Walking the Middle Path: How Medium Trade-Off Exposure Leads to Higher Consumer Satisfaction in Recommender Agents

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Abstract. Recommender Agents (RAs) facilitate consumers' online purchase decisions for complex, multi-attribute products. As not all combinations of attribute levels can be obtained, users are forced into trade-offs. The exposure of trade-offs in a RA has been found to affect consumers' perceptions. However, little is known about how different preference elicitation methods in RAs affect consumers by varying degrees of trade-off exposure. We propose a research model that investigates how different levels of trade-off exposure cognitively and affectively influence consumers' satisfaction with RAs. We operationalize these levels in three different RA types and test our hypotheses in a laboratory experiment with 116 participants. Our results indicate that with increasing trade-off exposure, perceived enjoyment and perceived control follow an inverted U-shaped relationship. Hence, RAs using preference elicitation methods with medium trade-off exposure yield highest consumer satisfaction. This contributes to the understanding of trade-offs in RAs and provides valuable implications to e-commerce practitioners.

Keywords: Recommender Agents, Preference Elicitation Method, Trade-off Exposure, Customer Satisfaction

14th International Conference on Wirtschaftsinformatik,
February 24-27, 2019, Siegen, Germany

1 Introduction

Demand for products customized to individual consumers' preferences (e.g., mass customized or custom-made) has grown hugely in recent years. Concurrently, the range of product variations available on the market has expanded [1]. As a result, consumers are increasingly in need of decision support systems that help them sift through the many variations by providing information transparency on product attributes (e.g., price, quality, performance) and their interrelationships (e.g., price-quality trade-offs). Prior research indicates that navigation aids and decision aids such as recommendation agents (RAs) help consumers understand their preferences and find suitable products [2]. A central aspect within RAs, which is still subject to discussion, are trade-offs.

Trade-offs are mutual dependencies between two attributes, where certain attribute levels become unavailable (e.g. low price) as a result of having selected a specific level of another attribute (e.g. high quality) [3; 4]. How trade-offs are integrated and presented in RAs is an important issue since trade-offs can be difficult to process and imply losses in certain attributes, which tends to make consumers unhappy and frustrated – and in turn reduces their willingness to use the RA [5].

Recommender agents use a number of different strategies to elicit consumer preferences and, hence, present trade-offs differently [6]. Trade-off exposure reflects the degree to which the consumer is forced to recognize and deal with trade-offs. In other words, trade-off exposure refers to how much the user is forced to think about availability and unavailability of product attributes dependent on prior choices in other attributes. For example, when choosing a specific level of quality automatically rules out a variety of choice options (e.g., cheap alternatives), the user is confronted with high trade-off exposure, while an RA with low trade-off exposure hides such consequences. Lower levels of exposure reduce decision difficulty but have the drawback of depriving consumers of important information [7]. In contrast, higher levels of exposure increase recommendation accuracy but tend to be cognitively more challenging for consumers [8].

While traditional RA designs have either hidden trade-offs from users or forced them to explicitly compare attribute levels, recent designs exhibit a medium level of trade-off exposure [5; 9]. While the level of trade-off exposure in an RA may significantly affect users' perceptions (e.g. effort of using or satisfaction with the result), its impact is not yet fully understood. Xu et al. [5] have found that a medium level of trade-off exposure leads to highest usage intentions, however, they have only varied the number of trade-offs while using the same RA in all conditions. Hence, we are investigating the follow research question:

How do preference elicitation methods with different levels of trade-off exposure affect consumers' satisfaction with an RA?

Our study contributes to understanding the role of trade-off exposure by comparing RAs of low, medium and high trade-off exposure in a laboratory experiment with 116 participants. To investigate the influence of trade-off exposure on satisfaction with an RA, we examine cognitive and affective perceptions [10], and how they in turn affect decision quality and decision effort, preceding consumers' satisfaction with the RA.

The results of our study provide valuable contributions to theory and practice. From a theory perspective, we contribute to the understanding of how medium trade-off exposure affects consumer perceptions and, ultimately, how it affects consumers' satisfaction with RAs. From a practitioner's perspective, this study helps RA designers to facilitate consumers' purchase processes. It advances their understanding of how the level of trade-off exposure affects consumers and which level to choose when designing an RA. This in turn can lead to increased sales as consumers find the right products more easily among an extensive range of product variations.

