Investigating the Decision-Making Behavior of Maximizers and Satisficers in the Presence of Recommendations

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ABSTRACT

Psychological theory distinguishes between maximizing and satisficing decision-making styles. Maximizers tend to explore more or all alternatives when making a choice, while satisficers evaluate options until they find one that is good enough. There is limited research that examines how the existence of a recommender influences the choice process and decisions of different types of decision-makers. We report the results of a controlled study, in which we monitored the choice process of participants when provided with automated recommendations and different types of additional information regarding available options.

Our analyses show that *none* of the differences that were expected based on the literature manifested itself in the experiment. Maximizers neither inspected more items, nor invested more time to study them. Instead, like satisficers, they mostly picked one of the top-ranked items recommended by the system, which emphasizes the value of recommenders in particular for maximizers, who would otherwise face a more challenging decision problem. The analysis of the preferences of participants over different types of additional information revealed that highlighting key pros and cons was perceived as particularly helpful for the maximizers, an insight that can be used for the design of explanation approaches for recommenders.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; *Decision support systems*; • **Human-centered computing** → **User studies**;

KEYWORDS

Explanations; decision making policies; maximizer; satisficer

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1 INTRODUCTION

Psychological theory suggests that people adopt different decision-making styles [14]. At one extreme, there are *maximizers*, who have a tendency to explore many or all available options before making a decision, whereas *satisficers* usually only scan the options until they find a satisfactory one [5, 24]. Interestingly, even though maximizers, as a result, tend to invest more time, they are often less happy with their final decisions [10].

Helping users in the decision process is one of the major goals of recommender systems (RS) [11, 13, 22], and a large amount of evidence exists on the impact of these systems on decisions made by their users [12, 15, 27]. While the recommendations of such systems are in many cases personalized according to the assumed preferences or personality of users, recommenders usually do not take possible differences in the users' decision making styles into account. There are only a few approaches in this context [6, 18]. They investigate, for example, the value of providing different user interfaces for different types of consumers or user interfaces that adapt themselves, e.g., according to the consumers' assumed expertise.

The long-term goal of our research is to customize recommenders to better support users with different decision-making styles. Examples of possible customizations are the presentation of larger choice sets for maximizers or the provision of certain types of complementary information to support users in the decision-making process according to their decision-making style. In this paper, we make a step towards achieving this goal and investigate foundational aspects by means of a user study. A first main question addressed in our study is to what extent the observations regarding the choice behavior of maximizers and satisficers manifest themselves in the context of a recommendation scenario. Differently from studies in the field of psychology, the decision process in our application scenario is supported by a recommender system and the choice set is presented to the study participants in a certain order determined by the system. Furthermore, to investigate if maximizers and satisficers have different information needs, we provided participants with different types of explanations [20] and measured their acceptance and perceived value for the different user groups. Differently from typical user studies on explanations, instead of only asking participants about their subjective experience regarding, e.g., the choice difficulty, we also rely on objective measures such as the time needed to make a decision, the number of inspected items, or the position of the selected item in the recommendation list.

The rest of the paper is organized as follows. After discussing previous work and our expectations in Section 2, we report the design of our user study in Section 3. The results of our analysis and our conclusions are discussed in Sections 4 and 5.

2 BACKGROUND AND EXPECTATIONS

As mentioned, a number of psychology studies have shown that maximizers generally spend more time on making decisions, yet ultimately experience more regret and less satisfaction with their choices than satisficers [5, 24]. For example, in a study about job seeking behavior [10], in which maximizers secured higher-paying jobs on average, they felt more negative affect during the decision process and lower satisfaction with their (objectively better) choices. In contrast to our study, in which we collected objective measurements about the participants decision behavior, such as time taken, many of the influential studies on this topic rely on self-reported experiences or thought experiments.

