Fostering Knowledge Exchange Using Group Recommendations

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ABSTRACT

The more domain knowledge individual participants of a group decision process share with each other, the higher the probability of high-quality decision outcomes. In this paper we report the results of an initial empirical study conducted on the basis of a group decision support environment. In this study, groups were confronted with recommendations with a varying degree of diversity. The higher the diversity of recommendations provided to groups, the higher was the degree of knowledge exchange.

Keywords

Group Recommenders, Decision Support, Hidden Profiles.

Categories and Subject Descriptors

H.5.3. [**Group and Organization Interfaces**]: Computer-supported cooperative work.

1. INTRODUCTION

In contrast to single user recommenders [7], group recommenders determine relevant items for whole groups [6, 10]. For example, Jameson [5] introduces a prototype application that supports groups of users in the identification of a holiday destination. Masthoff [9] introduces concepts for sequencing television items for groups of users on the basis of different models from social choice theory (see also [10]). O'Connor et al. [16] introduce a collaborative filtering based movie recommender system that determines recommendations for groups of users. Ninaus et al. [15] show the application of group recommendation technologies in requirements engineering scenarios where stakeholders are in charge of cooperatively developing, evaluating, and prioritizing requirements. Finally, McCarthy et al. [12] introduce a critiquing-based recommender that supports groups of users in a skiing holiday package selection process. CHOICLA[1] is a group decision support environment which includes group recommendation technologies – this system was used as a basis for the user study presented in this paper.

Psychological aspects of group decision making play an increasingly important role in the development of (group) recommendation technologies [8]. Especially decision biases which denote suboptimal shortcuts in decision making can lead to low-quality decision outcomes. Masthoff and Gatt [11] discuss approaches to the prediction of user (group member) satisfaction with recommendations – in this context, conformity and emotional contagion are mentioned as major influence factors. Felfernig et al. [4, 20] analyze the impact of conformity in the context of group decision making and report an increasing diversity of the preferences of group members the later individual preferences are disclosed to the whole group. Chen and Pu [2] show how emotional feedback from group members can be integrated in group (music) recommendation. An outcome of their study is that emotional feedback can enhance mutual awareness of user preferences in the group. For a short overview of decision biases in recommender systems we refer to Felfernig [3, 21].

The frequency of knowledge exchange within a group can have a major impact on the quality of the decision outcome [14]. The more decision-relevant knowledge is exchanged between individual group members, the higher is the probability of discovering the hidden profile which can be characterized as the relevant knowledge to take a good (if optimality criteria exist, also an optimal) decision [22]. A consequence for group decision environments is that decision support has to include mechanisms that *pro-actively encourage knowledge exchange*. One reason for increased knowledge exchange between group members is *group diversity* (in terms of dimensions such as demographic and educational background), i.e., the higher the degree of diversity the higher the probability of higher quality decision outcomes (measured, e.g., in terms of the degree of susceptibility to the framing effect [23]). Schulz-Hardt et al. [17] discuss the role of *dissent* in group decision making: the higher the dissent in initial phases of a group decision process, the higher the probability that the group manages to share the decision-relevant information (discover the hidden profile).

The major focus of our empirical study was to analyze the impact of *recommendation diversity* on the frequency of knowledge exchange between group members. A major reason for increasing the diversity of recommendations is the

[1] www.choicla.com.

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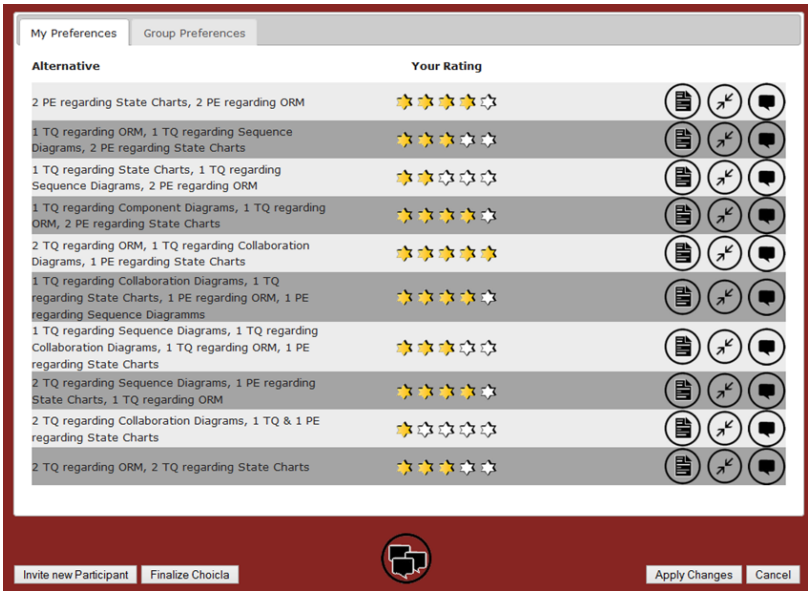