2 Theoretical Background

Recommender agents are virtual assistants which aim to help consumers find, with as little effort as possible, the product that fits their requirements best [11]. The two most common approaches for RAs, collaborative filtering and content-based recommender systems, use information about consumers' past purchases to predict future purchase decisions [12]. However, due to lack of data for new consumers and new products (the so-called cold-start problem), recommendation quality may be quite low [9]. Systems that do not suffer from these problems are based on multi-attribute value theory (MAVT). MAVT-based RAs use consumer-specific value functions and attribute importance weights, estimated at the time of purchase, to provide recommendations [13].

How well an RA is able to support consumer decisions depends, among other factors, on how it deals with trade-offs. Trade-offs are mutual dependencies between two attributes, where certain attribute levels become unavailable as a result of having selected a specific level of another attribute [3; 4]. The trade-offs can be shown explicitly to the consumer or implicitly which is referred to as trade-off exposure. RAs with high trade-off exposure explicitly inform consumers when certain attribute levels become unavailable as a result of having selected a specific level of another attribute. Unavailable attribute combinations are presented to consumers and require consumers to take corrective action. RAs with low trade-off exposure hide consumers from this information, which means unavailable attributes are not shown or attribute selection is decoupled from product presentation. Hence, RAs with high trade-off exposure generally provide users with a more transparent (i.e., users can inspect choice consequences) but also more challenging decision process.

The level of trade-off exposure depends largely on the preference elicitation method implemented in a MAVT-based RA. Common preference elicitation methods are absolute measurement, pairwise comparisons, ordinal judgments, rankings, and matchings [14].

Consumers are forced into explicit trade-offs in preference elicitation methods like pairwise comparisons or rankings. In such explicit trade-off decisions, consumers are made aware of attribute dependencies at each step of the process. When attribute levels become unavailable, consumers can either change the configuration to make a broader range of attribute levels for the other attributes available, or they can accept the unavailability of some attribute levels and choose within the reduced ranges. They cannot continue the recommendation process before a specific attribute conflict is solved [7]. Implicit trade-offs are required in absolute measurement methods. In implicit trade-off decisions, consumers are not made aware of attribute interdependencies: consumers merely indicate their preferred attribute levels or the importance of attributes. If attribute conflicts arise, the RA interface does not point them out and does not ask to resolve the conflicts. Informed consumers may detect low accuracy in the recommendation output as a result [15].

So far, only few studies have examined the role of trade-offs in RAs. Although explicit consideration of trade-offs apparently improves decision accuracy [8], consumers often attempt to avoid considering trade-offs because they do not like the uncomfortable issue of having to accept (perceived) losses in certain attributes [16–18]. Another drawback of explicit trade-offs is the fact that processing trade-off information is cognitively challenging; depending on the number of attributes, levels and products to be compared, it can lead to information overload. Implicit trade-offs reduce decision stress [14] but choices based on explicit trade-offs are perceived to be more consistent and reliable [15; 19]. While Xu et al. [5] have found consumers to prefer a medium level of trade-off exposure, compared to high and low levels, their results were not confirmed in the context of different preference elicitation methods. We aim to improve the understanding of trade-off exposure by explicitly distinguishing low, medium and high trade-off exposure across different preference elicitation methods.

3 Research Model and Hypothesis Development

We investigate how preference elicitation methods with different levels of trade-off exposure affect consumers' satisfaction with an RA. To study the effect of different levels of trade-off exposure on users' satisfaction with an RA, we propose a research model based on cognitive and affective perceptions of an RA. The choice of latent variables and causal mechanisms is based on previous work, incorporating existing theory on the mechanisms driving users' perception [5; 7]. A summary of the research model is presented in Figure 1.

Trade-off exposure is an environmental cue that affects consumers' cognitive and affective reactions [20]. It becomes apparent to users as a visual cue (aside other cues, e.g. colors or layout), being part of the preference elicitation method implemented in a RA. Cognitively, providing information on unavailable options directly facilitates attaining a shopping goal [2], while the interactive nature of its presentation (e.g. moving sliders or crossed out options) can trigger affective reactions [21].

