

# Investigating Mere-Presence Effects of Recommendations on the Consumer Choice Process

Sören Köcher, Dietmar Jannach, Michael Jugovac, and Hartmut H. Holzmüller  
TU Dortmund University, Germany  
firstname.lastname@tu-dortmund.de

## ABSTRACT

In various application domains, recommender systems explicitly or implicitly act as *virtual advice givers*. They are not only used to filter large item sets or point users to unknown but relevant items, their recommendations can also help users to make a decision given a limited choice set. Such a system is usually considered effective if the users adopt the recommendations because, for example, the system's suggestions match their preferences or because they generally trust in the system's benevolence and competence.

With this work we aim to further explore the *persuasive potential* of automated recommendations. Our specific goal was to investigate whether the mere presence of a recommendation has effects on the user's choice process. We conducted two online studies in which participants received either no recommendation or a random recommendation for a given decision scenario. The obtained results showed that the pure existence of recommendations can, depending on the decision scenario, make users more confident in their choices and reduce choice difficulty. Furthermore, we observed that in both studies even random recommendations led to an anchoring effect as the participants' choices were measurably biased by the characteristics of the recommended item.

## Keywords

Consumer Choice Behavior, Persuasiveness, Anchoring

## 1. INTRODUCTION

Recommender systems (RS) can serve different purposes for their users. They, for example, help users to locate relevant items within large item collections or support them in discovering additional items of interest outside their typical preference patterns. A somewhat less explored role of recommenders is their capability of serving as *virtual advice givers* in scenarios where users make decisions given a limited set of choices.

Such systems are often more interactive and can implement a number of persuasive cues to increase the users' confidence in their decision. Additionally, providers can employ the persuasive potential of such systems to "convince" users to choose a certain recommended option, e.g., by providing appropriate explanations or by helping them understand the relevant decision factors [7, 11, 19].

Previous works on this topic focus, for example, on analyzing the influence of specific decision-support functionalities,

like explanations, on persuasiveness [8, 10]. In contrast, our work aims to examine if the *mere presence* of an arbitrary advice or recommendation has an effect on the user's decision making process. There are different reasons why we conjecture that such effects might exist: Recommender systems are omnipresent today and users might generally assume that such systems are benevolent and competent [12]. As a result, they might consider the recommendations in some form during their decision making process. If users are, in contrast, skeptical, the recommended items could at least serve as reference points when comparing the options. Finally, the recommended items could serve as *anchors* [17], which bias the users' decisions.

To investigate the existence of such effects, we conducted user studies in which the participants had to make purchase decisions on fictitious e-commerce shops. One participant group received one randomly chosen element from the choice set as a recommendation; the other group received no recommendation at all. We decided to rely on random recommendations in our studies as this allows us to rule out potential effects related to the (perceived) quality of the recommendations themselves. Besides the question if a randomly chosen recommendation can represent an anchor and bias the final user decisions, our expectation was that the *mere presence of recommendations has a positive effect on choice confidence*, e.g., because the users are given a reference point for their decision. Higher choice confidence might lead to higher choice satisfaction, which in turn is supposed to increase the users' intention to actually make a purchase [16].

In summary, our research questions are as follows:

- **RQ1:** To what extent has the mere presence of a recommendation an effect on the customer's decision process?
- **RQ2:** Can the characteristics of a recommendation serve as an anchor for decision making?

## 2. STUDY DESIGN

*Research Model.* Figure 1 shows our research model. The independent variables are the presence of a recommendation (RS) and the user's domain expertise (Dom. Exp.). We include the latter variable assuming that expertise may have an impact on the users' decision confidence (Dec. Conf.). We include choice difficulty (Ch. Difficulty) as a construct as we hypothesize that users – utilizing the recommendation as reference point – might focus on a subset of the items as choice set. In turn, lower choice difficulty should also lead to higher decision confidence. We measure choice difficulty with indicators variables that assess the degree to which making

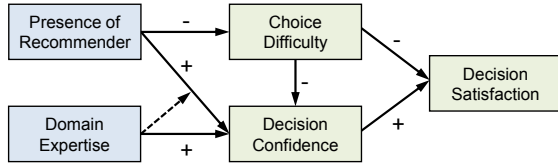


Figure 1: Research Model

the decision was perceived as (emotionally) challenging<sup>1</sup>. Finally, both decision confidence and choice difficulty are assumed to impact the users' decision satisfaction (Dec. Sat.).