Figure 1: CHOICLA group decision support environment: in the description of the alternatives (alternative exam modes) TQ denotes *theoretical assignment* and PE denotes a *practical assignment*.

fact that otherwise recommendations are too similar to each other and thus provide only a limited coverage of the whole item space [13, 18]. There is always a trade-off between similarity and diversity since too diverse recommendations can lead to situations were relevant items are omitted, i.e., are not recommended although relevant for the user.

In this paper we do not focus on the prediction quality of recommendation algorithms but analyze in which way recommendations can be used to increase knowledge exchange between the members of a group. In the context of group decision making it is often more important to increase the performance of the group rather than predicting decisions that will be taken by the group. In this paper we analyze three different basic group recommendation heuristics (min, avg, and max group distance) with regard to their impact on the communication behavior inside a group. The basis for our analysis is an empirical study that was conducted in a computer science course at our university. The results of our analysis show that recommendation diversity can trigger additional (decision-relevant) communications.

The remainder of this paper is organized as follows. In Section 2 we describe the design of our user study and discuss related results. In Section 3 we discuss open issues for future work. With Section 4 we conclude the paper.

2. USER STUDY

The task of each group (of undergraduate students) in the empirical study (N=256 participants, 12% female, 88% male) was to select their preferred exam mode for their Software Engineering course, for example, *1 theoretical assignment on Object-Relational Mapping (ORM), 1 theoretical assignment on Sequence Diagrams, and two practical assignments on State Charts* (see Figure 1). The participants were informed about the fact that there is no guarantee that the articulated preferences will be taken into account in upcoming exams. Each participant was a member of exactly one group (team) that had to implement a software within the scope of the course. Alternative exam modes (different topics and different shares of theoretical and practical assignments) were modeled in CHOICLA (see Figure 1).

Each group had the task to use the CHOICLA group decision support environment to cooperatively identify a ranking for the different assignment types. Each group member had to define his/her own ranking (see Figure 1) and was not able to see the preferences of the other group members. Participants of the study were encouraged to take a look at the group recommendations (tab *group preferences*) which was done by 91.41% of the participants at least once. Different group decision heuristics were used in our study and each group was assigned to a CHOICLA version that implemented exactly one of these heuristics.[2] Related group recommendations d differ in terms of their *diversity* compared to the individual user ratings (rating scale: 1-5 stars) of an alternative s determined by $eval(u, s)$ (see Formula 1).

$$diversity(d) = \frac{\sum_{u \in Users} |eval(u, s) - d|}{\#Users} \quad (1)$$

The (low diversity) *minimum group distance* heuristic ($GD_{\min}$) returns a rating d that represents the minimum distance to the ratings of group members (see Formula 2).

$$GD_{\min}(s) = \arg \min_{d \in \{1 \ldots 5\}} \left(\sum_{u \in \text{Users}} |\text{eval}(u, s) - d| \right) \quad (2)$$

The (highly diverse) *maximum group distance* heuristic ($GD_{\max}$) returns a rating d that reflects the maximum distance to current ratings of group members (see Formula 3).

$$GD_{\max}(s) = \arg \max_{d \in \{1 \ldots 5\}} \left(\sum_{u \in \text{Users}} |\text{eval}(u, s) - d| \right) \quad (3)$$

Finally, *average group distance* represents a value between maximum and minimum group distance (see Formula 4).

[2]Note that CHOICLA includes a set of group heuristics from social choice theory [10], GD_{max} and GD_{avg} have been included for the purpose of the empirical study.

$$GD_{avg}(s) = \frac{GD_{\min}(s) + GD_{\max}(s)}{2} \quad (4)$$

An overview of the assignment of groups to the different decision heuristics is depicted in Table 1.

heuristic	#groups	#participants
min	17	92
avg	12	69
max	16	95
total	45	256

Table 1: Group distribution in the empirical study.

Hypotheses. The basic assumption of hypothesis H1 is that group decision heuristics with a higher diversity lead to an increased knowledge exchange between group members. The reason for this is that recommendations can act as an anchor [1] and also have the potential to induce the feeling of dissent in the group which needs to be resolved by the group members. An increased amount of knowledge exchange can help to discover the hidden profile of a group decision [14, 22], i.e., the amount of decision-relevant knowledge is increased. Furthermore, we assume that a higher frequency of knowledge exchange is correlated with higher time efforts per group.

