THE DUAL ROLE OF PERCEIVED EFFORT IN PERSONALIZED RECOMMENDATIONS

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Abstract

Effort has been central in decision-making and effort saving is one of the main benefits of the use of recommendation agents (RAs). Since human-computer interactions tend to mimic human social encounters, we focus on two distinct types of perceived effort, namely user and RA effort. In two experimental studies in diverse empirical contexts, we provide generalizable insights on how these types can influence perceived RA quality. More specifically, we show that perceived RA effort increases perceived RA quality. User effort decreases RA quality but, based on equity and reciprocity theories, such an effect is attenuated when users perceive greater RA effort. Furthermore, this interaction is less evident the more familiar users are with the recommendation setting. Our findings enrich the understanding on the conflicting role of user effort in user behavior and can offer insights into how online retailers can improve their RAs.

Keywords: Product Recommendations, perceived user effort, recommendation agent quality, familiarity.

1 Introduction

According to eMarketer (2014), an average growth in e-commerce sales of 17.4% is expected in 2012-2017. An important factor for this growth is a 12% increase in average order value for transactions from personalized product recommendations compared to sales without the use of such tools (Siwicki, 2011). As a result it is not surprising that the ratio of online retailers that offer product recommendations increased from 32.6% (of top-500) in 2010 to 76,4% in 2012 (Demery, 2013). Such tools are widely researched in IS (Komiak and Benbasat, 2006; Tam and Ho, 2006) and marketing (Häubl and Trifts, 2000). An essential advantage of recommendation agents (RA) is that they can adapt their offers to users' demand specifications and as a result, they can improve users' decision accuracy (Xiao and Benbasat, 2007). Another important benefit of recommendation systems is the reduction of the effort needed to reach a decision (Gretzel and Fesenmaier, 2006; Häubl and Trifts, 2000). The concept of effort, which is defined as the total use of resources required to complete a task (e.g. cognitive), has been central in the field of decision-making (Johnson and Payne, 1985; Payne et al., 1993). Decreased effort has been presented as one of the most powerful predictors of increased spending and repurchasing intention (Dixon et al., 2010). Several studies have focused on explaining why consumers want to reduce effort (Bettman et al., 1990; Zipf, 1949) and how can effort saving be accomplished with the use of decision support systems (Todd and Benbasat, 1994; Bechwati and Xia, 2003; Xiao and Benbasat, 2007). However, the inherent desire of users to minimize their own effort might jeopardize the accuracy of their decisions. Therefore, they welcome any effort invested by other social actors to help them decide (Bechwati and Xia, 2003), regardless of whether the effort reduction comes from other human users or the recommendation agent itself. Users tend to anthropomorphize the RAs and treat the interaction with them similarly to a social encounter (Murray and Häubl, 2009; Nass et al., 1994).

In this paper, we focus on two distinct social actors that may contribute to the total effort exerted in the context of generating personalized recommendation systems. First, using a recommendation agent requires some effort from the users themselves (i.e., user effort), ranging from minor performed tasks to more interactive and rather extensive methods of preference elicitation. For example, online retailers (e.g., Netflix, Amazon) aim at replacing most of the explicit input from users with implicit browsing information in order to generate recommendations, whereas product advisors (e.g., MyProductAdvisor.com) ask users to make choices over an abundance of options as well as rank numerous attributes based on importance weights. Such different approaches influence perceived user effort, which, in turn, can shift the overall utility of the experience with the RA. A second source of effort is the effort invested by the RA. As online recommendations are offered immediately after users make a request, the tasks of a RA (calculations and searches) are not easily noticeable. However, users tend to respond in human-computer interactions in a manner similar to the rules of a social encounter (Nass et al., 1994). In the context of personalized recommendations, RA is perceived to use resources in order to provide the best recommendations that would eventually minimize the effort needed by users to make a decision. Studies found a positive effect of perceived third party effort reduction on process satisfaction and quality perception (Bechwati and Xia, 2003). Thus, it is important to examine what is the effect of users becoming aware of the effort exerted by the RA while generating the recommendations.

The objective of this paper is to provide insights on ways to increase consumers' quality evaluation of RAs by examining users' perceptions of the effort exerted by all relevant social actors. We built upon the theories of equity (Adams, 1965) and reciprocity (Gouldner, 1960) to explain an interaction between user and RA effort. More specifically we focus on how the effort required during the preference elicitation process vis-a-vis a more saliently presented effort by the RA can influence the evaluation of the RA across different levels of user familiarity. That way we provide an additional theoretical explanation on the conflicting evidence on the role of user effort when dealing with an information system (Dabholkar and Sheng, 2012; Häubl and Trifts, 2000). We collected data using two studies. In the first study we developed a web-based recommendation agent to test the interplay between user and RA effort, across different levels of familiarity in a car recommendation context. In the second study, we tested our hypotheses using a controlled experiment in a dating recommendation context. The findings suggest that perceived RA effort has a positive effect on RA quality. Also, user effort negatively influences the perceived quality of the RA. However, this effect is attenuated when users perceive a greater RA effort. Users mind less putting more effort in eliciting their preferences as long as they feel that the RA puts an equitable amount of effort. Yet, such interaction is less evident the more familiar users are with the recommendation setting. Our findings offer online retailers insights in how to effectively fine-tune their recommendation system by reducing user effort or by making the RA effort more explicit. Such structural changes can improve acceptance and usage intention of the RA. In the next section we introduce the theoretical background and develop the hypotheses. Then we present the two studies in terms of method and results, and finally we discuss the theoretical and managerial implications.

