Let me decide: The importance of user autonomy in accepting online recommendations

Leorre Newman  
*Ben-Gurion University of the Negev, leorre@post.bgu.ac.il*

Uriel Haran  
*Ben-Gurion University of the Negev, uharan@bgu.ac.il*

Lior Fink  
*Ben-Gurion University of the Negev, finkl@bgu.ac.il*

Follow this and additional works at: [https://aisel.aisnet.org/ecis2022_rip](https://aisel.aisnet.org/ecis2022_rip)

**Recommended Citation**  
[https://aisel.aisnet.org/ecis2022_rip/18](https://aisel.aisnet.org/ecis2022_rip/18)

This material is brought to you by the ECIS 2022 Proceedings at AIS Electronic Library (AISeL). It has been accepted for inclusion in ECIS 2022 Research-in-Progress Papers by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
LET ME DECIDE: THE IMPORTANCE OF USER AUTONOMY IN ACCEPTING ONLINE RECOMMENDATIONS

Research in Progress

Leorre Newman, Ben-Gurion University of the Negev, Beer-Sheva, Israel, leorre@post.bgu.ac.il
Uriel Haran, Ben-Gurion University of the Negev, Beer-Sheva, Israel, uharan@bgu.ac.il
Lior Fink, Ben-Gurion University of the Negev, Beer-Sheva, Israel, finkl@bgu.ac.il

Abstract

The ubiquity of artificial intelligence (AI) algorithms has increased interest in the willingness of online users to accept the recommendations generated by recommendation system (RSs). The present study advances the discourse on how to facilitate the adoption and acceptance of such algorithms and systems by emphasizing the importance of user autonomy. As a first step, the hypothesis that user autonomy increases recommendation acceptance was tested in a controlled online experiment, in which we varied the number of recommendations presented to the user. A total of 240 participants used an online website, specifically developed for this study, to describe their vacation preferences and then chose their preferred vacation. Results show that users are more likely to accept recommendations when more recommendations are presented, highlighting the importance of user autonomy to the acceptance of RS and AI, while informing vendors about ways to tweak their algorithms to increase user compliance.

Keywords: Recommendation, Autonomy, Decision making, Online experiment.

1 Introduction

Artificial intelligence (AI) based recommendation systems (RSs) have become an integral part of our daily lives. The movies we watch, the music we listen to, and the products we consume are all affected by algorithms, designed to support online users in their decision-making processes by indicating which alternatives are best aligned with user preferences. Online recommendations seek to assist users by producing personalized recommendations, which reduce search effort and improve decision quality (Häubl & Murray, 2006; Häubl & Trifts, 2000). From an economic standpoint, recommendations play a vital role, offering retailers an effective approach to customized marketing. Accordingly, recommendations were found to increase product sales (Lee et al., 2020; Lee & Hosanagar, 2019).

Prior research has evaluated the effectiveness of recommendations mainly through algorithm accuracy and performance, studying ways to develop better prediction methods (Al-Ghuribi & Mohd Noah, 2019; Bag et al., 2019; Burke, 2002). There seems to be an ongoing race in research and practice to improve algorithm accuracy in order to increase compliance with recommendations. Recently, it has been suggested that accuracy and performance of recommendation algorithms are insufficient (Brunk et al., 2019; Pu et al., 2012). Users may receive high-quality recommendations, but nevertheless reject them (McNee et al., 2002). Hence, RS design should consider various factors that influence users’ tendency to accept recommendations, focusing on users’ experience while using the system. Such
factors include users’ perceived accuracy and quality of the system, ease of use, system transparency, user control, and user trust (Pu et al., 2011; Yoo & Gretzel, 2011).

One of the factors found to influence user attitudes and perceptions is user autonomy (Caplan & Samter, 1999). Despite the importance attributed to user autonomy in various contexts of system use, this factor has received little attention in the study of recommendation acceptance. We suggest in this work that user autonomy has an important role in facilitating user acceptance of recommendations. Moreover, we suggest that increasing user sense of autonomy may be achieved through minor platform tweaks, without changing the algorithm itself, thereby avoiding any time consuming or costly undertaking. In so doing, a small adjustment in the environment may produce a significant change in user tendency to accept recommendations. The user must feel in control while considering whether to accept or reject online recommendations. Therefore, a recommendation that restricts the freedom of a user to make decisions, possibly due to the absence of alternatives, may violate the user’s sense of autonomy. Some ways to increase the sense of autonomy explored in the literature are explaining the algorithm’s process, displaying recommendation accuracy, and letting the user choose between different logics (Harper et al., 2015; Helberger et al 2018).

