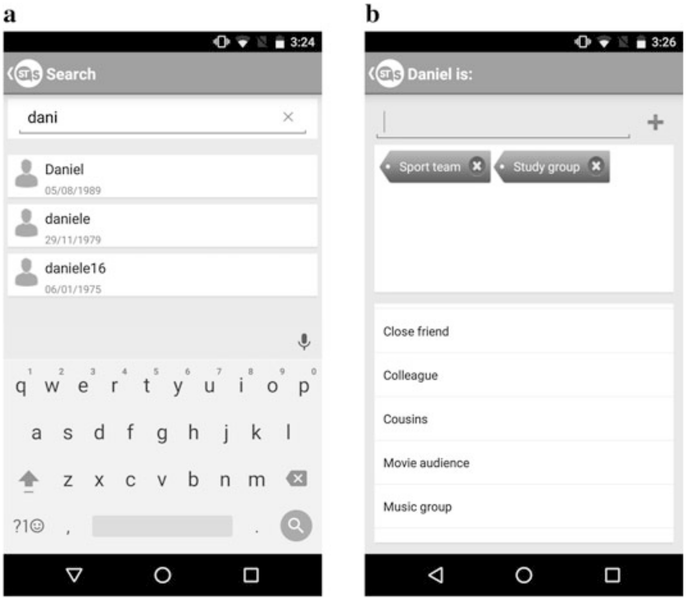

Fig. 1 **a** Search companions and **b** tag companions

(Braunhofer, Elahi, & Ricci, 2014), a context-aware places of interest (POIs) recommender devoted to individuals. In the following, we will describe a typical interaction with our system.

Let us assume a tourist or a citizen is looking for a POI (in South Tyrol, Italy) for her group to visit together. After the registration to the system, the user can specify her companions through appropriate system screens including: searching companions by user name (see Fig. 1a), sending connection requests and tagging companions (see Fig. 1b). Once a group of people that are connected by the "companion" relation wants to visit a POI, the discussion/chat is ready to start. Note that users can always access functions that are already available in STS; for instance, they can specify context variables such as their mood, or browse their personalized recommendations which are computed by taking into account only their personal preferences (ratings for previously experienced POIs). As soon as a group is connected, one member can send messages to the other group members and a discussion session is started (see Fig. 2a). The users can exchange messages in a chat application (similar e.g. to WhatsApp). Any user can autonomously search in STSGroup for interesting POIs and propose them to their group companions. All proposed POIs are displayed chronologically in the group discussion space, together with other messages. Group members can react to a proposed POI with a: like (thumb up), dislike (thumb down), or best (crown icon). User can also tag proposed POIs with comments and emoticons (Fig. 2b). A summary comparison panel aggregating and comparing the members' likes, dislikes and best is always shown on the top of the screen in order to keep users aware of the other members'

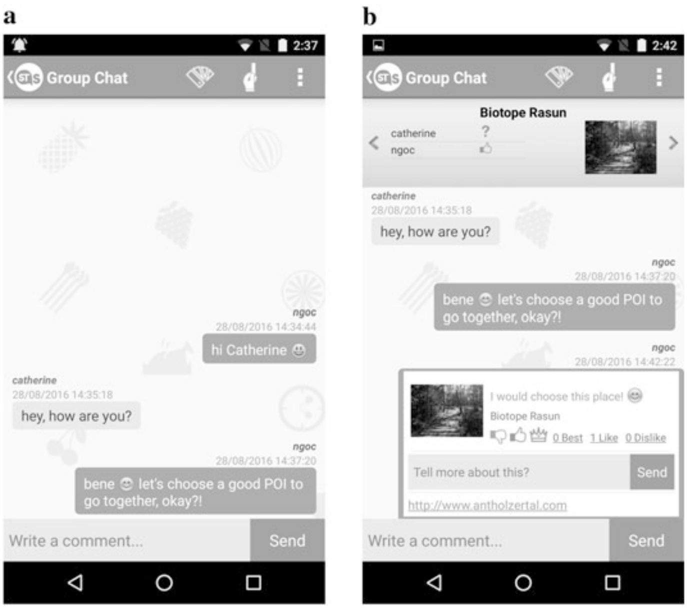

Fig. 2 **a** Group chat and **b** group chat with proposed items

preferences. The panel is updated automatically when there is any change in the preferences expressed by any group member.