2 Theoretical background and Hypotheses

2.1 Personalized Recommendations Agents

The abundance of available products and online sources has made the role of product recommendation agents fundamental. Recommendation agents elicit user preferences and accordingly filter out the non-relevant products in order to provide the most appropriate products (Xiao and Benbasat, 2007). RAs vary based on the degree of interaction between users and firms in creating the recommendations. One RA type (collaborative filtering) uses implicit user information and lets users passively receive recommendations based on past browsing behavior of the user or other likeminded users (Ho and Tam, 2005). However, since preferences are tacit and heterogeneous over time, the relevance of such recommendations is in question. To overcome that, firms sometimes use a more explicit type of RA that collects user input by asking users for their active rule-based preference elicitation (Häubl and Trifts, 2000; Xiao and Benbasat, 2007). Therefore, based on the users' input, the RA can recommend alternatives that best fit their demand specifications. The latter type of RA, which offers product choice sets based on previously specified rules from the users, is typically used in most of the online retailers and is the focus of this study. RAs help consumers narrow down their consideration set into a final choice set which better fits their preferences. The main advantages of such recommendation systems are that they improve the users' accuracy and reduce the effort needed to make a decision (Häubl and Trifts, 2000). When these outcomes of using a RA are achieved, the user evaluation of the RA improves substantially and, as a result, the overall usefulness and overall quality assessment of the RA increases (Xiao and Benbasat, 2007). The perceived RA quality is essential for websites since it signals higher user satisfaction and can lead to consumers' repeat usage of the RA (Bechwati and Xia, 2003; Venkatesh et al., 2003).

2.2 The Role of Effort

Effort in the field of decision-making is defined as the total use of cognitive resources required to complete a task (reach a decision) (Johnson and Payne, 1993). In the context of using a RA, effort is related to the cognitive resources required to generate the recommendations. Effort can increase by the amount of information or by the intrinsic (due to personal interest of the user) or extrinsic (due to procedural reasons due to RA requirements) involvement (Celci and Olson, 1988; Malhotra, 1982). Users treat human-computer interaction in a rather similar way as a social encounter, and therefore, they accordingly respond in a social manner to the effort put by the involved agent in the system (either the RA or other users that contribute value in the system) (Burgoon et al., 2000; Murray and Häubl, 2009; Nass et al., 1994). We further discuss the relationships between the two main sources of effort, namely, perceived user and RA effort, along with users' familiarity of the recommendation setting.

2.2.1 The Role of Perceived User Effort on Perceived RA Quality

User effort has been widely studied in the field of decision-making, yet providing conflicting evidence regarding its effect on various behavioral outcomes. A normative approach would suggest that effort, as a form of cost, would be undesirable for users (Bettman et al., 1990). According to the principle of least effort, individuals have limited cognitive resources to use, and therefore any additional use of these resources is considered as a form of cost (Zipf, 1949). Decision makers are cognitive misers that wish to minimize the cognitive effort associated with decision-making (Fennema and Kleinmuntz, 1995). However, they also want to maintain a high level of decision accuracy, which requires more effort needed from them (Bechwati and Xia, 2003). Therefore, an alternative perspective would suggest that effort can be considered as a form of investment, in that it improves the odds of making a more accurate choice (Häubl and Trifts, 2000). The sunk-cost fallacy could explain such a viewpoint; since individuals value higher a decision outcome in order to justify the effort they put in that decision (Arkes and Blumer, 1985). In the context of recommendation systems, it has been shown that a larger amount of user input can lead to increased satisfaction (Dabholkar and Sheng, 2012; Zhang et al., 2011). As users expend more effort, their decision accuracy is more likely to increase, yet research has shown that when these two goals conflict, they choose effort saving over increased accuracy even if that would make them settle for suboptimal options in return for a further reduction in effort (Bettman et al., 1990; Häubl and Trifts, 2000; Payne et al., 1993; Todd and Benbasat, 1994). The reason is that effort expenditure is perceived immediately, whereas feedback on decision quality is delayed and less observable (Einhorn and Hogarth, 1981; Kleinmuntz and Schkade, 1993). In practice, multiple studies tested innovative algorithms in order to minimize the input needed from the users to increase the speed of the process and improve the assessment of the RAs (De Bruyn et al., 2008; Toubia et al., 2003).

Effort reduction is tightly linked to technology ease of use as this has been defined as the extent to which a person believes that using a technology will be free of effort (Venkatesh, 2000), which in turn leads to more perceived effectiveness of the RA (Knijnenburg et al., 2012; Pommeranz et al., 2012). Freeing cognitive resources in the preference elicitation process leaves more resources to be used for assessing the recommendations to make an optimal choice. Effort reduction is the most important goal of users, especially when searching for the best available product (Lee and Benbasat, 2011). It is also one of the main motivations for using a RA (Häubl and Trifts, 2000). However, when effort reduction is not evident to the user, it is an indication that the system fails to provide the expected decision assistance. Therefore, when users feel that they exerted increased effort to interact with the RA, the expectation of effort reduction is disconfirmed, leading to a lower assessment of the RA (Bhattacherjee, 2001). We believe that effort is predominantly considered as a form of cost and the alternative approach becomes evident when linking user effort with the perceived effort put by the system.

H1: Perceived user effort decreases the perceived quality of the RA.