Perceived control and perceived enjoyment reflect the cognitive and affective reactions to the exposed trade-offs. Perceived control reflects the perception of a consumer's impact on an activity or given condition [22]. In the context of an RA, perceived control expresses to which extent consumers feel they can use the RA to accomplish their intended goal of finding a suitable product. Perceived enjoyment is an affective measure of the consumer's perception whether the interaction with the system is interesting and fun or not [23–25].

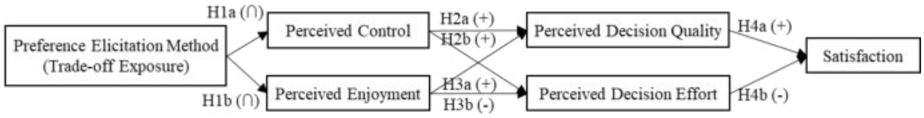

Figure 1. Research Model

Users' final reaction to using the RA is their satisfaction with the recommendation. Prior research has shown that this ultimate response is preceded by perceived decision quality and perceived decision effort [4; 26] – known as the effort-accuracy-framework [27]. Its central idea is that consumers make some compromise between a most accurate decision and the desire to minimize cognitive effort involved. Overall, this research model is based on prior theoretical justification to investigate the role of trade-off exposure as it incorporates both cognitive and affective reactions as well as a rationale for understanding trade-off exposure's effect on consumer satisfaction.

Since preference elicitation methods with low trade-off exposure do not point out attribute conflicts [15], consumers experience discrepancy between current and intended state, leading to lower perceived control [28; 29]. Similarly, the lack of transparency about attribute conflicts may give rise to unrealistic expectations about the decision space, leading to equally unrealistic inputs and in consequence to empty or very small result sets – and in turn, to lower perceived control about the recommendation process.

Trade-offs generally decrease perceived control because they require that "losses" in product attributes, i.e. divergence between current and intended state, are accepted [7; 10]. High trade-off exposure forces the consumer to accept a loss in at least one attribute [16–18] since the consumer cannot continue the recommendation process before a specific attribute conflict is solved. In this case, too, the consumer experiences a discrepancy between current and intended state, resulting in lower perceived control.

A medium level of trade-off exposure makes explicit trade-offs not compulsory but possible. Further, the consumer is informed about changes in attribute level availability after explicitly making a trade-off decision. By giving consumers the choice to only select preferred levels for the attributes of their choice, consumers can apply mitigation strategies. In other words, they can avoid making trade-off decisions between attributes they have little knowledge about and focus on familiar attributes instead. Losses in unfamiliar attributes may be felt less acutely, and the consumer may form more realistic expectations of the decision space. In summary, we expect that:

H1a: Perceived control will follow an inverted U-shape as the level of trade-off exposure increases.

In the context of RAs, the pleasure of using an attractive technology-based tool, as well as the prospect of finding the ideal product, cause enjoyment [30; 31]. An important driver of consumer's perceived enjoyment is the flow state [24]. This concept, central to flow theory, defines a state in which a person is completely focused on an activity, being rewarded just by doing the activity itself, independent of its end result or extrinsic motivation [32].

With respect to enjoyment, low trade-off exposure may leave consumers in a state of underutilizing their knowledge or decision skills. However, "challenges at a level appropriate to one's capacities" are a main antecedent of experiencing a state of flow [32], which drives perceived enjoyment. In contrast to low trade-off exposure, high trade-off exposure may overmatch consumer's cognitive capacity or knowledge, which also prevents flow [32]. RAs with medium trade-off exposure allow consumers to be more active and involved in the process. In addition, consumers can act with a higher degree of self-determination [33] in selecting attributes and proceed in accordance with their capacities. This creates a challenge that matches consumers' existing skills and thereby drives flow [32].

H1b: Perceived enjoyment will follow an inverted U-shape as the level of trade-off exposure increases.

When people perceive high control, they believe that their actions have a higher likelihood of achieving their intended state [28; 29]. In the context of RAs, this translates to the belief that suitable products will be found and suggested by the RA [28]. Consumers who perceive higher control in using the system may expect a higher likelihood of getting a suitable recommendation, hence a higher level of decision quality [34]. When consumers are in full control of the RA, they are able to express the intended state more precisely. They will expect the RA to provide a correspondingly high-quality recommendation [35]. Following these arguments, we propose:

H2a: Higher perceived control leads to increased perceived decision quality.