During a chat session, in case a user would like to identify other POIs to propose, in addition to those already made, she can ask for group recommendations (see Fig. 3a). System recommendations are augmented with explanations that provide a rationale for the system recommendations (e.g. referring to the item features that might draw the attention of the group members). The system also takes group members' actions and contexts into account. Specifically, the more items a user rates, the higher the importance she will have in the preference aggregation step of the recommendation computation. Similarly, a higher importance is assigned to users who are in somewhat vulnerable contexts such as bad mood, or tiredness (declared by users in their context management section of the application). The system also offers hints as supplementary information about items, which are added automatically by the system to the flow of the comments, or suggestions for better using some of the system functions. In STSGroup, the comparison between proposed items in terms of ratings (displayed as a bar chart) is additionally provided if necessary.

When facing difficulties in arriving to a final decision, any user can refer to the choice suggestion function (see Fig. 3b). Here the system computes an accumulated score for each item, based on the evaluations given by all group members; each item receives plus 2 and plus 1 for best and like feedback respectively, and minus 1 for a dislike evaluation. The ranking list and explanations are constructed with respect to this score.

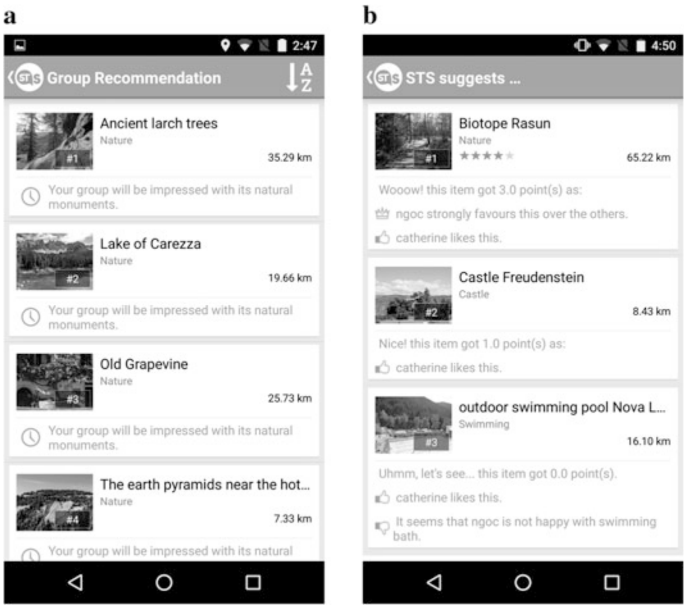

Fig. 3 **a** Group recommendation and **b** choice suggestion

4 Recommendation Logic

As we mentioned above, STSGroup monitors and uses the preferences of users while they are changing in a group decision making process. User preferences expressed in a group discussion could either be consistent with the user long-term (group-independent) interests, which are acquired by the system as item ratings, or in conflict with them. This largely depends on the other group members and on the group decision making dynamics. Thus, the system observes group members' actions during the group discussion in order to infer novel information about the current user preferences in that specific context. The system implements this idea by modelling the users' utility function and by learning it on the base of the observations of the users' evaluations for POIs.

STSGroup models the user utility function as follows:

$$f(u, i) = \sum_{k=1}^{n} w_k^{(u)} x_k^{(i)}, \tag{1}$$

here $x^{(i)} = (x_1^{(i)}, \ldots, x_n^{(i)})$ is a n dimensional Boolean feature vector that represents the item i whereas n is the number of item features. For example, if $x^{(i)} = (0, 1, 1, 0)$, this means that item i possesses the second and the third features and does not have the first and the fourth ones. In STSGroup, item features model various sources of information including categories of the item such as "castle" or "museum", and key words extracted from the item short-description like "waterfall" or "lake". All information of items is obtained through a web-service provided by the Regional Association of South Tyrol's Tourism Organizations (LTS[1]). After removing redundancy, each item is represented by 84 features in total. In Eq. (1), a vector of weights $w^{(u)}$ models the importance that user u assigns to the item attributes. We have: $w_k^{(u)} \geq 0$ and $\sum_{k=1}^{n} w_k^{(u)} = 1$. In case the user has not rated any item, all vector $w^{(u)}$ elements are set to 1/84, otherwise the vector is computed as follows:

$$w_k^{(u)} = \frac{\sum_{i \in I_u} r(u,i) x_k^{(i)}}{|i : x_k^{(i)} \neq 0|}, k = 1, \ldots, n. \tag{2}$$