2.2.2 The Role of Perceived RA Effort on Perceived RA Quality.

A major benefit of using RAs is the agents' competence in facilitating the decision process and improving the decision outcomes by providing high quality recommendations that fit the users' preferences (Gretzel and Fesenmaier, 2006, Häubl and Trifts, 2000; Xiao and Benbasat, 2007). The quality of a RA is defined by its ability to better match these preferences and to save the effort needed to generate the recommendations (Häubl and Trifts, 2000). In the context of personalized recommendations, RA is perceived to use its resources in order to provide the best fitted recommendations that would minimize the effort further needed by users to reach a decision. Therefore, users welcome effort invested by others to help them decide because it would signify a higher amount of effort saving (Bechwati and Xia, 2003; Bitner et al., 1990; Mohr and Bitner, 1995). Even in the case of an accuracy-effort trade-off, users weigh in for the latter (Todd and Benbasat, 1999). However, users believe that higher effort from an RA, equally contributes to the accuracy goal they have. So the effort reduction does not happen in the expense of a less accurate choice, but rather allows users to reallocate cognitive resources from screening options and training the RA, to elaborate on the final recommended set. As a result, the recommendation outcome is more positively evaluated when they perceive that the RA has put more effort in generating these recommendations (Gretzel and Fesenmaier, 2006). Also, perceived effort reduction from the RA is expected to positively influence process satisfaction (Bechwati and Xia, 2003). Additionally, the effort heuristic for quality suggests that there is a positive relationship between the amount of perceived effort invested by the producer of a product and the consumer's quality perception of the product (Cardozo, 1965; Kruger et al., 2004); in the case of RAs, the product being the actual recommendation generation. Finally, the effort RAs put in improving the interaction with their users can increase the feeling of trust about the benevolence of the agent in maximizing the service quality (Wang and Benbasat, 2007).

H2: Perceived RA effort increases the perceived quality of the RA.

There is evidence that users tend to treat their interactions with computers similarly to other human interactions and apply the same social rules as they would to other humans (Burgoon et al., 2000). They therefore consider a recommendation system as an equitable social agent, especially when the system explicitly communicates information in a humanlike way (Murray and Häubl, 2009). As with any human interaction, there are several norms that govern all social encounters and can also be applied in a human-computer interaction.

Equity theory suggests that in any given social interaction, the social actors are concerned about their inputs and outcomes, but also for the fairness in the relative distribution of resources across them (Adams, 1965). More positive perceptions of equity improve satisfaction, increase the psychological value of the outcomes, and further motivate and increase an individual's willingness to put more effort in the interaction (Carrel and Dittrich, 1978). Equity perception has also a very strong influence on the degree of user satisfaction of an information system (Joshi, 1989). In essence, when users feel that their input requirements (i.e. user effort) in their interaction with an information system are unfair compared to the benefits gained from its use (input from the system), they become dissatisfied (Au et al., 2008).

An additional social norm that characterizes individual behavior is the principle of reciprocity (Gouldner, 1960). According to that, individuals reciprocate the benefits they receive from others during social encounters. In such a way, they can ensure an ongoing mutual value exchange. The effect of reciprocity is predominant in various transaction situations and is one of the most influential drivers of persuasion (Cialdini, 1993) as well as cooperative behavior (Falk and Fischbacher, 2006). In electronic networks, even though the value exchange occurs many times among weak ties of social actors, reciprocity operates as a strong motivation to participate and contribute value (Wasko and Faraj, 2005). When such a norm is evident, individual users believe that their contribution efforts will be in turn reciprocated, thereby showing a higher motivation and tolerance towards own effort.

As individuals tend to apply similar norms in their interactions with information systems, we expect that reciprocity would be concurrent and users would be willing to work together with the RA to maximize the outcome quality. Therefore, the amount of effort (use of resources) that users perceive they put into the process is dependent on how much effort they perceive the RA puts as well. If RA effort is high, then the effort users expend can be considered as a benefit as it feels like it outweighs the cost of using the available cognitive resources (Swearingen and Sinha, 2002). If they feel that the RA expend more effort than they have, they do not mind expending more effort themselves, whereas if they feel that the RA expend a lower amount of effort than them, they might find this to be unfair and decrease their perception of the overall quality of the RA. Thus, we expect that the negative effect of perceived user effort on perceived RA quality is reduced as the perceived RA effort increases.

H3: Perceived effort of the RA (i.e., RA effort) negatively moderates (attenuates) the negative relationship between perceived user effort and perceived quality of the RA.

2.2.3 The Moderating Role of User Familiarity

User familiarity can be defined as the increase of understanding of a certain entity based on previous interactions, experiences and improved learning (Gefen et al., 2003; Komiak and Benbasat, 2006). It is one basic component of consumer knowledge and has the ability to decrease the actual effort needed to perform a certain task (Alba and Hutchinson, 1987; Pereira, 2000) but also the perceived effort needed to accomplish it (Murray and Häubl, 2009). Users with high familiarity have the ability to focus on the most relevant information (Alba and Hutchinson, 1987) and therefore, are less prone to framing effects during the preference elicitation stage (Coupey et al., 1998; Kramer, 2007; Xiao and Benbasat, 2007). Also, they need fewer (time or cognitive) resources to assess the same amount of information compared to novice users. As a result, for such users, the amount of effort required in the decision making process is undervalued. Users with high familiarity, due to their higher product involvement, are more intrinsically motivated and therefore they show higher interest and enjoyment in the process. Conversely, non-familiar users tend to show higher trust on the RA and are more likely to be prone to overvalue its contribution throughout the interaction (Nah and Benbasat, 2004).

We expect user familiarity to moderate the interaction effect of perceived user and RA effort on perceived quality of the RA. As discussed earlier, when users perceive that the RA expended much effort, the negative impact of their own effort on perceived quality is weakened. We argue that this only holds true when user familiarity is relatively low. The reason is that these users may have no reference point regarding the effort needed and thus are more easily impressed by the RA that exerts a lot of effort. That is, the perceived usefulness of the RA increases because the perceived effort saving increases as the task becomes more complex (Lee and Benbasat, 2011), especially for the users with low familiarity. On the contrary, when user familiarity is high, the interaction effect of user and RA effort on RA quality is weakened. In other words, these users have higher expectations and may appreciate less the exerted effort from the RA. Therefore they undervalue the RA effort.