To understand the consequences of user autonomy on recommendation acceptance, we empirically test the hypothesis that greater user autonomy leads to greater acceptance of recommendations. This hypothesis is tested in a controlled online experiment, using an online website developed specifically for the purposes of this study. The experiment confirms that autonomy level, defined through the number of recommendations presented to the user, increases recommendation acceptance. Following this experiment and its encouraging findings, we plan on investigating whether the positive effect of user autonomy on recommendation acceptance can also be observed when using alternative approaches to creating variance in user autonomy.

This study has both theoretical and practical implications. The study highlights the importance of user autonomy in facilitating the adoption of AI and RS algorithms. The notion that increasing the number of available options has negative effects on decision making, possibly due to information overload, has been repeatedly supported in the marketing literature (Jacoby et al., 1974; Keller & Staelin, 1987; Malhotra, 1982). We demonstrate the favorable effects of doing so in the context of online recommendations. From a practical standpoint, companies that utilize RSs to gauge online consumer behavior may draw on our findings to redefine their RS design to provide a superior user experience.

2 Literature Review and Hypothesis

2.1 Online recommendations

One of the challenges that users face daily in the information era is an overwhelming amount of data that is available online, due to the exponential growth of digital technology. This abundance of data fuels the problem of information overload, which occurs when input surpasses its processing capacity (Milord & Perry, 1977). Information overload in the literature usually refers to several attributes, such as the amount of information, the number of alternatives, and the number of information cues (Speier et al., 1999). In general, as tasks get more complex and demanding, the required information processing increases as well, resulting in increased use of heuristic strategies (Payne, 1982). Considering people’s restricted cognitive processing capacity (Simon, 1979), when information overload takes place, it is likely that a reduction in decision quality will follow. Therefore, it is a challenge for users to identify their exact goal in a manner that best suits their demands and preferences (Çano & Morisio, 2017). To overcome the problem of information overload, RSs have been designed to support users in the process of decision making. This support aims to assist decisions associated with complex information by suggesting advice to targeted users. Indeed, RSs have been found to reduce users’ search effort and improve their decision making (Häubl & Murray, 2006).

People are generally amenable to using RS. There is a consensus in the literature that RSs have a positive effect on sales for various products (De et al., 2010). These systems increase product views...
and demand (Lee et al., 2020; Lee & Hosanagar, 2019), for both promoted and non-promoted products (De et al., 2010). Pathak et al. (2010) suggest that recommendations not only improve sales but may also affect product prices. Apparently, as consumers receive stronger recommendations of a product, they deduce that it is more compatible with their preferences. This impression increases the product’s perceived value to the customer, who is therefore willing to pay a higher price. This effect enables retailers to adjust their prices and charge slightly more. Thus, RSs may increase item prices as well as total sales, resulting in higher revenue.

The existing literature has evaluated RSs mainly through algorithm accuracy and performance, investigating ways to develop better prediction algorithms (Al-Ghuribi & Mohd Noah, 2019; Bag et al., 2019; Burke, 2002). However, in recent years, it has been found that user satisfaction and willingness to purchase are not determined by recommendation accuracy alone (Choi et al., 2017; Fazeli et al., 2018; Pu et al., 2012). Thus, users may receive high-quality recommendations, but nevertheless reject them (McNee et al., 2002). This phenomenon occurs due to the user’s overall perception of the RS, which can alter her recommendation acceptance. Therefore, building a suitable RS is often challenging, for such a system must incorporate both an adequate user interface and an accurate algorithm. Taking the user perspective into account, numerous studies have suggested user-centric evaluation frameworks for RSs, which consider various factors that influence user experience, alongside accuracy (Pu et al., 2011; Yoo & Gretzel, 2011).

2.2 User autonomy

The literature on advice taking and decision making typically defines advice as a recommendation regarding a prudent action the decision maker is about to take, often favoring a particular option (Harvey & Fischer, 1997). The decision maker is exposed to a potential conflict between her initial assessment and the advice, typically given by a human advisor. The decision maker is responsible to take the final decision and is not required to accept the advice.