In Eq. (2), I_u and $r(u, i)$ are respectively the set of rated items by user u and a rating of user u for item i before the user enters in the group discussion. The equation takes the frequency of features in the items rated by the group members into account. For instance, assume that $r(u_1, i_1) = 5$ and $r(u_1, i_2) = 2$, and the feature vectors of item i_1 and i_2 are $x^{(i_1)} = (0, 1, 1)$ and $x^{(i_2)} = (1, 0, 1)$. Based on the Eq. (2), $w^{(u)}$ is computed as follows:

$$w_1^{(u)} = \frac{2}{1} = 2,\ w_2^{(u)} = \frac{5}{1} = 5,\ w_3^{(u)} = \frac{(5+2)}{2} = 3.5$$

Then vector $w^{(u)}$ is normalized by dividing it by $\sum_{k=1}^{n} w_k^{(u)}$, so that we finally obtain the vector $w^{(u)} = (0.19, 0.48, 0.33)$, as initial preference model of the user.

We denote with $w^{(G)}$ the aggregated utility vector of group G. This, in principle, can be computed by many different aggregation functions such as *Least Misery*, *Most Pleasure*, or *Average* (Masthoff, 2015). In our system, at the beginning of the group discussion, we use the *Average* approach to initialize vector $w^{(G)}$: it is quite straightforward and considered to be acceptable by group members due to its fairness.

Different from the previous critique-based techniques, our system does not ask users to explicitly provide feedback on item features, so information about the importance of item features assigned by each group member is missing. We instead infer the user utility function based on constraints on the definition of that function that are derived from the user expressed preferences. Specifically, users can evaluate the POIs proposed for a group chat, as either: best choice; or like; or not evaluated (neither like nor dislike); or dislike. Moreover, we assume that users prefer items with larger utility, so if the user prefers item i and dislikes item i', we

[1]LTS: http://www.lts.it.

deduce that $f(u, i) > f(u, i')$. For example, during the group discussion, if the user marks as best choice a POI that is described by the attributes "castle" and "fortress", and dislikes one having the attribute "swimming", then the constraint $\left(w_{castle}^{(u)} + w_{fortress}^{(u)}\right) > w_{swimming}^{(u)}$ is inferred to hold in the definition of the user utility function. Each group member is therefore described by multiple constraints depending on what POIs she has evaluated.

Finally, the expected user utility for each POI is estimated by finding the vector of weights $w^{(u)}$ that satisfies the inferred constraints, and maximizes the cosine similarity with the vector $w^{(G)}$. Our approach assumes that the true user utility function reflects both the personal and group preferences. The vector $w^{(G)}$ is then updated by using the *Weighted Average* approach, a variant of the *Average* strategy, in order to take the role of group members into account. The implemented strategy is as follows:

$$w^{(G)} = \sum_{u \in G} \alpha(u, G) w^{(u)}, \tag{3}$$

where $\alpha(u, G)$ is a non-negative coefficient associated to user u in group G and $\sum_{u \in G} \alpha(u, G) = 1$. The coefficient depends on the activity of the user in the group: the more feedback the user provides, the higher the value of her coefficient is. Precisely, the coefficient is the proportion of the number of user's actions (POI proposals, POI evaluations and POI comments) to the total number of actions acquired from all group members. The system also increases the coefficient by a pre-defined value for users who are in somewhat vulnerable contexts such as bad mood, or tiredness.

When a user is in a group discussion and requests some group recommendations, items are ranked according to the group utility function defined as follows:

$$f(G, i) = \sum_{k=1}^{n} w_k^{(G)} x_k^{(i)}. \tag{4}$$

The system then suggests the POIs with the highest utility for the group, so the returned recommendations are the same for all group members.

5 Experimental Evaluation

The objective of the conducted experiments was to assess the usability of STSGroup, the perceived quality of the system proposed group recommendations and the group choice satisfaction, i.e., the satisfaction of the group for the POI that is finally selected by the group for a visit. We used the System Usability Scale—SUS (Bangor, Kortum, & Miller, 2008) to evaluate STSGroup usability. SUS is one of the most popular post-study standardized questionnaires and it also allows to measure the perceived system usability with a small sample population (i.e. 8–12 users) (Sauro & Lewis, 2012).