H4: There is a three-way interaction effect among user familiarity, perceived user effort, and perceived RA effort, i.e., when the user familiarity is low, the negative effect of user effort on RA quality is reduced as the perceived RA effort increases; but the opposite is true when user familiarity is high.

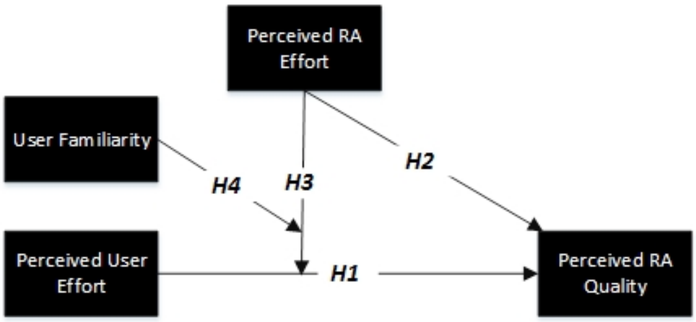

Figure 1. Conceptual Model.

3 Research Methodology

To examine the impact of perceived effort on RA quality, we conducted two studies. Study 1 is a quasi-experimental study in the context of car recommendations. To monitor user behavior in such a technical and search product, we developed a RA, which generates recommendations based on user preferences. Study 2 tests the hypotheses in a controlled experiment where we are able to control the recommendation set composition and examine perceived effort in an experience product (dating).

3.1 Study 1: Car Recommendation System

Study 1 is based on a realistic web-experiment in the context of car recommendations. The domain is suitable for our study because cars are complex products that require deliberation, which makes effort central. Familiarity also has a prominent role due to users' varying technical expertise.

Study Design. We developed a web-based RA, using 73 cars, each containing 22 attributes. We informed the respondents that they could use the RA to select a car from a pool of available company cars for leasing, to make sure that the role of brand and price is demoted compared to a choice of a car for private use. First, participants specified their preferences for a list of attributes. Then, they were asked to choose a car from a personalized set recommended based on their stated preferences. We used a 2×2 between-subject experiment design where participants were randomly assigned to one of the four conditions. We manipulated two types of effort: perceived user effort (high, low) and perceived RA effort (high, low). Perceived user effort was manipulated based on the effort heuristic proposed by Kruger et al. (2004). Both high and low conditions have the same visual design but differ in the number of tasks the participants need to complete. In the high user effort condition, the participants were asked to first choose importance weights for 13 attributes.[1] In the low user effort condition, they were asked to pick the three most important attributes from the same list of attributes. Usually a RA

[1] Importance weights were given for: power, acceleration, fuel usage, CO2 emissions, green energy label, new model, air conditioning, MP3/iPod connection, navigation system, fiscal additional tax, lease price. Categorical answers were given for transmission (manual or automatic) and fuel type (petrol, diesel or hybrid).

performs the search and calculation task at a very high speed and thus it remains unnoticeable to most users. Users may become more aware of the RA effort if this effort is brought to their attention (Bechwati and Xia, 2003). Thus, in the high RA effort condition, we explicitly brought the RA effort to the attention of the users by informing the participants about the search progress while waiting for the results. A continuously rotating loader with the text "calculating results" was displayed for seven seconds to make sure the participants can notice the delay. In the low RA effort condition, the participants received the results without any intermediate message and delay.

Perceived RA Effort (Bechwati and Xia, 2003)		
PRAE1	The RA put a lot of effort generating recommendations.	(1, 2)
PRAE2	The RA worked hard generating the recommendations.	(1, 2)
PRAE3	The RA did not invest a lot of effort generating the recommendations (R)	(1, 2)
Perceived User Effort (Bechwati and Xia, 2003)		
PUE1	I put a lot of effort into supplying the RA with my preferences.	(1, 2)
PUE2	I worked hard filling in my preference list.	(1, 2)
PUE3	I did not exert a lot of effort filing in my preferences. (R)	(1, 2)
User Familiarity (Gefen and Straub, 2000; Ho et al., 2010)		
FAM1	I am familiar with car searching websites like …	(1, 2)
FAM2	I am familiar with buying cars on the Internet.	(1, 2)
FAM3	I am familiar with the processes of purchasing cars on the Internet	(1, 2)
FAM4	I know the product category of the personalized recommendations well.	(1, 2)
Perceived RA Quality (Li and Unger, 2012; McKinney et al., 2002)		
PRAQ1	The RA provides valuable recommendations to me.	(1, 2)
PRAQ3	The RA provides relevant recommendations to me.	(1, 2)
PRAQ2	The RA improves my search performance. .	(1, 2)
PRAQ4	The RA provides up-to-date recommendations to me.	(1, 2)
PRAQ5	The RA provides easy to understand recommendations to me.	(1, 2)
PRAQ6	The RA saves me time	(1)

Note. The numbers indicate in which study the items are included in the measurement.

Table 1. Measurement of Constructs.

Measurement. After making a choice, participants were asked a series of item-based questions that measured the main constructs. The measurement items were adapted from prior studies and contextualized for the car recommendation setting (see Table 2). All statements are measured on a 7-point Likert scale, ranging from "strongly disagree" to "strongly agree". By conducting a factor analysis we found that all items load in the respective factors and we further conducted tests to address the common method bias. We also measured user demographic information (age, gender, education) as well as the perceived ease of use of the RA[2].