In the field of recommender systems, there is only limited research that takes the user's decision making style into account. For example, the users' decision making styles were considered in a study about diversification for recommender systems [26]. Based on the applied Structural Equation Model, the conclusion was that the maximization tendency of the participants did not affect any of the other measured variables, such as choice difficulty, recommendation attractiveness, or perceived diversity. Similarly, in a study about an energy-saving recommender system [18], maximizers and satisficers also showed no differences in terms of perceived control, interface satisfaction, recommender system effectiveness, etc. However, in contrast to the psychology literature, maximizers were actually *more* satisfied with their decisions.[1]

One hypothesis that could explain the above-mentioned observations is that the presence of a recommender system, which pre-ranks the available options, influences the decision making behavior of users. In fact, changes in decision making policies have been previously observed, for example by Schnabel et al. [23], in which more users behaved like maximizers when they had access to a *shortlist* user interface element. In contrast, based on previous studies from the recommender systems literature, we expect that the presence of a recommender system can make more users behave like satisficers, i.e., engage less in search and comparison as would be expected for maximizers. Differently from previous studies, we also test this hypothesis based on *objective* measures, such as the decision time or the number of inspected items, which has not been done so far in recommender systems studies [18, 26].

Psychology literature, furthermore, suggests that maximizers and satisficers differ in their information needs. Maximizers, for example, tend to rely more on relative rather than absolute comparisons and consult external influences more frequently, such as expert opinions or social comparisons [24, 25]. Thus, in addition to examining the overall user decision behavior, we also investigate the effect of *additional explanatory information* provided during the decision making process. We compare three different explanation styles to find out whether they can be useful in the decision making process of maximizers or satisficers in different ways.

3 EXPERIMENTAL SETUP

In this section, we provide details about the study design and the recruited participants.

[1]In another recommender systems study, the maximization tendency was measured, but in the final model the construct did not converge and was excluded [17].

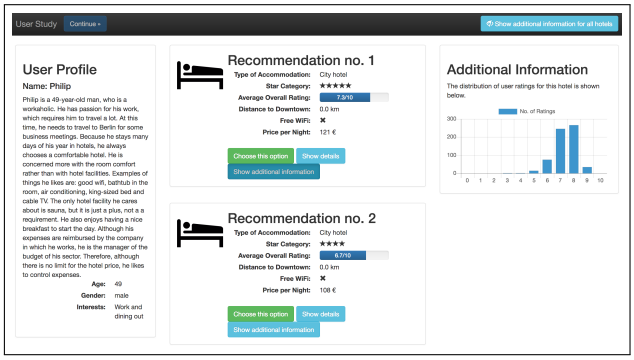


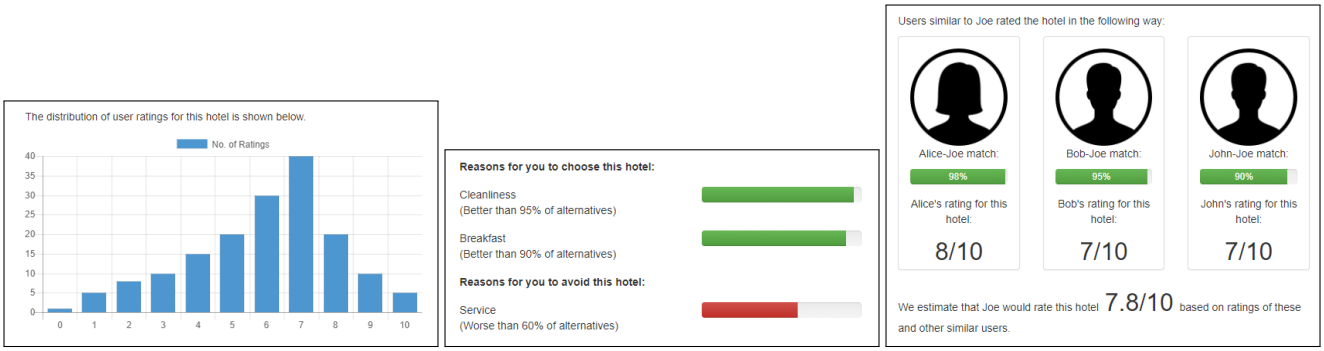
Figure 1: User interface of the recommender system.