Higher effort may translate into longer processing times, the need for additional information, or a higher level of energy input (physically and mentally) [36]. At low levels of control, consumers need to find workarounds to bridge the gap between current and intended state, which leads to additional effort [37]. If an RA provides, for instance, insufficient filtering options and consumers are forced to manually search and compare alternatives, they must expend additional effort in terms of both time and cognitive resources. Similarly, the number of iterations required to obtain a satisfactory recommendation affects perceived effort. The more iterations are needed, the more likely it is that consumers must come up with a workaround to produce a state that is different from last iteration and closer to the intended state. This increases cognitive demand since the consumers have to think simultaneously about their actual preferences for the decision task and how to avoid ending up in the same (unsatisfactory) result state as before. Taken together, we suggest that:

H2b: Higher perceived control leads to higher perceived decision effort.

Perceived enjoyment positively affects consumer's future usage intentions [24] as well as their loyalty intentions [38]. In the context of information systems, higher levels of perceived enjoyment are associated with improvements in attitudes and satisfaction with system interfaces [21; 39; 40]. Users who experience higher levels of perceived enjoyment have been found to be more actively involved with the information they process [40]. In terms of a decision task a more active, careful selection of attributes increases the likelihood of ending up with a higher quality product alternative, i.e. higher perceived decision quality. In contrast, not enjoying the decision task leads to being less focused and less careful about the attribute selection and may in turn reduce decision quality perception. Therefore, we expect that:

H3a: Higher perceived enjoyment leads to increased perceived decision quality.

Effort and enjoyment are closely related [41]. For instance, developing software is an effortful task, and software developers are compensated for this effort with wages. However, an astonishingly high number of open source developers are willing to waive such compensation and contribute for free to the open source community [41], motivated by the fun element (i.e. enjoyment) of the task [41]. We expect this effect is observable in decision makers, i.e. they will perceive less effort during a decision, if they enjoy the process. Such perception is related to a flow state where users feel active and creative in contrast to a task experienced as tedious or laborious [42]. Higher perceived enjoyment can also lead consumers to underestimate the difficulty of a task [43]. Consequently, we suggest that:

H3b: Higher perceived enjoyment leads to lower perceived decision effort.

The effort-accuracy framework suggests two main determinants for a positive perception of decision outcome: to increase decision quality and to decrease decision effort [44–46]. This effort-accuracy framework has been widely applied in the research on RAs, for instance to shed light on consumers' intention to reuse RAs [5; 7]. We draw on the same rationale, using satisfaction as a measurement for perception of the decision outcome. Satisfaction has been found to have cognitive [47–49] and affective [50] antecedents [51], which are reflected in perceived decision quality (cognitively) and perceived decision effort (affectively). Harnessing the effort-accuracy framework, we suggest:

H4a: Perceived decision quality positively influences satisfaction.

H4b: Perceived decision effort negatively influences satisfaction.

4 Research Methodology

We conducted a between-subject laboratory experiment to test our research model. The between-subject design was chosen to avoid learning effects and cognitive exhaustion. Participants were randomly assigned to one of three treatments, which were operationalized by different preference elicitation methods with varying levels of trade-off exposure (i.e., low, medium and high). Participants received instructions to use an RA to find the most suitable digital camera they would buy for personal use. We used digital cameras since they are sufficiently complex so that consumers may wish to use an RA [52]. The cameras were composed of 6 attributes with 7 levels each. The product database was identical across treatments. After reading the instructions, participants' attribute preferences were elicited by having them rate and rank 7 random cameras. Subsequently, participants were provided with the respective RA and asked to make a camera purchase decision.

The preference elicitation methods implemented by the RAs were taken from literature, each corresponding in its characteristics to the specifications outlined in section 2 for the respective level of trade-off exposure. Figure 2 illustrates all three preference elicitation methods. In the low trade-off exposure condition, participants were described a situation in which they are stuck between alternatives and asked to assign 100 points to the most important attribute [53]. Participants were then asked to continue with the second most important attribute and assign a lower number of points than to the previous one. This process continued until all attributes had been assigned points.