Descriptive Statistics. We recruited our participants through the network of a large European University. We obtained a valid sample of 306 respondents (median age = 26; 61.1% males). They were randomly assigned to the four experimental conditions. Participants showed a relatively high familiarity ($M_{familiarity}$ = 4.35, on a 7-point scale) and no respondents were found with familiarity lower than 2.

Manipulation Checks. Perceived user effort was significantly higher in the high user effort condition (M_{high}=5.27, M_{low}=2.94, F=283.21, p=0.00). Regarding RA effort, we asked participants in the high

[2] Perceived ease of use was based on a 7-points scale with 5 items based on Gefen and Straub (2000) (Strongly disagree - Strongly agree): (1) The RA is easy-to-use. (2) It is easy to become skilful at using the RA. (3) Learning to operate the RA is easy. (4) My interaction with the RA is clear and understandable. (5) It is easy to interact with the RA.

RA effort condition if they indeed noticed the rotating loader. All respondents in the high RA effort condition were affirmative. Also, perceived RA effort was significantly higher in the high RA effort condition (M_{high}=5.32, M_{low}=3.49, F=160.88, p=0.00).

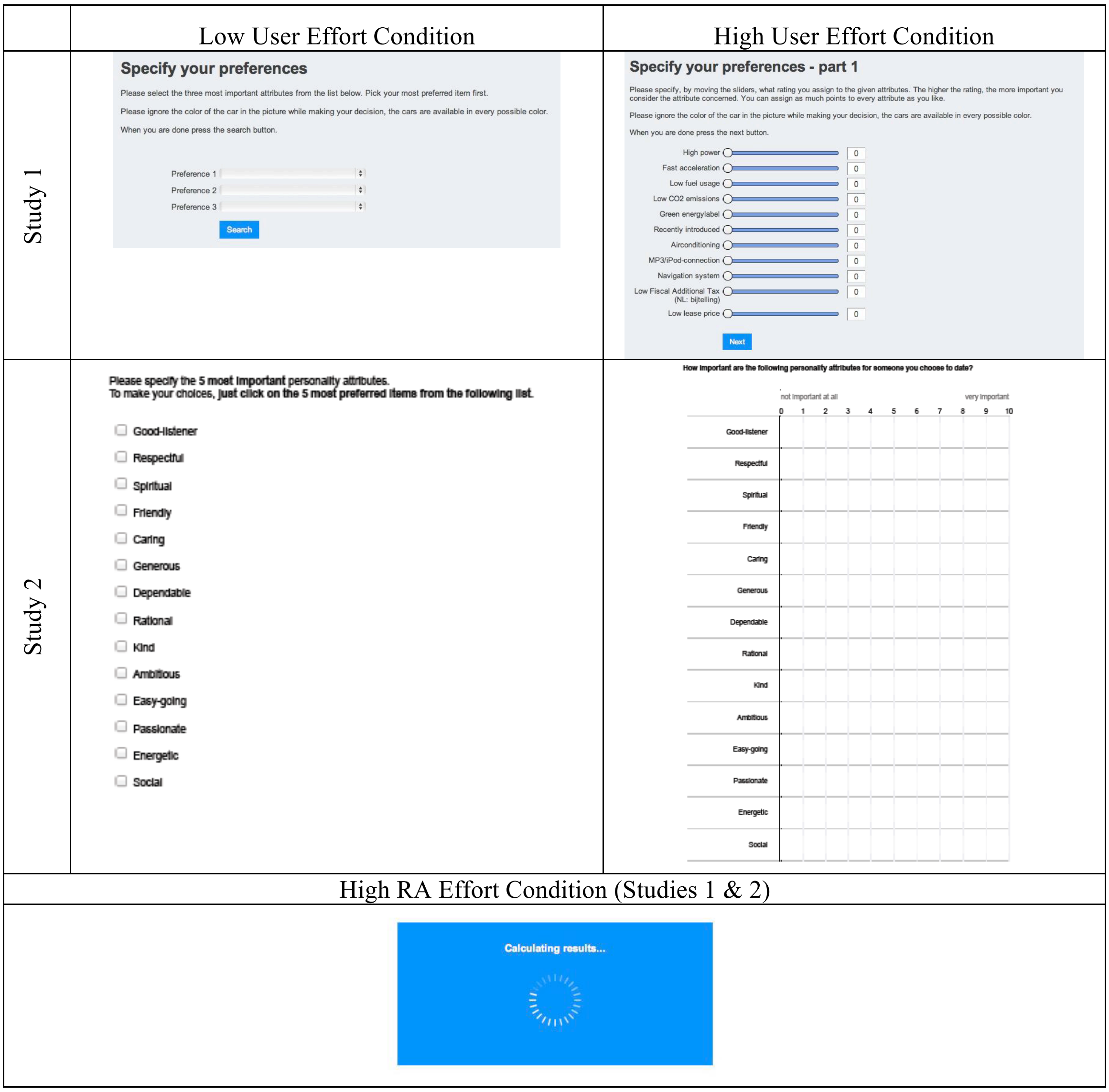

Figure 2. Manipulations of Perceived User Effort (Studies 1 & 2)

Results. To test our hypotheses, we conducted a linear regression on perceived RA quality. The independent variables were the direct effects of perceived effort measures, as well as all 2- and 3-way interactions between user effort, RA effort, and user familiarity. Also, we controlled for RA ease of use and user demographics. The results are shown in Table 3. In the model with only direct effects, we found a positive effect of user familiarity and perceived RA effort on RA quality. Therefore we can support H2. Then we estimated the model including all interactions. The interaction effect between perceived user effort and RA effort is significant and positive, which supports H3 and suggests that a larger perceived user effort increases perceived RA quality, the larger the perceived RA effort is. The three-way interaction between user and RA effort with familiarity is also significant and negative, supporting H4. The Johnson-Neyman technique (Spiller et al., 2013) identified that the effect of the interaction between user and RA effort is positive for any familiarity level below 2.85 (b=0.046, SE =