Our user study involved 15 participants (students and colleagues). Some of them have computer technical knowledge (i.e., 6 out of 15). The users were divided into groups of 2 or 3 people. In total, we composed 6 groups; 3 groups of two and 3 groups of three members. One member in each group was assigned to be the "initiator", who starts the discussion by proposing the first POI to the group. All participants were invited to meet physically in our lab, and at the beginning of the group meeting, each one received a mobile device where STSGroup was previously installed. The experiment was performed using LG Google Nexus 5 smartphones running Android 6.0.1. The participants were asked to introduce themselves to their group's members, exchange their STS user id, and send or accept friend requests. Then we gave them the task scenario: "*Imagine that you and your group members have a plan to visit a place in South Tyrol together. According to your own preferences, STS offers you a suggestion list. Your task is first to select one or more places in the list that you think are suitable for your group to experience together and propose them to your group. Afterwards, you and the group members could discuss the proposed options and decide which place your group will choose to visit*".

We explained that STS offers each member a personal suggestion list. They, and similarly their friends, could select places in the suggestion list and propose them to their group. Additionally, they and their friends could discuss the proposed options —in the supported group chat—and eventually chose one to visit. We also requested that group members not to be at that same place during the group discussion, and to communicate with each other by only using the system chat. Finally, participants filled out a survey including three questionnaires: SUS, perceived recommendation quality and choice satisfaction which measurements are adopted from Knijnenburg, Willemsen, Gantner, Soncu, and Newell (2012). In particular, for each questionnaire item, users reply on a five points Likert scale ranging from "strongly disagree" to "strongly agree". The 10 SUS statements are: **S1**: "*I think that I would like to use this system frequently*". **S2**: "*I found the system unnecessarily complex*". **S3**: "*I thought the system was easy to use*". **S4**: "*I think that I would need the support of a technical person to be able to use this system*". **S5**: "*I found the various functions in the system were well integrated*". **S6**: "*I thought there was too much inconsistency in this system*". **S7**: "*I would imagine that most people would learn to use this system very quickly*". **S8**: "*I found the system very cumbersome to use*". **S9**: "*I felt very confident using the system*". **S10**: "*I needed to learn a lot of things before I could get going with this system*".

Each SUS item's score contribution ranges from 0 to 4. For positively phrased statements (odd numbers) the score contribution is the scale position minus 1. For negatively worded statement (even numbers), the contribution is 5 minus the scale position. To get the overall SUS score, the sum of the item score contribution is multiplied by 2.5, so the overall system usability scores range from 0 to 100. Several benchmarks for the SUS across different systems have been published (Bangor et al., 2008), and an average SUS score computed in a benchmark for cell phones is around 67. In our user study, we used this value as a baseline to determine whether our application usability exceeds the benchmark.

The next section of the survey is composed of 5 statements about perceived recommendation quality and 3 statements about choice satisfaction, which are listed as follows: **RecQual1**: "*I liked the final choice suggested by the system*". **RecQual2**: "*The final choice recommended by the system was well-chosen*". **RecQual3**: "*I didn't like the suggested final choice*". **RecQual4**: "*The new item recommendations for a group, excluding the proposed items were relevant*". **RecQual5**: "*I didn't like any of the recommended new items*". **ChoiceSat1**: "*I was excited about the place that we have chosen*". **ChoiceSat2**: "*The chosen place fits my preference*". **ChoiceSat3**: "*I didn't prefer the chosen place, but it was fair*".

6 Evaluation Results

In this section, we report the results of the usability study, the perceived quality of the group recommendations and the users' choice satisfaction. Figure 4 shows the SUS score of each test user. Most of them gave the score that is higher than the benchmark.

Overall, STSGroup obtained a SUS score of 76 (over 15 users). We calculated one sample t-test to verify if the score is higher than the benchmark of 67, and got the result $t = 4.42$ and the probability associated with this score is 0.001. This means we can 99% confidence that the average SUS score of STSGroup exceeds the benchmark.