Maintaining autonomy has been found to be an influential factor on advice acceptance in the advice-taking literature (Caplan & Samter, 1999). According to Wertenbroch et al. (2020), the broad philosophical definition of autonomy is the ability to have free will and to act in accordance with one’s goals and values. From a commercial point of view, autonomy is specifically the free will to choose from a set of possible products or services. Therefore, advice that leads to a restriction of freedom violates the decision maker’s claim of autonomy (Dalal & Bonaccio, 2010). In view of the rapid growth and expanding use of RSs, where advice is given by an algorithm rather than by a human advisor, it has become critical to draw on the advice-taking literature to acknowledge the consequences of affording online users with autonomy when they are presented with recommendations. The present study aims at empirically testing this assertion about the importance of user autonomy in the context of compliance with RSs.

Considering this potential impact of autonomy on behavior, RSs can be designed to generate more positive reaction from the user, resulting in higher acceptance rate of recommendations. To increase user autonomy, the user must feel in control during the process (Helberger et al., 2018). This feeling of control can be created either by better understanding how the algorithm operates or by adjusting the system interface. This technique affords the user a real or perceived sense of control, without necessarily changing the algorithm itself (Burton et al., 2020). Transparency may come into play in various ways; it can manifest by explaining the general algorithm decision process, by presenting the reasons for selecting the specific recommendations, or by displaying the algorithm accuracy percentage. Indeed, it was found that explaining the recommendation process may increase user satisfaction (Bostandjiev et al., 2012). Helberger et al. (2018) suggest different designs for increasing user control by allowing adjustments, such as being able to reset the settings back to default, letting the user choose between different logics, and providing feedback to the system (e.g., expressing dissatisfaction with the recommendations). One final benefit is the possibility to apply user-configurability and transparency into any existing RS, without the need to change the system’s logic.
2.3 Research hypothesis

This study aims at investigating how user autonomy affects the likelihood that a user accepts a recommendation presented by an RS. In the context of consumer behavior, autonomy is defined by the free will to choose from a set of possible products or services. Whereas technological developments, such as AI and big data, can “contribute to consumer well-being by making consumer choices easier, more practical, and more efficient”, they also have the potential to “undermine consumers’ sense of autonomy, the absence of which can be detrimental to consumer well-being” (André et al., 2018, p. 28). We argue that users need to feel autonomous when making a decision and that undermining this sense of autonomy may lead users to reject recommendations and search for alternatives to regain their autonomy. According to self-determination theory, users need to feel that they have free will and that their actions are internally driven (Deci & Ryan, 2000; Wegner & Wheatley, 1999). They need to causally link their thoughts to outcomes and consider the outcome as caused by their own thoughts and desires. A sense of autonomy can be created by allowing people the freedom to choose from among multiple options in the pursuit of a goal (André et al., 2018). By contrast, restricting people in choice can reduce their motivation to pursue goals. Several other approaches to generating autonomy have been suggested by RS research and practice. For instance, a sense of control may stem from transparency of the algorithms. Another approach is granting users the ability to influence the recommendations by adjusting the system according to their preferences. While feeling in control and being aware of how the system operates, users evaluate the RS more positively and find the recommendations to be personalized (Harper et al., 2015). These positive consequences, we hypothesize, are likely to increase the odds of accepting an online recommendation.

**Hypothesis 1 (H1):** User autonomy increases the likelihood of online recommendation acceptance.

3 Experiment

3.1 Methodology

The first stage of our empirical investigation was to test H1 with a specific operational definition of user autonomy. For the first experiment, we defined user autonomy as arising from allowing people the freedom to choose from among multiple options (André et al., 2018). Accordingly, user autonomy was defined as a between-subjects independent variable (IV), which we manipulated by presenting to the participant either one recommendation in the low autonomy condition or three recommendations in the high autonomy condition. As described in the literature review, one definition of autonomy is the freedom to choose from a variety of options, unrestrictedly (Wertenbroch et al., 2020). Therefore, when a user receives three recommendations to choose from, as opposed to one, she experiences a greater sense of autonomy. To avoid confounding the quantity of recommendations with their quality, we ensured that the single recommendation in the low autonomy condition was superior (i.e., more consistent with user preferences) to the three recommendations in the high autonomy condition. Given recent evidence that the likelihood of recommendation acceptance varies depending on whether a mobile device or a personal computer (PC) is being used (Lee et al., 2020), a second between-subjects variable in the experiment was the device, with participants randomly assigned to using either their own smartphone or PC. Consequently, the experiment followed a $2 \times 2$ between-subjects factorial design with four randomly determined groups. The dependent variable (DV) was whether the participant accepted an online recommendation (“1”) – either the single recommendation in the low autonomy condition or one of the three recommendations in the high autonomy condition – or chose one of the alternatives that were not recommended (“0”).