0.023, p = .050) and negative above 5.28 (b=-0.034, SE = 0.017, p = .050). This suggests that users are willing to exert personal effort when they feel that the system invests high effort as well, yet this effect is lower for highly familiar users. Such users are more experienced and have already formed expectations from RAs, in that they expect that their use would decrease the required effort. Yet, if the user effort is increased, they do not appreciate as much the effort from the recommendation system. Regarding the control variables, we found no significant demographic effects and only a positive effect of ease of use on RA quality.[3]

Study 1 shows that the effect of user effort on RA quality depends on both the perceived RA effort as well as the user's familiarity. However, though 57% of the respondents chose one of the first two recommended cars, we could not collect information about the composition of the personalized recommendation sets. As a result, we cannot rule out that the effects on RA quality are due to differences in the attractiveness of the recommendation sets (e.g. inclusion of specific brands in the set, or average attractiveness of the recommended cars).

Dependent variable: Perceived RA Quality	(1) Main Effects		(2) Main & Interaction Effects	
	β	*S.E.*	*β*	*S.E.*
Intercept	2.71**	0.45	3.59**	1.26
User Effort	-0.02	0.03	-0.33	0.23
RA Effort	0.28**	0.03	-0.18	0.24
Familiarity	0.11**	0.03	-0.10	0.23
User Effort × RA Effort			0.11**	0.05
User Effort × Familiarity			0.08	0.05
RA Effort × Familiarity			0.11*	0.05
User Effort × RA Effort × Familiarity			-0.03**	0.01
Control Variables	*Included*		*Included*	
N	306		306	
R^2	0.32		0.36	

Note. (1) * p<.5; ** p<.01; (2) Control variables: user demographics, ease of use, car ownership.

Table 2. Study 1 Results: Car Recommendations.

3.2 Study 2: Dating Recommendation System

Study 2 tests the hypotheses in an experimental environment where we control for the composition of the recommendation set and perceived user effort in a more objective measure. The context of this study is dating recommendations. Online dating is increasingly popular and humans are defined as the ultimate experience product (Frost et al., 2008). Also, dating is a context where familiarity has a demoted role (no technical expertise needed) and the decision quality is extremely subjective, rendering the role of the RA even more critical (Senecal and Nantel, 2004).

Study Design. We created a web-based experiment where participants could choose a potential date from a recommendation set based on elicited preferences. Participants specified importance weights of a list of personality traits and demographic characteristics that an ideal date should possess.[4] Then,

[3] We further tested if the effect of user effort can be explained by gender. We found that there is a negative interaction of user and RA effort with gender. This suggests that for females, the effect of user effort is negatively influencing perceived RA quality whereas the RA effort is positively influencing RA quality. Given that the car context is typically male oriented, we also found a higher familiarity of male respondents (M_{male}=4.65, M_{female}=3.87, F=24.48, p=0,00)

[4] Personality traits were: Good-listener, Respectful, Spiritual, Friendly, Caring, Generous, Dependable, Rational, Kind, Ambitious, Easy-going, Passionate, Energetic, and Social. Demographic characteristics were: Hotness, Being Athletic, Non-Smoking, Education, and Income.

they were asked to select their most preferred date from a set of recommendations based on their own preferences. We used a 2 (high vs. low user effort) × 2 (high vs. low RA effort) between-subject experimental design where participants were randomly assigned to one of the conditions. Both conditions of user effort included the same list of attributes (see Figure 4). In the high user effort condition, participants were asked to give importance weights to all 19 attributes whereas in the low user effort condition, participants were asked to pick the 7 most preferred items from the list. RA effort was manipulated similarly to study 1. After eliciting their preferences, participants accessed a recommendation set of the 6 closest matches and were asked to choose the person that they would most likely choose to go on a date with. Given that the setup was fictional and the nature of our context was highly subjective, we used the same recommendations regardless of the demand specifications of each participant. To guarantee that the options could be considered as personalized for all respondents, we (a) ran a pre-test where participants had to evaluate the physical attractiveness of potential dates and used in the study, a diverse set of options that could cover a larger spectrum of preferences[5]; (b) mentioned that the ranking of recommendations was based on alphabetical order; and (c) offered quantifiable information for the recommended dates[6]. In such a way we could control for the content of the recommendation output and be able to estimate a fair proxy for the decision quality of the participants.

Measurement. After fulfilling their task, respondents answered some questions related to their experience with the dating recommendation system. The measurement items used in this part were similar to study 1 but were adapted to the context of this study (table 2). We controlled for user demographic information, past offline dating history (number of people dated and number of dates), trust in dating websites, as well as various choice set characteristics (recommended set gender, recommended set and chosen option attractiveness based on stated importance weights). We conducted a factor analysis and found that all items used load in the respective factors. Further, consistent with Lee and Benbasat (2011), we found no single factor explaining the majority of the variance in perceived RA quality, which alleviates the concerns for common method bias.