Trade-off exposure is low because no explicit trade-off between two attributes is supported, and no feedback is given on how the order or the points assigned affect the decision space.

In the high trade-off exposure condition, participants were asked to compare two product alternatives that differed in only two attributes. They were then told to adjust the level of one attribute until both alternatives are equally preferred. This principle is used widely and in many variations [6; 54]. Figure 2 presents the different preference elicitation methods and illustrates high trade-off exposure on the example of zoom and Megapixels (MP).

In the medium trade-off exposure condition, participants were presented with a configuration interface [9] and asked to change attribute levels according to their preferences. The RA determined the price interval for each new configuration and disabled unavailable levels for other attributes. This approach allows for mitigation strategies but enables the participant to perform explicit trade-offs, if required, corresponding to the requirements for a medium level of trade-off exposure.

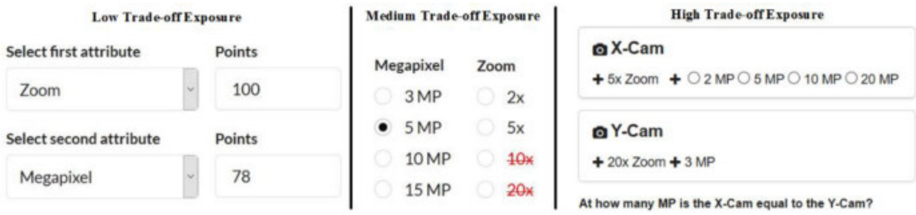

Figure 2. Treatment interfaces

In the questionnaire following the treatment, we collected six variables regarding RA perceptions measured on a 7-point Likert scale. We elicited perceived enjoyment [41; 55], perceived control [55], perceived decision effort [55], perceived decision quality [5; 7; 19] and satisfaction [51]. In addition, participants gave their age, gender and prior experience with RAs and a manipulation check was conducted.

116 students from the University of Passau took part in the laboratory experiment and were assigned randomly to the three treatments (40 participants to low trade-off exposure, 34 to medium trade-off exposure and 42 to high trade-off exposure).

Each participant received a payoff of 10 euros. 36% of the participants were female. Participants' age ranged from 18 to 46 ($\mu = 23$, $\sigma = 5.00$). Familiarity with RAs was average ($\mu = 3.20$, $\sigma = 0.95$). None of the control variables had a significant effect on satisfaction (linear regression results: $p_{age} > 0.1$, $p_{gender} > 0.1$, $p_{experience} > 0.1$).

5 Analysis and Results

We use a two-step analysis approach as previously applied in related studies [5; 7]. First, we examine the influence of trade-off exposure on perceived control and perceived enjoyment (H1a and H1b; Kruskal-Wallis-test and Mann-Whitney-U-tests). Second, we examine the effects of perceived control on effort and quality and how the latter affect satisfaction. (H2-H4; PLS path modelling). We chose Mann-Whitney-U-tests because Kolmogoroff-Smirnoff tests indicated that our data was not normally distributed ($p_{control} < 0.001$, $p_{enjoyment} < 0.001$) [56].

We first compared perceived control across the three levels of trade-off exposure using a Kruskal-Wallis test, indicating that values of different groups have significantly different distributions ($X^2 = 33.35, p < 0.001$). For perceived enjoyment, we found significant group differences as well ($X^2 = 11.08, p < 0.01$). To shed light on how the values are different across groups, we used pairwise, one-sided Mann-Whitney-U tests between low and medium trade-off exposure and between medium and high trade-off exposure, respectively. Perceived control had its highest mean of 4.87 for medium trade-off exposure: it was significantly higher than in a low trade-off exposure condition ($4.87 > 4.00, p < 0.001$) as well as in high trade-off exposure ($4.87 > 3.52, p < 0.001$), supporting H1a. For perceived enjoyment, the mean in the medium trade-off exposure group was also significantly higher than in low ($4.32 > 3.76,\ p < 0.01$) and high ($4.32 > 3.59,\ p < 0.01$) trade-off exposure groups. This supports the inverted-u shaped relationship proposed in H1b, which is also illustrated in Figure 3.