*Study Environment and Procedure.* We created fictitious online shops for two different domains: backpacks (Study A) and hotels (Study B). In both studies, the scenario for the participants was that they were searching for an item to purchase, and we asked them to select one of the available items on the online site. The choice set sizes were 18 (backpacks) and 24 (hotels), respectively. In each case, additional item information was provided. We presented the weight, dimensions, volume, and price of the backpacks and the star category, community rating, distance to the city center and the price for the hotels. Half of the participants of each study received one *randomly* selected item as a recommendation, which was clearly marked as being a recommendation as sketched in Figure 2.

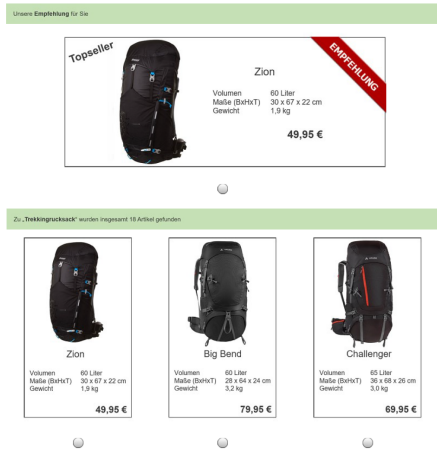


Figure 2: Fragment of the Fictitious Online Shop. Not all items are shown in the screen capture.

We recruited 164 and 239 participants for Study A and Study B, by distributing the URL of the online shop via email and on social network groups. The average age of the respondents was about 22 for both groups; more than two thirds were female participants. When accessing the website, the participants read the scenario and task description, were instructed to selected one of the options, and answered a post-task questionnaire. The participants were randomly assigned to the treatment groups.

### 3. RESULTS

The recommended item was actually chosen by 6.7% of the participants of Study A, and by 3.8% in Study B. These numbers roughly correspond to the theoretical chance that the recommended item was indeed the preferred option for a

<sup>1</sup>The questionnaire items can be found at <http://ls13-www.cs.tu-dortmund.de/homepage/intrs13q>.

user. Simply displaying a random recommendation therefore *did not persuade* users to adopt the recommendations.

### 3.1 Structural Equation Modeling Results

We used Structural Equation Modeling (SEM) as an analysis instrument to detect relationships between the variables of our research model from Figure 1. Specifically, we used the PLS-SEM method, which is particularly recommended for this type of exploratory research for which no strong theory exists yet [9]. All constructs except the recommendation condition are measured with multiple questionnaire items.

#### 3.1.1 Model Validity and Reliability

We applied different validity and reliability tests to our models and excluded indicators that were not reliably measuring a construct [9]. To check for *internal consistency* of the constructs, we measured *composite reliability* and *Cronbach's alpha* of our final model. The composite reliability values in both studies range from 0.88 to 0.95; Cronbach's alpha was between 0.79 and 0.93, i.e., all values were above the suggested minimum threshold of 0.7. To check for *convergent validity*, we calculated the AVE (Average Variance Extracted) value. The minimum AVE value across both studies was 0.68, which is again above the minimum threshold of 0.5. Finally, we verified *discriminant validity* by checking (a) that all cross loadings were smaller than the respective outer loadings and (b) that no squared variable correlations exceeded the AVE values of the respective constructs.

#### 3.1.2 Observed Effects

In SEM models, *path coefficients* ( $\beta$ ), which range from  $-1$  and  $+1$ , express the strength of the relationships between two variables. The empirical t-values obtained through bootstrapping help us assess statistical significance. According to the literature [9], t-values above 1.96 indicate significance at the 5% level, values above 2.57 at the 1% level.

The middle columns of Table 1 show the  $\beta$ -values and t-values for the backpack study. The results confirm the hypothesized effects of the presence of a recommender on decision confidence and choice difficulty, which in turn both affect decision satisfaction. The main insight of this study is therefore that the mere existence of a random recommendation can (a) have a positive, statistically significant effect on the user's decision confidence and (b) lead to lower choice difficulty for users. This finding is relevant in practice as lower choice difficulty contributes to higher decision confidence ( $\beta = -0.228$ ) and decision satisfaction ( $\beta = -0.322$ ). Likewise, decision confidence is strongly tied with decision satisfaction ( $\beta = 0.608$ ).

