FULL PAPER

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Information Overload and Usage of Recommendations

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ABSTRACT
This research examines the antecedents of information overload and recommendation agents' consultation and their effects on reactance and choice quality. We propose that information overload and the user need for cognition affect the tendency to employ decision heuristic (consulting a recommendation agent) and shape the user reactance to recommendations. A fully randomized experiment with different levels of information loads that involved 466 individuals with the task of choosing a laptop and the option to consult a recommendation agent is performed. Results show that users opted to consult the recommendation agent more as information loads and as perceived overload increases and that product recommendations were salient in enhancing choice, particularly when the information was less diagnostic (for choice sets with proportional distribution of attribute levels across alternatives). Results further reveal that as perceived overload increases, people show less reactance to recommendations. Whereas users consulting the recommendations at higher overload levels had generally better choices, they showed higher confidence in their choices only when they conform rather than react to recommendations.

Categories and Subject Descriptors
I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents, Agents and Web-services.

General Terms
Management, Measurement, Human Factors, Performance, Design, Theory.

Keywords
Recommendation Agents, Information Overload Theory, Reactance Theory.

1. INTRODUCTION
When making purchase decisions, users typically process large amounts of information. As people shop online to save time and effort, retailers are required to effectively manage product information delivered on their e-stores. The many choice possibilities associated with large choice sets represents an opportunity and challenge for consumers and retailers [7, 9]. To help customers reduce the cognitive effort while enhancing their decision, retailers incorporate on their e-stores agents that filter, optimize, and organize product information. Product recommendations are decision-aid tools that support rather than replace consumer decision-making by suggesting one or more product that closely matches consumer preferences [26]. In effect, decision support systems are heuristics that partly alleviate processing effort while maintaining an acceptable level of choice accuracy [10]. Xiao and Benbasat [28 p. 137] recently provide an extensive review of the RA literature, and conclude that "by providing product recommendations based on consumers' preferences, RAs have the potential to support and improve the quality of the decisions consumers make when searching for and selecting products online as well as to reduce the information overload facing consumers and the complexity of online searches." This explains why 40% of retailers plan to integrate some personalized recommendations on their e-stores [6].

While research studied various designs of recommendation agents, it has not investigated the factors triggering consumers to consult the recommendations nor the cases where product recommendations are vital to choice enhancement [10, 27, 28]. Indeed, research is yet to assess the factors that lessen the user reactance to recommendations [7]. Lurie [18 p. 484] indicates that "… in the age of the Internet, developing an understanding of how information-rich environments affect consumer decision making is of crucial importance. Given the disparate ways in which product information can be presented to consumers and the high potential for information overload in online environments, it is important to use measures that capture the multiple dimensions of information."

The contribution of this article is four-fold. First, the article examines the relation between the delivered information load in the choice set and perceived overload by simultaneously manipulating the number of alternatives, number of attributes, and the distribution of attribute levels across the alternatives. Second, it assesses the role of information overload on employing decision heuristics (the tendency to consult the recommendation agent) while considering the role of need for cognition. Third, it investigates how information overload and need for cognition shape users' reactance to recommendations. Fourth, it examines the impact on choice quality and confidence. We next briefly review the literature and present the study conceptual framework. The methodology section reports the details of the pretest and the experiment. Results are then presented. The paper concludes with a summary of findings and implications on theory and practice.

2. CONCEPTUAL FRAMEWORK
Research showed the effects of information overload on the choice and purchase of different products: Laundry detergent [13], rice and prepared dinner [14], peanut butter [25], houses [19], calculators [18], and CD players [17]. Research indicates that variations in the amount of information impact the decision processes, which affects decision quality. Information overload

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happens because of humans' limits in assimilating and processing information within any timeframe [13, 19]. When consumers are faced with high levels of information, their limited capacity to process information becomes overloaded, which results in dysfunctional consequences such as cognitive fatigue and confusion [8, 16, 20, 21, 25].