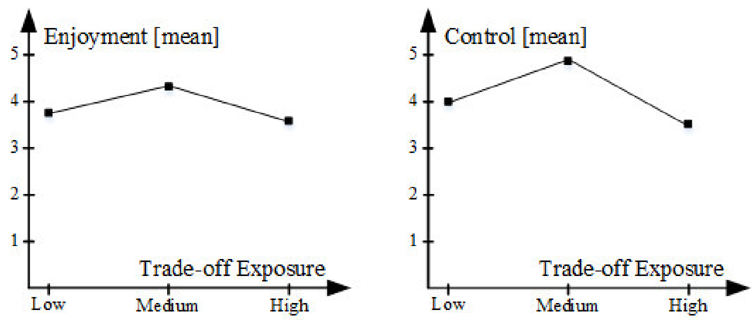

Figure 3. Visualization of U-shaped relationships

Turning to H2-H4, we used a PLS path model to investigate the relationships leading to consumers' satisfaction perception. We analyzed the PLS path model following the two-step process of outer and inner model assessment [57]. This approach is used to ensure reliable results as the analysis of the inner models' paths relies on the reliability and validity of the outer models' constructs [58]. Following Ringle et al. [59]'s call for thorough PLS reporting, we would like to clarify that the analyses were carried out with R 3.1.3, using the plspm library with standard settings.

First, we checked for individual item reliability. Each item should show a substantial correlation with its construct. For reflective items, as solely present in our model, this can be assessed by item loading, i.e. its variance explained by the construct. Loadings should not be lower than 0.7 [60], which is fulfilled in our model. Second, internal consistency was assessed based on item intercorrelations, measured by Cronbach's alpha [61] and composite reliability [62]. Values exceed the recommended threshold of 0.7 for all constructs [63]. Taken together, these results indicate that the measurement model is reliable.

We then assessed convergent validity, i.e. whether all items in a construct's block unidimensionally represent their construct [58]. As recommended by Fornell and Larcker [63] we calculated the average variance extracted (AVE) for every latent

variable. Table 1 shows that AVE is greater than the recommended threshold of 0.5 for every construct [64].
Finally, discriminant validity was examined to confirm that different latent variables actually exhibit significant difference [58]. We checked the Fornell-Larcker criterion [63], stating that the AVE of each latent variable should be greater than its squared correlation with any other variable (which is equal to the AVE's square root being greater than the variables' correlations, which we used for simpler reporting). This is the case, as the values in Table 1 confirm. We also checked the Heterotrait-Monotrait Matrix (HTMT). This criterion has shown superior performance in detecting discriminant validity in a Monte Carlo simulation study compared to cross-loadings analysis and the Fornell-Larcker criterion [65]. The computed HTMT values for our model can be found in Table 1. All values are below 0.85, which satisfies $H_{0.85}$, the HTMT criterion with highest specificity [65]. We conclude that overall measurement model validity has been established.

Table 1. Structural model discriminant validity measures

	Enjoyment	Control	Quality	Effort	Satisfaction
Enjoyment	0.893	0.440	0.373	0.433	0.569
Control	0.397	0.949	0.392	0.421	0.727
Quality	0.346	0.354	0.921	0.320	0.751
Effort	-0.399	-0.383	-0.290	0.876	0.570
Satisfaction	0.509	0.631	0.690	-0.518	0.844
Latent variable correlations		$\sqrt{\text{AVE}}$		HTMT matrix	

Analyzing the structural model next, we focus on perceived control first: We found a significant positive influence on perceived decision quality (β = 0.257; $p < 0.01$), supporting H2a. Moreover, there was a positive influence of perceived control on perceived decision effort (β = 0.267; $p < 0.01$) supporting H2b. Higher levels of perceived enjoyment were found to lead to an increase in perceived decision quality (β = 0.245; $p < 0.01$), while perceived decision effort was reduced (β = -0.293; $p < 0.01$). Hence, hypotheses H3a and H3b are supported. Turning to the effort-accuracy framework, perceived decision quality had a significant positive effect on satisfaction (β = 0.590; $p < 0.001$), supporting H4a. Finally, higher perceived decision effort had a significant negative effect on satisfaction (β = -0.347; $p < 0.001$), which supports H4b.