Participants were 240 Amazon Mechanical Turk workers, aged 21-75, who received a reimbursement of $1.20US for their participation. All participants were native English speakers from native English-speaking countries.

To simulate a decision task, an online website was developed for the purposes of this study. The website simulated an RS for choosing a vacation. The participants were asked to enter the website
through one of two devices that was randomly assigned to them, either their smartphone or PC. If the device with which participants entered the website was different from the device randomly assigned to them, they were asked to switch devices, implying that device assignment was strictly enforced. Participants were also asked to indicate their informed consent to participant in the experiment. First, the participants were presented with the task of choosing a vacation deal that they would like to purchase if given the opportunity, assuming that the prices of all vacation deals are the same. For the RS to provide a recommendation that fits the participant’s preferences, participants provided information about their vacation preferences. Specifically, participants ranked the importance of three vacation-related criteria: continent, vacation type, and sleeping arrangement. Afterwards, they selected one preferred option out of four in each criterion. The criteria and options were carefully selected for the experiment, to avoid a single preferred option for all the participants. The vacation data set contains all possible combinations of these options. Each unique combination was represented by a single vacation, and each participant had an optimal solution (i.e., vacation) according to her preferences among the options in the vacation data set.

To minimize participants’ awareness of the RS logic, we employed two methods of distraction. First, participants answered four additional questions regarding their vacations. These questions served as distractions and were not weighed by the RS. Second, the actual vacation deals presented to participants in the decision-making phase were specific cases of the options that participants preferred in the preference-elicitation phase. For example, the vacation deals referred to specific countries instead of continents. The criteria with the options presented in the elicitation and decision phases are presented in Table 1.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Options</th>
<th>Option 1</th>
<th>Option 2</th>
<th>Option 3</th>
<th>Option 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continent</td>
<td>Elicitation</td>
<td>Africa</td>
<td>America</td>
<td>Asia</td>
<td>Europe</td>
</tr>
<tr>
<td></td>
<td>Decision</td>
<td>South Africa</td>
<td>California</td>
<td>Japan</td>
<td>France</td>
</tr>
<tr>
<td>Vacation type</td>
<td>Elicitation</td>
<td>Backpacking</td>
<td>Leisure</td>
<td>Package tour</td>
<td>Cultural</td>
</tr>
<tr>
<td></td>
<td>Decision</td>
<td>Trekking</td>
<td>Relaxation</td>
<td>Package tour</td>
<td>Landmarks &amp; museums</td>
</tr>
<tr>
<td>Sleeping arrangement</td>
<td>Elicitation and decision</td>
<td>Hotel</td>
<td>Rental apartment</td>
<td>Guesthouse</td>
<td>Cabin</td>
</tr>
</tbody>
</table>

Note: Elicitation rows show the options presented in the preference-elicitation phase, whereas decision rows show the options presented as part of vacation deals in the decision-making phase.

Table 1. The criteria and options presented to participants.

Following the preference-elicitation phase, the website created an impression that recommendations were being calculated and participants moved to the decision-making phase. Participants in the low autonomy group received a single recommendation, whereas those in the high autonomy group received three recommendations. Below the recommended vacations (one or three), the RS presented a list of 18 additional vacations the participant could choose from. Importantly, the top recommendation(s) provided by the RS never included the participant’s ideal vacation (i.e., the vacation that matched the options preferred by the participant on all three criteria), which instead appeared in the list of 18 other alternatives. This approach was taken to avoid confounding the ideal option with the recommended option (i.e., “rational” agents in our experiment should not accept one of the recommendations). When a single recommendation was presented (low autonomy), the recommendation matched the ideal vacation on the participant’s most important and second-most important criteria, but not on the criterion ranked third in importance. For example, if a participant ranked vacation type as most important, continent as second in importance, and sleeping arrangement as least important, the single recommendation differed from the ideal vacation for that participant only in the sleeping arrangement criterion. When three recommendations were presented (high autonomy),
one recommendation differed from the ideal vacation only in the criterion ranked second in importance by the participant, one differed only in the criterion ranked first, and one differed in the criteria ranked third and second. Therefore, the single recommendation in the low autonomy condition was superior (i.e., more consistent with participant preferences) to any of the three recommendations in the high autonomy condition, meaning the high-autonomy condition offered more recommended options than the low-autonomy condition, but never better options. This approach was taken to ensure that greater acceptance in the high autonomy condition was driven by recommendation quantity rather than by quality. Participants could choose a recommendation (acceptance is ‘1’) or scroll down the list of 18 alternatives and choose one of those (acceptance is ‘0’). This number of alternatives was used to require the user to expend reasonable search costs if a recommendation was not chosen. The 18 alternatives were constructed based on participant preferences to be similar in quality (i.e., match to preferences) across participants, and, as noted above, always included the ideal vacation. The order of alternatives, both recommended and additional, was randomized between participants. After choosing the desirable vacation, the participants were asked to answer background questions about their age, gender, and experience with RSs, as well as five questions about the extent to which the environment during the experiment was noisy, spacious, crowded, dark, and public (using 7-point Likert-type scales). In addition, we recorded the time it took the participant to reach a decision (‘decision time’) and to complete the entire experiment (‘total time’).