Study Tasks. Based on empirical evidence that maximizing and satisficing behavior also transfers to decisions that are made on behalf of others [4], we implemented a web-based system (Figure 1) through which participants were asked to choose a hotel for someone else. The fictitious profile of the target user was displayed along with a set of recommendations, which were computed using a user-based nearest neighbor algorithm on a historical dataset of hotel rating data. At the start of the experiment, an initial set of 10 recommendations was displayed, and users could request more (up to 40) recommendations, which allowed us to roughly track how many options users inspected before they made a decision.

To investigate if the different user groups have different information needs, participants could request "additional information" for each item. During the experiment, participants were asked to make decisions for three different profiles for three different cities. In each round, a different type of information (explanation) was presented (initially hidden), which could be used as a further basis for their decisions. The explanations (see Figure 2) were based on three fundamentally different knowledge sources: the quality perception of other consumers in the form of the rating distribution (Style A) [9], a pros-and-cons comparison with other hotels with respect to certain features (Style B) [16, 19, 21], and information about the recommendation process itself in terms of selected neighbor ratings (Style C) [1, 2, 8]. Before each of the three tasks, participants received a detailed interactive tutorial on the user interface, decision task, and additional information shown in the respective trial. The order of the profiles, cities, and types of additional information were randomized in a round-robin fashion during the trials.

After participants had made their three choices, they provided demographic data, after which they were shown three four-item questionnaires (using 7-point Likert scales) regarding the provided additional information types, namely, if they found the explanations transparent, useful, trustworthy, and if the information made them more confident in their choice. Finally, the participants answered the 13-item questionnaire proposed by Schwartz et al. [24], which we used to classify the participants into maximizers and satisficers. As usual in the field [10, 24], we used the median maximization scores to distinguish between maximizers and satisficers.

Study Variables. Overall, the *independent* variables are (i) the participants' decision making style (maximizer or satisficer) and (b) the investigated explanation styles, a *within-subjects* variable with three possible values.



(a) Popularity-based Explanation (Style A) **(b) Feature-based Explanation (Style B)** **(c) Peer-based Explanation (Style C)**

Figure 2: Examples of the three types of additional explanatory information evaluated in the user study.

As *dependent* variables, we used the following *objective* measures to assess differences in the decision-making behavior of the participants.

- The time needed to complete the decision-making task.
- The number of times the participant requested to see a page with detailed item information (detail requests).
- The number of requested recommendations. For this, we recorded how many of the four recommendation pages were loaded by the participant (recommendation requests).
- The number of times the participants requested to see additional explanatory information (explanation requests).
- The list position of the hotel chosen by the participants (choice index).[2]

As *subjective* measures, we analyzed the participants' responses to the four questionnaire items mentioned above regarding the value of the additionally displayed information.

Participants. We recruited participants via email lists and social networks. Between October and December 2017, 243 subjects from 5 different countries participated, and 109 completed the study. The majority of the participants were in their twenties. Most of them were from Brazil and Germany and had a computer science or information technology background. We excluded 19 subjects from the study, because they completed the process in an unreasonable short or long time. We used a threshold of 60 seconds for task completion, which we determined as the minimum time to read the target user profile and make a decision. Additionally, we excluded participants who took longer than 90 minutes for one of the tasks, assuming they likely focused on something else during the study.

4 OBSERVATIONS

Decision-Making Behavior of Maximizers and Satisficers. Table 1 shows the outcomes of our objective measurements. The results are provided in accumulated form as well as separated based on the participants' decision making styles and the provided explanation styles. To test if any of the observed differences across the different conditions were significant, we applied an ANOVA test or, in case its assumptions were not fulfilled, a Kruskal-Wallis test. The analyses showed that none of the differences were significant at a significance level of $p = 0.05$. In other words, independently of the explanation style, maximizers and satisficers did not differ significantly in their decision-making behavior in terms of the observed objective measures.