Several measures were used to capture the amount of product information. Researchers have traditionally manipulated the alternative and attribute levels in product choice sets [13, 19]. While this line of research has made substantial contribution, discrepancies were noted [12, 19, 20, 21]. More recently, the concept of information structure was introduced and shown to have a role in determining overload; this concept asserts that when measuring information loads, both the number and probability of outcomes should be considered (for a discussion, see [18]). When the distribution of attribute levels for instance is proportional across the alternatives (e.g., half the laptops in a given choice set are equipped with Intel and half with AMD processors), information load will be higher than for a disproportional distribution (e.g., 3/4 with Intel and 1/4 with AMD processors). This is because a disproportional distribution increases information diagnosticity [18]. Information load in a choice set can hence be affected by the number of alternatives, number of attributes, as well as the distribution of attribute levels across the alternatives (attribute distribution hereafter) [17, 18]. One purpose of this research is to manipulate these three dimensions over a range that is wider than prior work and to assess the impact on perceived overload and choice. After information-processing capacity is surpassed, information increments were found to lead to modest or insignificant reductions in decision quality [8, 18]. As research stipulates a complex rather than a linear relation between information load and perceived overload [8, 14], we expect a nonlinear relation to better describe the relation between these two factors (P1).

It is plausible to assume that under high overload levels, consumers do use heuristics to maintain the cognitive effort at acceptable levels. Indeed, consumers adapt decision strategy according to product information, task, and environment [5, 23]. In complex choice situations, consumers for instance become more selective in acquiring and processing information [23]. Because consulting product recommendations can be seen as information-processing heuristic [10, 27, 28], we theorize that the utility of consulting product recommendations increases with information overload. Under high overload levels, consumers behave as satisficers (vs. optimizers) and thus use more an information-processing reduction strategy [19]. Therefore, we expect that (P2) consumers will tend to consult the recommendations more as (a) information load increases and as (b) perceived overload increases. Figure 1 depicts the study conceptual framework.

Consumers have divergent needs for information. Need for cognition (the consumer tendency to engage in effortful thinking) was cited as an important factor of attitudinal and behavioral change [4]. Consumers low on the need for cognition tend to avoid activities requiring high cognitive effort and to engage in heuristic strategies [11]. We thus expect need for cognition to attenuate the tendency to consult the recommendations such that as information overload increases, the lower the need for cognition is, the more the consumer will consult product recommendations (P3).

Consumers do react to product recommendations because they limit their choice freedom [7]. Under high overload levels, consumers behave as satisficers as opposed to optimizers [19]. Because consumers are adaptive decision makers [3], we propose that the higher the information overload becomes, the more the consumer will conform to recommendations (P4). This proposition finds support in the self-regulation research; information overload can be seen as a resource depletion mechanism that "enhances the role of intuitive reasoning by impairing deliberate, careful processing" of information [24, p. 344]. Need for cognition is also expected to shape reactance so that under higher levels of overload, the lower the need for cognition is, the less the consumer will react to product recommendations (P5).

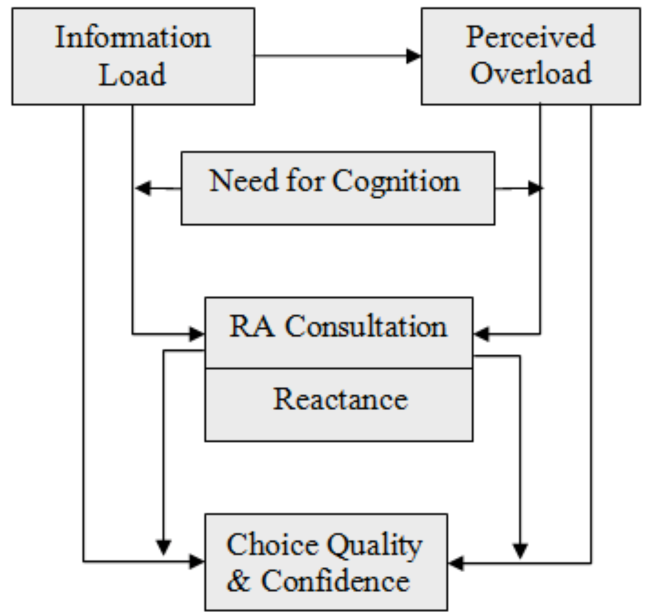

Figure 1. Research Framework.

We finally study the impact of information overload and product recommendations on choice quality and confidence. Theory posits a salient role for recommendations on choice quality in complex choice situations [27]. In effect, choice quality suffers when the processing effort exceeds processing limits [23]. As product recommendations help consumers improve choice by concentrating on the alternatives that best match their preferences [10], product recommendations should uphold choice quality as information overload increases (P6) [3, 10, 15, 19, 28]. Because the negative role of information overload on choice is prominent in the case of a proportional versus disproportional attribute distribution [18], we theorize that the impact of product recommendations on choice quality will be particularly salient for choice sets with proportional attribute distribution (P7). According to Fitzsimon and Lehmann [7], recommendations reduce uncertainty for consumers who do not react to recommendations. We hence expect that consumers who consult and conform to product recommendations will have higher choice confidence than consumers who consult but react to recommendations (P8).