3.2 Results

We excluded from the statistical analyses 22 participants out of the 240 who completed the experiment: five due to technical difficulties (e.g., technical failures during the experiment), nine who reported having performed the experiment with a different device than that recorded by the website, and eight outliers in terms of the time it took to complete the experiment (below 60 seconds or above 3 standard deviations from the mean). The final dataset included 218 participants, 88 (40.3%) women and 130 (59.6%) men. Their distribution by age group included 59 (27.0%) in the 21-29 group, 71 (32.5%) in the 30-35 group, 35 (16.0%) in the 36-41 group, and 53 (24.3%) in the 42-75 group.

Overall, 71 participants (32.6%) accepted the recommendation and 147 participants (67.4%) rejected it (i.e., they chose from the list of 18 vacations that followed the recommendations). As shown in Table 2, acceptance was higher for high autonomy compared to low autonomy, regardless of the device used in the experiment. These rates are consistent with H1.

<table>
<thead>
<tr>
<th>Autonomy</th>
<th>Recommendation acceptance</th>
<th>Device</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>PC</td>
<td>Mobile</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
<td>46</td>
<td>48</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>High</td>
<td>No</td>
<td>31</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>Total</td>
<td>No</td>
<td>77</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>36</td>
<td>35</td>
</tr>
</tbody>
</table>

Table 2. Frequencies of recommendation acceptance.

To formally test H1, and also whether the effect of autonomy is device-specific, we estimated a logistic regression model (generalized linear model), with fixed effects for autonomy (high vs. low), device (mobile vs. PC), and the interaction between them. The model also included effects for the following control variables: age, RS experience, gender, decision time, total time, and the five environmental variables. The outcome variable was recommendation acceptance.

Table 3 presents the regression results. We find that autonomy had a significantly positive effect on recommendation acceptance ($p < 0.001$), providing support for H1. The device, by contrast, had
User Autonomy in Online Recommendations

... neither significant main effect on acceptance \((p = 0.506)\) nor an interaction with autonomy \((p = 0.536)\). None of the control variables significantly affected acceptance.

<table>
<thead>
<tr>
<th>Fixed effect</th>
<th>Estimate</th>
<th>Std. error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-0.417</td>
<td>1.203</td>
<td>0.729</td>
</tr>
<tr>
<td>Autonomy (high)</td>
<td>2.086</td>
<td>0.519</td>
<td>0.000</td>
</tr>
<tr>
<td>Device (mobile)</td>
<td>-0.411</td>
<td>0.617</td>
<td>0.506</td>
</tr>
<tr>
<td>Autonomy (high) (\times) device (mobile)</td>
<td>0.455</td>
<td>0.735</td>
<td>0.536</td>
</tr>
<tr>
<td>Age</td>
<td>0.009</td>
<td>0.018</td>
<td>0.641</td>
</tr>
<tr>
<td>RS experience</td>
<td>0.107</td>
<td>0.362</td>
<td>0.767</td>
</tr>
<tr>
<td>Gender</td>
<td>0.063</td>
<td>0.359</td>
<td>0.861</td>
</tr>
<tr>
<td>Decision time</td>
<td>-0.003</td>
<td>0.008</td>
<td>0.677</td>
</tr>
<tr>
<td>Total time</td>
<td>-0.004</td>
<td>0.002</td>
<td>0.055</td>
</tr>
<tr>
<td>Noisy environment</td>
<td>0.083</td>
<td>0.153</td>
<td>0.586</td>
</tr>
<tr>
<td>Spacious environment</td>
<td>0.076</td>
<td>0.140</td>
<td>0.587</td>
</tr>
<tr>
<td>Crowded environment</td>
<td>-0.192</td>
<td>0.144</td>
<td>0.183</td>
</tr>
<tr>
<td>Dark environment</td>
<td>-0.156</td>
<td>0.108</td>
<td>0.149</td>
</tr>
<tr>
<td>Public environment</td>
<td>-0.119</td>
<td>0.103</td>
<td>0.249</td>
</tr>
</tbody>
</table>

Table 4. Results of logistic regression for recommendation acceptance.