Thus, against our expectations and the existing research literature, maximizers did *not* take more time to make the decision, they did *not* look at more pages showing further alternatives, they did *not* inspect more item details or explanations, and they did *not* choose items further down the list than satisficers. In fact, from all participants, about 25% selected the first recommended hotel as their final choice, indicating that the recommendations were generally adopted well. The provision of different types of explanations also had no significant influence on their behavior. While we could not measure (e.g., through eye-tracking) how many alternatives the participants were looking at and for how long, the combination of measures (needed time, request for item details) suggest that there is no strong difference in the given sample.

As a result, our research leads to the hypothesis that the differences between maximizers and satisficers diminish or even disappear in the presence of recommendations, as was indicated in previous studies in the field of recommenders [18, 26]. One of the underlying reasons could be that maximizers (like satisficers) trust the recommendations and assume that there will be no better choices in the lower-ranked options. The recommendations in our study were, in fact, ordered by their assumed relevance for the given profiles, but there was no "objectively-best" ordering where one option strictly dominates another. Generally, the observed behavior might also be influenced by our everyday experiences, e.g., when using search engines, where users rarely inspect more than the first few pages [3]. Overall, to the best of our knowledge, no previous work in the field of psychology has examined the maximizer-satisficer theory for situations where the alternatives are pre-ordered according to some expected utility.

The Effect of Different Types of Additional Information. Table 2 shows the results obtained for the *subjective* measures regarding the different explanation styles. Combined with the objective results from Table 1, we can make the following observations.

Generally, we can observe that explanation style B (using pros and cons) received the highest absolute scores in all subgroups and all dimensions except trust. Considering the participants without distinguishing them based on their decision-making styles, the overall preference was for style B over styles A and C in terms

[2]The hotels in each city were presented in the same order for all participants.

Table 1: Mean (M), standard deviation (SD) and Median (Med) of scores obtained for objective variables. Choice=choice index, Detail=detail requests, Reco=recommendation requests, Expl=explanation requests. Results are shown separately by explanation style and combined in the last row of each group. Time is given in minutes.

Meas./	Expl.	Satisficer M±SD	Satisficer Med	Maximizer M±SD	Maximizer Med	All M±SD	All Med
Time	A	4.69± 3.50	3.55	4.69± 3.88	3.06	4.69± 3.67	3.18
	B	6.18± 9.29	4.12	5.08± 4.83	3.40	5.63± 7.38	3.87
	C	5.84± 6.29	3.79	4.85± 4.42	3.61	5.34± 5.43	3.64
	All	5.57± 6.77	3.84	4.87± 4.36	3.18	5.22± 5.69	3.58
Choice	A	5.47± 7.29	4	6.58± 6.31	6	6.02± 6.80	4
	B	7.87± 8.21	4	5.64± 5.78	4	6.76± 7.15	4
	C	5.60± 5.01	6	5.82± 8.37	2	5.71± 6.86	4
	All	6.31± 7.00	4	6.01± 6.87	4	6.16± 6.93	4
Detail	A	8.73±11.66	4	6.42± 6.00	5	7.58± 9.29	5
	B	7.04± 7.27	5	5.76± 7.53	3	6.40± 7.39	4
	C	6.73± 6.52	4	6.20± 7.81	4	6.47± 7.16	4
	All	7.50± 8.76	5	6.13± 7.11	4	6.81± 7.99	4
Reco.	A	0.76± 1.07	0	1.13± 1.32	1	0.9± 1.21	0.5
	B	0.89± 1.05	1	1.00± 1.43	0	0.94± 1.25	0
	C	0.69± 1.02	0	1.04± 1.45	0	0.87± 1.26	0
	All	0.78± 1.04	0	1.06± 1.39	0	0.92± 1.23	0
Expl.	A	7.82±10.39	3	9.56±12.87	4	8.69±11.66	3
	B	9.09± 9.49	6	10.56±10.91	10	9.82±10.19	7
	C	8.87±10.37	4	11.42±10.88	10	10.14±10.65	10
	All	8.59±10.03	4	10.51±11.53	8	9.55±10.83	5

of transparency, usability, and confidence, with statistically significant differences (based on the corresponding statistical tests). Because style B is the only one that focuses on item features, this observation corroborates previous findings [7], in which different explanation styles were compared and "content-based" explanations were favored over, e.g., rating-based ones, in different dimensions. In contrast to this work, which used a slightly different visual representation, our pros-and-cons approach did not lead to a loss in decision efficiency, i.e., participants did not take more time when confronted with this type of explanations.