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3. METHODOLOGY

3.1 The Experimental Site and the Recommender System

An e-store was created for "Portable Direct" using professional Web design service; a fictitious retailer name was used to control for retailer preferences [1]. The computer laptop was chosen as product category because (a) it is a complex product thus consumers are expected to be attentive during choice, (b) it has many known attributes, which allows a meaningful manipulation at high number of attributes, (c) it is a search product (attributes can be communicated using the Web), and (d) it is a product that consumers shop for online, which improve the ecological validity. Though pretested (see the Appendix), manipulation levels were adapted from the literature. Three levels of alternatives (6, 18, and 30) were chosen because research investigating this factor along with attribute distribution considers only two alternative levels (18 and 27 in [17, 18]) and because little research manipulated for choice sets with low alternative level [19]. Three levels of attributes (15, 25, and 35) were chosen because research investigating this factor along with attribute distribution considers only two attribute levels (9 and 18 in [17]). Whereas few studies manipulated for 20 attributes or more [8, 19], including higher number of attributes is necessary as consumers consider many attributes when shopping for complex products. Akin to prior work [17, 18], the distribution of attribute levels across the alternatives had two levels (proportional vs. disproportional distribution); the attributes provided in a choice set were manipulated according to one of these levels.

The participant rates the importance (weight; 1-7) of each of the 35 attributes (this step is performed before the participant is randomly assigned to one of the eighteen experimental conditions). Then, the score of each potential choice (each laptop in the choice set provided under a particular condition) can be determined by the following formula (Weighted Additive Rule; Payne, Bettman, and Johnson 1993):

$$S_{jk} = \sum V_{ij} P_{ik}$$

Where: S = Global score of alternative j for consumer k.

i = Attribute;

j = Alternative (laptop);

k = Consumer;

P = Weight of attribute i for consumer k;

V = A priori value of attribute i applied by system and associated with alternative j.

That is, the WADD determines the score of a given alternative j (for consumer k) by multiplying the weight of each attribute (provided by consumer k) by its a priori value, and then adding the obtained values of all attributes. The alternative with the highest score (i.e. the one that optimizes consumer k's utility function) is then suggested by the recommendation agent (should consumer k choose to consult the agent by clicking the link provided).

3.2 Pretest and Measure

Each participant had to choose a laptop with the option to consult the recommendations (between-subject design). Recommendations consultation and if consulted whether the recommended product was chosen are observed variables. Perceived overload was measured using two seven-point items (There was too much information to make a choice; I wanted to receive more information about the different products before making my choice). Similar to [13, 19], choice confidence was measured using three items (I am confident that I made the best possible choice based on my needs; I am satisfied with the choice I made; I am certain that I made a good choice; α=0.93). Need for cognition was measured using the 18-item scale ([4], α=0.82). As decision makers draw on their experience and knowledge of product category, product experience (three-item from [22], α=0.95) and product category involvement (four items adapted from [2], α=0.92) were measured and controlled for. See the Appendix for details of the pretest and manipulation checks.

3.3 Stimuli

Participants were informed that their task consisted of choosing a laptop as they would in an actual purchasing situation. The task page described "Portable Direct" as a well-established online retailer of product category and asked the participants to navigate its e-store (made available through a link provided after the participants entered personal attribute preferences) to choose the "The laptop you would seriously consider buying". Participants were told to take as much time as needed and to freely consult the information available on the website. A time constraint was not imposed because this would be inconsistent with real-life situations and because this would result in eliminating a portion of participants based on some cut-off value. In effect, time pressure was shown to influence information overload [8]. Before a participant was randomly assigned to one of the eighteen conditions, a second page asked the participant to rate the importance of each attribute (to estimate the participant utility function so that the recommendation agent could suggest the optimal choice; Weighted Additive Rule WADD as in [23]). Depending on the assigned condition, the e-store provided the participant with a finite choice set (e.g., six alternatives each with fifteen attributes for conditions one and two in the Appendix). Similar to factual e-stores, each alternative appeared in a tabular format with the attributes headed by the laptop photograph. The alternatives that made the choice set were presented on the same page. To avoid presentation bias, the order of alternatives was randomized for each participant in a given condition. Brand was concealed to reduce the possibility of following a brand heuristic and to entice participants to make choice using the information provided. This is akin to prior work [17]. Participants had the option to consult the recommendations by clicking on a hyper link labeled "Click here for our recommendation according to your preferences" located at top of the choice set provided. After making their choice, participants were presented with the measure items.