Descriptive Statistics. Participants were members of an Internet-based research panel in Netherlands. We obtained 271 valid responses in this study. We excluded cases where average trust in a dating site is zero (2-items), because such behaviors can also be attributed to the social stigma that embodies dating platforms.[7] Further, we excluded participants who spent less than 15 seconds eliciting their preferences for 19 attributes.[8]

Manipulation Checks. The manipulations were successful in triggering a larger variance of the perceptions. Perceived user effort was significantly higher in the high user effort condition compared to the low condition (M_{high}=3.72, M_{low}=3.37, F=3.01, p=0.08). The marginal significance can be due to the less extreme differences between high and low condition compared to study 1. In addition, the total time spent (in seconds) eliciting personal preferences was longer in the high versus the low user effort condition (M_{High}=78.1, M_{Low}=35.5, F=117.21, p=0.00). To check the manipulation of the RA effort, we first asked participants in the high RA effort condition if they noticed the rotating loader and excluded those who did not (9 respondents). Perceived RA effort was significantly higher in the high RA effort condition compared to the low RA effort condition (M_{high}=3.93, M_{low}=3.59, F=8.21, p=0.00).

[5] We blurred the faces of the options for privacy issues and to demote the role of a more objective based on average standards, physical attractiveness of some options. The message "On this page, due to some privacy restrictions, you are only able to access limited information about the persons" was displayed.
[6] We displayed scores for "Body" & "Face" (based on ratings from other members of the website) and "Intelligence" & "Humor" (based on the dates' answers in personality tests). All options had the same expected attractiveness (based on equal weights).
[7] These respondents had no difference in their answers on user and RA effort as well as RA quality across the 4 conditions. Such insensitivity can be attributed to a strong preoccupation against dating websites.
[8] The results remain consistent also when we relax the time cut-off point to 10 seconds.

Results. The model with only main effects shows a positive effect of perceived RA effort on RA quality (supporting H2). In the model including the interactions, we find a negative main effect of user effort (supporting H1). The interaction between perceived user and RA effort is significant and positive, (supporting H3) showing that perceived RA effort negatively moderates the negative effects of user effort on perceived RA quality. Also, the three-way interaction between user and RA effort with familiarity is significantly negative (confirming H4). The Johnson-Neyman technique (Spiller et al., 2013) identified that the effect of the interaction between user and RA effort is positive and significant for any familiarity level below .097 (b=0.07, SE = 0.033, p = .05) and marginally negative above 5.37 (b=-0.09, SE = 0.057, p = .10). Regarding the control variables, we found a positive effect of trust on dating sites on RA quality.

Dependent variable:	(1) Main Effects		(2) Main & Interaction Effects	
	β	*S.E.*	*β*	*S.E.*
Intercept	2.44**	0.84	3.55**	0.94
User Effort	0.07	0.05	-0.27*	0.13
RA Effort	0.35**	0.06	-0.01	0.17
Familiarity	-0.04	0.04	-0.46**	0.16
User Effort × RA Effort			0.11*	0.04
User Effort × Familiarity			0.13**	0.04
RA Effort × Familiarity			0.13*	0.06
User Effort × RA Effort × Familiarity			-0.04*	0.01
Control Variables	*Included*		*Included*	
N	271		271	
R^2	0.30		0.33	

Note: * p<.05; ** p<.01; Control variables: user demographics, trust, rank of chosen option, recommended set characteristics.

Table 3. Study 2 Results: Dating recommendations.

4 Discussion and Conclusions

4.1 Summary of Key Findings

Recommendation agents are very popular tools that assist online companies to adapt their offers to users' preferences and as a result, improve the quality of their decisions (Xiao and Benbasat, 2007). An essential benefit of the use of recommendation systems by users is their achieved effort reduction (Häubl and Trifts, 2000). The concept of effort has been fundamental in decision-making (Johnson and Payne, 1985) as well as human computer interaction (Todd and Benbasat, 1994; Xiao and Benbasat, 2007). Yet, evidence on the role of effort has offered contradictory insights in whether it should be regarded merely as a cost for the user, or as a benefit, since it improves the odds of a better decision (Häubl and Trifts, 2000). However, past research has mostly focused on the level of effort that the user should expend in such interactions. However, since users regard their interactions even with inanimate systems in a humanlike nature, complying with the norms of any typical social interaction with other humans, we show that they also take into account the effort exerted by the system (RA) in a similar manner. Therefore, though they dislike any effort they have to put in a decision task, they welcome any effort invested by others to help them decide as that signifies a reduction of their own effort (Bechwati and Xia, 2003). In this research, we focus on two sources of effort expenditure that contribute to the total effort experienced in the context of RA use, namely, user and RA effort.

More specifically, in two studies, which differ in research methodology as well as the empirical context, we focus on how the user effort expended during the preference elicitation process vis-à-vis a more explicitly framed effort by the RA can influence the evaluation of the RA across different levels of user familiarity. The results suggest that user effort decreases perceived RA quality, since it opposes the main benefit expected from its use, consistent with the effort reduction argument. In addition, the perceived RA effort increases the perceived RA quality since users seem to appreciate the effort put from the RA in the current encounter. We find such an effect even though we manipulated perceived RA effort based on a simple interface cue (rotating loader). Results in both studies support our expectation that the negative effect of user effort is attenuated when users perceive a greater RA effort. Complying with the social norms of equity and reciprocity, which outlines most social interactions, as long as a RA is perceived as hard working in order to best serve the users, users do not mind much putting more effort. Further, the results in both studies confirm that such interaction is less evident the more familiar users are with the setting. Familiar users have higher expectations from RAs and appreciate less the exerted effort for them.