Table 1: SEM Results

Path	Backpacks		Hotels	
	$\beta$	t	$\beta$	t
RS $\rightarrow$ Dec. Conf.	0.15*	1.97	0.08 <sup>n.s.</sup>	1.31
RS $\rightarrow$ Ch. Difficulty	-0.17*	2.28	-0.04 <sup>n.s.</sup>	0.63
Dom. Exp. $\rightarrow$ Dec. Conf.	0.02 <sup>n.s.</sup>	0.22	0.09 <sup>n.s.</sup>	1.32
Dom. Exp. $\times$ RS $\rightarrow$ Dec. Conf.	0.10 <sup>n.s.</sup>	0.84	0.05 <sup>n.s.</sup>	0.72
Ch. Difficulty $\rightarrow$ Dec. Conf.	-0.23**	2.79	-0.37**	6.72
Ch. Difficulty $\rightarrow$ Dec. Sat.	-0.32**	5.97	-0.06 <sup>n.s.</sup>	1.23
Dec. Conf. $\rightarrow$ Dec. Sat.	0.61**	11.59	0.67**	16.55

Notes:  $\beta$  = Path coefficient with corresponding t-value, \*\*  $p < .01$ , \*  $p < .05$ , <sup>n.s.</sup> = not significant.

The right-most columns of Table 1 show the results for the hotels. The obtained path coefficients indicate similar trends but the effects did *not* reach significant levels in this scenario. This suggests that the hypothesized effects depend on specifics of the domain or the decision scenario.

In both scenarios, the expertise of the users – in contrast to our expectations – had no measurable direct or moderating effect on decision confidence. This indicates that the observed mere-presence effects in the backpack domain applied equally to both experienced and less-experienced participants.

Overall, the results indicate that the mere presence of recommendations *can* measurably impact the user’s decision process in terms of decision confidence and choice difficulty. However, while these effects were significant in the backpack domain, they did not reach significance in the hotel domain. Further research is therefore required to understand which factors cause these differences. One explanation could be that comparing item characteristics might be inherently easier in one of the domains. In fact, an analysis of the construct values related to choice difficulty revealed that choosing an item was considered significantly ( $p < 0.05$ ) more difficult in the backpack domain, which could, e.g., be due to domain-specific trade-offs, such as the backpack’s weight vs. its volume. This suggests that the presence of a recommender has more effects when the choice situation is more difficult. Another possible factor contributing to the perceived choice difficulty can be the size of the choice set [4]. In our studies, the choice set size was larger for the hotels than for the backpack domain. Nonetheless, the decision difficulty was perceived to be higher for the backpacks as mentioned above.

### 3.2 Analysis of Anchoring Effects

Besides the question to what extent a recommendation influences the decision making *process*, we aimed to investigate if the recommendations also had an effect on the *actual choices* of the participants. We have already mentioned above that participants did not blindly adopt the random recommendations. However, we hypothesize that the participants could (unconsciously) be biased in their final choice by the presented recommendation, i.e., that the recommendation served as an *anchor* for their decision. Specifically, we assume that participants select options that have *similar features* compared to the recommendation. To our knowledge, the existence of attribute-level anchoring effects has not been explored in the recommender systems literature so far.

Technically, we performed several univariate regression analyses to quantify to what extent the attributes of the chosen items were dependent on the features of the recommended item. Furthermore, as a simpler form of analysis, we calculated the correlations between the attribute values. The results of these analyses are shown in Table 2 and *clearly show the existence of anchoring effects for both scenarios*.

In the backpack domain, all features of the finally chosen item, i.e., weight, volume, and price, were positively and statistically significantly related to the recommended item. All correlation values ( $\rho$ ) were also positive and significant at  $p < 0.05$ . Similar effects were observed for the hotel domain. On average, participants chose items that were similar to the recommended item in terms of the distance to the city center, the community rating, and the price. No anchoring effect was, however, observed for the star category in this domain. A possible explanation for this phenomenon could lie in the comparably coarse grained scale of the star category and that

**Table 2: Result of the Anchoring Analyses**

<i>Backpack Scenario</i>	$\beta$	t	$\rho$
	Weight	0.257*	2.573
Volume	0.146*	2.127	0.233*
Price	0.178*	2.224	0.243*
<i>Hotel Scenario</i>	$\beta$	t	$\rho$
	Hotel Category	0.028 <sup>n.s.</sup>	0.381
Distance from City Center	0.333**	3.763	0.327**
Recommendation Rate	0.299**	3.762	0.327**
Price per Night	0.202**	3.106	0.275**

Notes:  $\beta$  = Regression coefficient with corresponding t-value,  $\rho$  = Correlation coefficient, \*\* $p < .01$ , \* $p < .05$ , n.s. = not significant.

the participants might have already had a comparably strong mindset before the experiment regarding the star category of hotels they would possibly book.