We also computed the average responses for 10 SUS statements. The highest average scores are for S6, S4 and S8. This implies that the participants have evaluated STSGroup as not complex as well as not difficult to use. They also do not think that the system is inconsistent or cumbersome, and they believe that they are able to use the system without technical help. S9, S7 and S5 received instead the lowest scores. This implies that the users were not fully confident of using the system and think that most people will not learn to use it quickly. They also found some of the functions in the system not well integrated. All these issues could be explained by the fact that in STSGroup, we support two types of recommendations

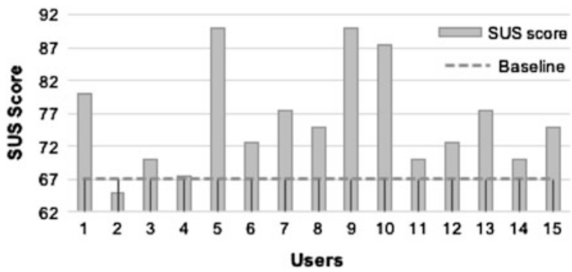

Fig. 4 System Usability Scale (SUS)

Table 1 Recommendation quality

Statement	Strongly agree (%)	Agree (%)	Neither disagree nor agree (%)	Disagree	Strongly disagree (%)
RecQual1	**26.7**	**60.0**	13.3	0.0	0.0
RecQual2	**33.3**	**53.4**	13.3	0.0	0.0
RecQual3	0.0	0.0	6.7	**53.3**	**40.0**
RecQual4	0.0	**73.3**	20.0	6.7	0.0
RecQual5	0.0	0.0	6.7	**60.0**	**33.3**

simultaneously: personal context-aware and group recommendations. It means that users are still able to use all functions that are already available in STS besides new ones designed for groups, and they can browse items appearing in their personal suggestion lists and propose them in the group discussion. With various support functions in one application, i.e. the combination between individual and group functions, users therefore may have not clearly understood the usage of each module.

Regarding the recommendation quality and choice satisfaction aspects, which are shown in Table 1, it is noteworthy that the majority of the participants (i.e. 86.7%) indicated that they liked the final choice suggested by the system (RecQual1) and found it well-chosen (RecQual2). In line with that, 14 individuals out of 15 (93.3%) disagreed with the statement "*I didn't like the suggested final choice*" (RecQual3). Next, the performance of the proposed recommendation model is remarkably high as more than a half (i.e. 11 out of 15) confirmed that "*the new item recommendations for a group, excluding the proposed items*" (RecQual4) were relevant and 93.3% of participant did not approve the statement "*I didn't like any of the recommended new items*" (RecQual5). We note that we did not check whether users were previously familiar with the recommended POIs or not, so their evaluations were based on user dependent combination of pre-existent POI knowledge and information acquired by using the system.

About choice satisfaction, the majority of participants (9 out of 15) confirmed that "*The chosen place fits my preference*" and for the remaining, 3 users neither disagree nor agree with the statement while the other 3 users disagree. However, the satisfaction with the final choice was quite high, particularly, 80% participants (12 out of 15) indicated that they are excited about the chosen place.

7 Conclusions and Future Work

In this paper, we have presented the recommendation algorithm and the interaction design of a novel mobile GRS that supports group decision making by offering a group chat environment in which a number of recommendation functions are integrated. We have argued that to make a better decision in groups, a GRS should support the whole decision process, and in this paper, we mainly focussed on supporting the discussion stage, where group members' preferences can be elicited and shaped. The proposed algorithm exploits users' feedback during the group discussion in order to update the system definition of the users' utility functions. We have conducted a live user study where we have measured the usability of the system, the quality of group suggestions and the choice satisfaction. The experimental results have shown the usability of our system is larger than a standard benchmark and it also provides high perceived recommendation quality and group choice satisfaction.

However, the system still has a number of limitations which ultimately are linked to the difficulty to understand the true meaning of certain recommendation functions, such as the difference between individual and group recommendations. In the future, we will address this limitation and we will also make the system able to proactively propose new items when it detects that this could be valuable: for instance, when users often change preferences for items, implying that they are unsure about the current proposals. Finally, we intend to analyse the textual group members' comments while they are discussing a set of options and trying to make a decision, so that their new preferences will be extracted and inferred. We believe these functions would further improve the usability and the effectiveness of the system.

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