Nonetheless, even though the participants preferred explanations of style B (for example, in terms of usefulness), this did not lead to an increased actual use of the explanations. As mentioned earlier, the analysis of the results shown in Table 1 shows that users did not inspect significantly more explanations of style B than other explanation styles, leading to a gap between the participants' reported utility and their objectively observed behavior.

An interesting side-observation is that the "social" explanation style C received the lowest scores in terms of transparency, even though this style reveals the internal reasoning of the underlying recommender algorithm. This indicates that the participants had troubles understanding the meaning of what is presented in explanations of style C.

The differences between maximizers and satisficers in terms of their assessment of the different types of explanations were mostly small and not statistically significant. Statistical tests revealed only a significant preference of maximizers for style B over style C in terms of transparency. One reason for the maximizers' preference towards the feature-based comparison of the hotels could be their tendency to rely more on *relative* than absolute information, as previously observed [25]. Overall, except for this special case, in which maximizers seem to find feature-based explanations more transparent than peer-based information, maximizers and satisficers did not exhibit different information needs in the given scenario.

Table 2: Mean (M), standard deviation (SD) and median (Med) scores obtained for each measurement across difference groups (explanation style and decision making policy).

Meas./	Expl.	Satisficer M±SD	Satisficer Med	Maximizer M±SD	Maximizer Med	All M±SD	All Med
Transp.	A	4.93±1.70	5	4.89±1.67	5	4.91±1.67	5
	B	5.56±1.14	6	5.73±1.07	6	5.64±1.10	6
	C	5.09±1.68	6	4.67±1.58	5	4.88±1.63	5
Useful.	A	4.80±1.60	5	5.11±1.35	5	4.96±1.48	5
	B	5.67±1.09	6	5.64±1.19	6	5.66±1.13	6
	C	5.13±1.34	5	5.00±1.12	5	5.11±1.23	5
Trust	A	4.93±1.44	5	5.07±1.36	5	5.00±1.39	5
	B	4.69±1.31	5	5.18±1.21	5	4.93±1.28	5
	C	4.22±1.43	4	4.22±1.28	4	4.22±1.35	4
Confid.	A	4.33±1.55	5	4.71±1.44	5	4.52±1.50	5
	B	5.11±1.27	5	5.33±1.24	5	5.22±1.25	5
	C	4.58±1.36	5	4.62±1.42	5	4.60±1.38	5

5 CONCLUSIONS AND IMPLICATIONS

In the presence of the recommender system that we employed in our user study, maximizers and satisficers did not exhibit significant differences in their observable decision-making behavior. This is in sharp contrast to existing psychology literature, but supports results of previous studies of this phenomenon in the context of recommender systems, which also observed no significant differences in terms of subjective measures. If these observations were generalizable, recommender systems could become a valuable assistive tool to mitigate the problems maximizers regularly face in decision-making tasks, such as negative affect and regret. However, further research is necessary to fully understand the effect that recommendations can have on users with different decision making styles, specifically in scenarios with different complexities, assortment sizes, and product domains.

Furthermore, the fact that participants from all groups preferred a pros-and-cons explanation style, which did not affect decision efficiency, could be a starting point for further detailed studies about the practical benefits of such explanations.

Finally, peer-based explanations received low scores overall, which is surprising, because maximizers are specifically known for engaging more in social comparison. Future work could focus on identifying the reason why maximizers did not prefer this social explanation type and which alternations should be made to better satisfy their information needs.

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