Examples of knowledge exchanged within the scope of our empirical study are the following (see Table 2).[3]

Content-related. A student only took a look at exercises related to *Object-Relational Mapping (ORM)* and asks for further information regarding the topic. Another student of the same group points out that there are only a few slides with very simple and understandable rules which are also very useful in industrial contexts.

Preference-related. A student emphasizes that he/she prefers to include appointments on *UML Class Diagrams* compared to appointments related to the *Unified Process*.

Recommendation-related. A student does not like the group recommendation since it does not take into account his/her preferences. Furthermore, he/she articulates an urgent need to further discuss assignment topics that are acceptable for the group as a whole. For recommendation-related comments we also evaluated the valence, i.e., how positive/negative a recommendation was perceived.

The assumption of hypothesis H2 is that a higher degree of knowledge exchange increases the flexibility of group members to change their initial preferences. Due to the fact that more decision-relevant knowledge is exchanged between group members, the amount of global decision-relevant knowledge is increased which improves the individual capabilities of taking into account additional decision alternatives. Increased knowledge exchange between group members helps to overcome a *discussion bias* (group discussions tend to be dominated by information group members already knew before the discussion [19]).

Hypothesis H1 can be confirmed, i.e., the amount of decision relevant knowledge exchanged between group members increases with the diversity degree of the used group recommendation heuristic. The higher the diversity, the higher the number of decision-relevant comments given within the scope of the decision process (see Table 2). Furthermore, also the overall time investments increase with the diversity of the decision heuristic (see Table 3).

heuristic	content	preferences	recommendation
min	22	0	27 (+4.2)
avg	31	26	35 (+0.9)
max	79	91	108 (-4.4)

Table 2: Content-, preference-, and recommendation-related comments (valence [-5 .. +5]).

heuristic	avg. endtime−starttime (h)	avg. efforts (min)
min	71.06 (13.05)	210.71 (20.19)
avg	85.64 (26.58)	234.56 (17.67)
max	101.18 (19.48)	278.46 (16.74)

Table 3: Time (and std.dev.) invested per group for decision task completion (i.e., rating of alternatives).

We can also confirm hypothesis H2. A higher degree of knowledge exchange between group members also provides flexibility regarding the final group decision. Table 4 provides an overview of the degree of opinion adaptation of groups depending on the supported decision heuristics.

heuristic	avg. change of rating
min	0.67
avg	1.32
max	2.46

Table 4: Changes of initial ratings depending on the supported decision heuristic.

Summarizing, the higher the diversity of the used decision heuristic, the higher the frequency of knowledge exchange between group members. Consequently, recommendations in the context of group decision support can also be exploited to adapt a user's group decision behavior which can lead to higher quality decision outcomes. Diverse recommendations can help to detect hidden profiles [17, 19] which represent an amount of global decision-relevant knowledge needed to take good (or even optimal) decisions. Online group decision support environments have to be aware of this fact and should also take into account diversity in group recommendations.

3. FUTURE WORK

Major issues for future work are the following. Our study is limited in the sense of having investigated a set of basic heuristics (diversity measures) (min, avg, and max group distance). In our future research we will investigate further decision heuristics (see, e.g., [10]) with regard to their capability to increase the frequency of knowledge exchange and to increase decision quality. We will also focus on a more fine-grained analysis of potential optimal degrees of diversity that help to maximize knowledge exchange while decreasing the perceived quality of recommendations as little as possible. The average diversity (Formula 1) of recommendations

[3]The categorization into the types *content-related*, *preference-related*, and *recommendation-related* was performed manually.

determined by the three different heuristics is depicted in Table 5. We want to emphasize that the satisfaction with group recommendations significantly decreases if the degree of diversity is too high – Table 6 summarizes user feedback regarding the perceived satisfaction with the group recommendations.

heuristic	min	avg	max
diversity	0.84	1.38	2.23

Table 5: Diversity of group recommendations.

heuristic	very satisfied	satisfied	average	unsatisfied	very unsatisfied
min	67	12	9	2	2
avg	17	14	12	14	12
max	2	1	15	25	52

Table 6: Satisfaction with group recommendations.

4. CONCLUSIONS

In this paper we presented the results of an initial empirical study that focused on possibilities of increasing the amount of knowledge exchange in group decision scenarios. In this context, we showed that the diversity of recommendations can have a significant impact on the frequency of knowledge exchange – the higher the diversity of group recommendations, the higher the corresponding number of comments included in the group decision process. The results presented in this paper are a first step towards the application of recommendation technologies to foster knowledge exchange in group decision making.

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