4 Planned Experiments

The first experiment confirmed that user autonomy has a favorable effect on the acceptance of online recommendations. In this experiment we defined autonomy by the number of recommendations presented to the user. In a series of future experiments, we plan to investigate additional operational definitions of user autonomy, to evaluate the full gamut of this favorable effect. We plan to increase autonomy by allowing the user to provide feedback to the system, expressing satisfaction or dissatisfaction about the recommendations (i.e., autonomy through self-expression). Another approach is providing the user with an option to reset the RS settings or ask for additional recommendations (i.e., autonomy through control). Finally, we will present accuracy rates for recommendations (i.e., autonomy through information). We intend to examine these variables independently, as well as the interactions among them. Particularly, we are interested in whether these definitions complement or substitute each other in affecting recommendation acceptance.

5 Discussion and Conclusions

This study examines whether and how user autonomy affects acceptance of online recommendations. Our first experiment confirms that increasing user autonomy by presenting three recommendations instead of only one has a positive effect on the likelihood of recommendation acceptance. This effect is the only statistically significant effect we found in our elaborate research model, which includes the device being used, user characteristics (gender, age, and RS experience), time-related controls (decision time and total time), and environment-related controls (noisy, spacious, crowded, dark, and public). We find this positive effect despite the fact that the three recommendations are all inferior to the single recommendation in terms of consistency with user preferences. This finding suggests that the effect of autonomy may be even stronger than that of recommendation quality. This issue is an interesting avenue for future research.

This study contributes meaningfully to both research and practice. First, we advance research on RS effectiveness that focuses on behavioral aspects and user adoption rather than on algorithmic accuracy.
Specifically, we advance the notion that the user must be given autonomy, freedom, and control over the system to facilitate compliance with its recommendations. Recently, there is a growing trend of narrowing down the alternatives available to users to lower their information overload, consistent with an earlier trend in marketing research (Jacoby et al., 1974; Keller & Staelin, 1987; Malhotra, 1982). We demonstrate the negative consequences of such an approach in RS implementation. Second, we contribute to the broader literature on online user autonomy by examining different mechanisms for operationalizing autonomy. While we focus in the first experiment on the number of alternatives available to choose from, we plan to extend this study to additional mechanisms and investigate how they interact with each other. Third, from a practical standpoint, companies that utilize RSs may draw on our findings to alter the design of their systems. We advise them to invest significant resources not only in improving algorithm accuracy but also in improving behavioral aspects that are likely to increase adoption and acceptance among users. We suggest that minor and inexpensive modifications in the system interface design can enhance user sense of autonomy and, consequently, user acceptance of recommendations.

Limitations of this work are mainly due to its methodological design. The first aspect is the way the recommendations were generated. In the experiment, recommendations were produced according to a simple algorithm, after eliciting little information from the user. Nowadays, existing RS algorithms are far more complex, taking into account many features and usually combining machine learning techniques. Additionally, our system presented vacations with three characteristics only, whereas in real life each vacation has more characteristics. Another limitation is a possible difference in information overload in the two different levels of autonomy. When given three recommendations, the higher recommendation acceptance rate we found could be attributed to a higher number of alternatives. The two additional recommendations in the high autonomy condition could have increased feelings of information overload, resulting in a tendency to employ heuristic strategies, such as accepting the recommendation. To mitigate this threat, the system interface in the experiment was designed to display a fixed number of vacations (18 vacations) following the one or three recommended vacations. Consequently, the two autonomy conditions differed in whether users saw a total of either 19 (1+18) or 21 (3+18) vacations. It is reasonable to assume that information overload did not vary considerably depending on whether participants saw 19 or 21 vacations to choose from. Furthermore, these differences in number of vacations to choose from were only observable if users scrolled down to the bottom of the list. Finally, while price is certainly an important determinant of choices, we had to fix the vacation prices to avoid this characteristic from dominating user decisions.

In conclusion, this study suggests that other factors, apart from accuracy, should be considered when designing RSs. We highlight the importance of user autonomy and its positive consequences for recommendation acceptance, thereby advancing research and practice on user acceptance of AI algorithms.

Acknowledgements

This work is supported by the Israel Science Foundation (Grant No. 604/18).

References


User Autonomy in Online Recommendations