4.2 Theoretical & Managerial Contributions

Our research makes contributions to the academic literature in several ways. First, building upon the notion that users-computer interactions mimic typical social encounters, we suggest that the perception of effort is not merely related to the effort the user exerts in the interaction the system, but also the effort that the system contributes in the interaction. In this paper, we introduce user effort as a disentangled construct in parallel with the perceived effort put by the RA. Such a distinction enriches our understanding about the conflicting findings on the role of user effort when dealing with an information system. We showed that user effort, in accordance with the normative perspective of effort as a cost (Häubl and Trifts, 2000; Zipf, 1949), reduces the perceived RA quality as it contradicts with the main benefit that RAs offer, i.e., effort saving. Although some studies offered evidence that increasing the amount of user input (i.e. user effort) increases satisfaction with the RA (Dabholkar and Sheng, 2012; Zhang et al., 2011), such a counterintuitive effect can be explained by taking into account the role of effort exerted by others. To that end, this paper empirically studied the impact of RA effort on users' perceived quality of RA, extending previous research (Bechwati and Xia, 2003). In our studies, we informed the users about the search progress while waiting for the recommendations and found that by increasing the RA effort perception we can increase users' assessment of RA quality. Of course, we expect that such an effect is non-linear, since delaying results for longer time would backfire as it is considered as delay. Second, by investigating the interaction between perceived user effort and perceived RA effort, we gave further evidence regarding the conflicting findings on user effort. Though user effort can be considered both a form of cost (expenditure of cognitive resources or time) or benefit (cognitive investment for better accuracy), the overall effect depends on the relative perception of these two sources of effort. Based on the equity theory (Adams, 1965) and the norm of reciprocity (Gouldner, 1960), we showed that users positively evaluate the RA if they feel that the overall effort was fairly distributed across all actors in the process. In other words, a positive effect of user effort can be explained in cases where the perceived RA effort is relatively high and therefore, users are also positively inclined to exert additional effort to maximize the accuracy of their outcomes. Third, we provided evidence on the importance of taking into account users' familiarity. User familiarity is an essential determinant of user behavior as it influences both the actual and perceived effort needed to perform a certain task (Alba and Hutchinson 1987; Murray and Häubl 2009; Pereira 2000). We showed that familiar users respond differently regarding effort perceptions but also when it comes to the interaction between user and RA effort as they are less prone to framing effects (and hence are not easily influenced by perceived RA effort cues) (Kramer, 2007). Therefore the norm of reciprocity is less evident with familiar users as they tend to undervalue the effort exerted by the RA. Finally, the use of two studies across various product categories, allowed us to offer rather generalizable evidence on the role of user and RA effort. We found that the interaction between user and RA effort is evident both in the context of a search product (car recommendations in Study 1) as well as an experience product (dating recommendations in Study 2). Experience goods are more prone to recommendations as the objective quality is hard to assess without experiencing the product, whereas search goods can be assessed even without using the product (Senecal and Nantel, 2004). We found that the norm of reciprocity in effort perception can be applied in all these cases.

This paper also has implications for business practice. First, our studies suggest that online firms need to be cautious about the effect of required user input during the preference elicitation stage of a RA. Although, they should aim at minimizing the required effort of users (De Bruyn et al., 2008; Toubia et al., 2003), they need to be alert that such an approach does not compromise the accuracy of the recommendations. Though, behaviorally, users would welcome the effort reduction, the overall quality assessment would also be dependent on the quality of the recommendations. Second, the findings of this study with regard to the perceived RA effort suggest that it is important to inform users the search progress while they are waiting for results. Providing information to users about the search progress while waiting increases their satisfaction of the process (Xiao and Benbasat, 2007). We proposed a simple interface cue using a rotating loader image that largely improves consumers' perception of the quality of RA. Websites can use such an explicit way to communicate their efforts if they require increased user input. In such a way they can counterbalance the potential dissatisfaction of users due to additional effort requirements. Finally, the managerial importance of RA quality can be confirmed by its role on improving RA acceptance. Perceived quality of the system can influence the acceptance intention of the system (Venkatesh et al., 2003). In both studies, we measured RA acceptance as an additional behavioral outcome after using the RA. We found that RA quality is a strong driver of RA acceptance, which explains respectively, 72% and 48% of its variation. We found no direct effect of perceived effort on RA acceptance as these effects operate only indirectly through RA quality.

4.3 Limitations and Future Research

We recognize some limitations that offer prospective avenues for future research. First, since RA quality is a subjective measure of RA evaluations, it would be insightful to explore whether such a response might be due to the decision quality of the user. The RA quality is tightly linked to the outcome of a users' decision task. Therefore, it would be interesting to contrast the effects of effort on perceived RA quality with decision quality as well, and explore whether there are conditions under which, users make worse decisions yet feel very satisfied with the process. In addition, future research should take into account also the decision complexity as an additional source of user effort. Second, next to the subjective measures of perceived user effort, using a rather objective measure (such as time spent or number of information cues accessed) would enrich our understanding regarding the conditions where users tend to over- or undervalue their effort spent. Third, in all our experimental studies, we focused on the effect of perceived effort on perceived RA quality. We manipulated various types of effort to guarantee an adequate variation in our responses. We were very careful in our experimental design to trigger effort perceptions; nevertheless, we need to be cautious about how we interpret the self-filled information of perceptions and RA quality. To further address the common method bias concerns, future research can incorporate a marker variable that involves an unrelated construct that is prone to social desirability bias. In this paper we use a simple successful manipulation for perceived RA effort by showing a rotating loader. However, we cannot expect that such an effect is linear regardless the amount of time it is shown (in fact an inverted U-shape relationship between waiting time and perceived RA quality). Future studies can explore the optimal duration of such a manipulation. Finally, a higher level of informedness by the inclusion of various types of information displayed during waiting time (e.g., expected time remaining to complete the task, CPU usage, database size) could alleviate the potential negative effects of waiting time (by managing the expectations or distracting the user; Dellaert and Kahn, 1999), yet still communicate to users the exerted RA effort.

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