6 Discussion

Prior research has often made only a dichotomous distinction regarding the level of trade-off exposure, comparing high and low levels while neglecting a medium option. While Xu et al. [5] have showed the possibility for such a medium level, their study did focus on a single preference elicitation method. Our study makes a contribution to the understanding of the relevance of medium trade-off exposure as we investigated how preference elicitation methods with different levels of trade-off exposure affect consumers' satisfaction with an RA. The results support our supposition that medium-level trade-off exposure generates the highest levels of perceived control and perceived enjoyment, compared to low or high trade-off exposure, and that perceived control and perceived enjoyment follow an inverted U-shaped curve as the level of trade-off exposure increases. These findings conform the results of Xu et al. [5], however, in a different research setting and across different preference elicitation methods. Note, however, that preference elicitation methods with low and high trade-off exposure also achieved good levels of perceived enjoyment and control.

The results of our study are consistent with prior research on consumers' perceptions towards RAs, showing that stimuli like trade-off exposure affect cognitive and affective reactions, and those in turn affect the response of the customer. Specifically, our findings show that perceived decision quality was positively influenced by perceived control and perceived enjoyment, while perceived decision effort was affected negatively. In line with the effort-accuracy model, perceived decision quality had a positive effect and perceived decision effort a negative effect on consumer satisfaction. Overall, our results show that a preference elicitation method with a medium level of trade-off exposure creates highest consumer satisfaction with a RA.

6.1 Implications for theory and practice

On a theoretical level, our study contributes to a better understanding of the role of trade-offs in RAs. Specifically, this is the first study to investigate the effect of different levels of trade-off exposure as realized by different preference elicitation methods. The few studies that simultaneously investigated different levels of trade-off exposure mostly focused on high and low levels, neglecting a medium level option. Thus until now, researchers used a linear model for their studies and did not investigate a non-linear coherence of trade-off exposure and the acceptance of it. This study contributes to this knowledge gap by differentiating between high, medium and low trade-off exposure and points out that a medium level has the highest effect on affective and cognitive perceptions.

Our study also contributes to the understanding of the processes that affect satisfaction with an RA. Our research model combines perceived enjoyment and perceived control which each have been part of separate models on consumers' RA perception [5; 7]. Also, in contrast to these models, we have used satisfaction as a more proximate response variable as it is known to be the main determinant of reuse intention [66]. Our model helps to understand consumers' cognitive and affective processes during RA usage and can be used to investigate consumer responses to other RA cues.

Our study also provides practical implications for RA developers. Our results suggest that it is better to avoid using only implicit trade-offs but that forced trade-offs may overburden consumers. Rather, RA developers ought to devise ways of implementing medium trade-off exposure, for instance by using configuration-based preference elicitation methods [5; 9]. The increased influence of consumer actions on the elicitation process in combination with the interactive feedback design can help to leverage the positive effects of a medium level of trade-off exposure.

6.2 Limitations, Future Research

This research is subject to several limitations, to be addressed in future research. First, our experiment was conducted in a laboratory setting. Replicating the study in a field setting would help to establish external validity of our findings. Second, other consumer groups, e.g. older or less technology-savvy consumers, may show different reactions than the student sample used in this study. Further studies with other demographical groups and with other products are required for establishing generalizability of our results. Third, we have focused on trade-off exposure; however, there are multiple other aspects to differing preference elicitation methods. Further studies may try to isolate trade-off exposure or widen the aspects under investigation to provide a more fine-grained understanding of preference elicitation and trade-off exposure.

6.3 Conclusion

This study contributes to the understanding of trade-off exposure in RAs. We compare low, medium and high levels of trade-off exposure operationalized in three distinct preference elicitation methods. The results show that both perceived enjoyment and control follow an inverted u-shape when trade-off exposure increases. While low and high levels also yield good performances, a medium level of trade-off exposure leads to significantly highest results. We further presented a research model that shows how trade-off exposure influences consumers' satisfaction with a RA. While perceived enjoyment and perceived control are directly affected by trade-off exposure, they in turn affect perceived decision effort and perceived decision quality as central determinants of overall satisfaction.

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