To illustrate the strength of these effects, we looked at the item attributes and created different subsamples of the data (e.g., light vs. heavy backpacks). For example, when the system recommended a light backpack with a weight between 1.7 and 2.8 kilograms, the average weight of the chosen backpack was at 2.26 kilogram. When the weight of the “anchor” was higher and between 2.9 and 4.0 kilograms, the average weight of the selected backpacks went up by 13% to 2.60 kilogram. Similar effect strengths were observed for other item features, which we find remarkable, given that the recommendations were randomly selected.

In an additional analysis we tested if domain expertise had an impact on the strength of the anchoring effect and incorporated these aspects into our regression models. We could, however, not observe any statistically significant main or interaction effects, which suggests that both novice and expert users seem to be equally susceptible to anchoring effects.

### 3.3 Research Limitations

Our research is mostly based on responses from students of our university. While the group is homogeneous and students are potential customers in both tested domains, we cannot state with certainty that the findings are representative for other societal groups. Furthermore, the participants did not actually make a purchase in the end, and our scenario was purely fictitious. On the other hand, as the participation was voluntary, no strong motivators exist for the participants to act dishonestly during the study.

## 4. PREVIOUS WORKS

Anchoring effects, as observed in both of our studies, were first discussed in the 1970s in the context of research on human judgment under uncertainty [17]. Anchoring means that people derive their final judgments or estimations for a given task using a heuristic that consists of adjusting a (possibly even arbitrary) initial value. Anchoring effects have been researched in different estimation and decision scenarios and, in particular in the Marketing literature, in purchase decision contexts, e.g., [13, 15], and [18].

In the RS literature only few works on anchoring effects exist. To what extent displaying predicted ratings for unfamiliar items influences the ratings assigned by users is discussed in [2] and [5]; how recommendations can impact

the users' willingness-to-pay is furthermore discussed in [1]. Anchoring effects on the item feature level, as reported in our work, have to our knowledge not yet been investigated.

In a broader context, anchoring effects can be seen as one of several possible approaches to implement *persuasive* recommender systems [19]. System-provided explanations are probably the most prominent approach in the RS literature to convince users to adopt a recommendation or make a certain choice, see, e.g., [8, 10]. Another approach to persuasion is to engage the user in the choice process, e.g., using an interactive product advisor, with the goal to promote certain items [20]. Finally, more deceptive means of persuasion include the manipulation of the recommendation list with the intent to exploit psychological phenomena like decoy effects [6].

In contrast to these works, our studies indicate that the mere presence of random recommendations can have a persuasive and biasing effect. More research is however required to understand the underlying reasons of these effects. Past research showed that users see (personalized) recommendations as a decision aid that can reduce the perceived effort and choice overload [3, 14]. The fact that even *random* recommendations are effective can have different reasons, for example, because users generally trust that such systems are benevolent and competent [12]. As an effect, users might feel *safer* with their choices when they are close to a recommended option.

## 5. SUMMARY AND CONCLUSIONS

Our work suggests that the mere presence of random recommendations can measurably affect the choice processes of users. In both studies reported in this paper we could observe anchoring effects on the attribute level, i.e., the participants exhibited a tendency to select items that had similar characteristics compared to the recommended reference item. In one of the tested domains, the presence of the recommender furthermore led to lower perceived choice difficulty and higher choice confidence.

Overall, our work therefore contributes additional evidence of the persuasive capabilities of recommender systems and their potential as decision-making aids. In terms of practical implications, the observed anchoring effects emphasize that recommenders can be valuable instruments for providers to guide the customer choice toward a desired direction. Since not all effects could be observed in both studies, more work is required to understand the underlying factors that determine the effective persuasiveness of recommendations in different scenarios.

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