3.4 Sample

An invitation to participate in a "Study on e-commerce" was sent to consumers randomly chosen from a large consumer panel belonging to a North American market research company. Of the 472 responses received, 466 were complete and retained. Sample demographics distribution (see the Appendix) shows that the

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sample was well distributed across consumer population with no important bias toward a particular segment.

4. RESULTS

A comprehensive analysis of the data with a path model was not performed because it was not feasible (i.e., central variables in the model such as RA consultation and reactance to recommendation were binary; in addition, an important exogenous variable-information load-is ordinal and reflected by one item). As such, ANOVA and regression analysis were used in testing the propositions (except for P2 through P5 where logistical regression were used because the dependent variable was binary).

The main effect for information load (called interchangeably information bits; [17, 18], see the Appendix section) on perceived overload was significant (F=23.88, p<0.001); this result stays reliable when controlling for product involvement and experience (only product experience was significant covariate; B= -0.085, F=5.34, p=0.021). A curvilinear quadratic curve solution explained more variance (R^2=0.264) in the relationship between information load and perceived overload than a linear (R^2=0.224) or a logarithmic (R^2=0.248) solution (Figure 2).

Binary logistical regression was performed to test the impact of information load on recommendations consultation as well as the attenuating role of need for cognition. Information loads increment led to more recommendation consultation by means of main effect (B=0.164, Wald=6.00, p<0.05). In addition, the interaction between information loads and need for cognition was significant in the predicted direction (B=-0.031, Wald=5.587, p<0.05). Similarly, logistical regression was performed to test the impact of perceived overload on recommendations consultation and the attenuating role of need for cognition. Perceived overload did lead to more consultation of recommendations (B=0.344, Wald=4.06, p=0.044) and the interaction between perceived overload and need for cognition was significant in the predicted direction (B=-0.077, Wald=5.71, p=0.017). The direct effects of the alternative, attribute, and attribute distribution levels and their interactions on recommendations consultation were examined and showed insignificance (all p's>0.10 NS).

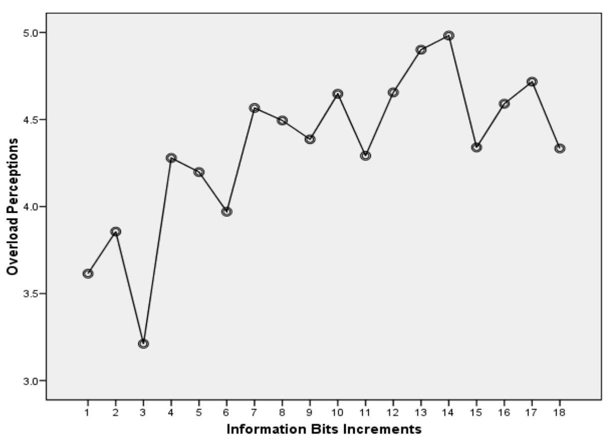

Figure 2. Information load effect on perceived overload.

To test the impact of perceived overload and need for cognition on reactance, we applied binary logistical regression on the observations that consulted the recommendations (n=178). As expected, perceived overload was significant factor in predicting the conformation (vs. reactance) to recommendations (B=0.91, Wald=8.10, p=0.004). In addition, the interaction between perceived overload and need for cognition was significant (B= -0.131, Wald=4.52, p=0.034), which shows that as perceived overload increases, the lower the consumer was on need for cognition, the less reactance to recommendations the consumer would exhibit. Alternatively, neither information load nor its interaction with need for cognition were significant in predicting reactance (all p's>.34 NS). We further tested the direct impact of the levels of alternatives, attributes, and attribute distribution on reactance and found no significant effects (all p's>.31). These results collectively show that perceived overload, rather than information loads, was the determinant factor in predicting reactance to recommendations.

Choice quality was measured by the distance between the participant actual and optimal choice (Weighted Additive Rule WADD; [23]). This is akin to past work [13, 16, 19]. The expected interaction between information load and recommendations consultation was significant (F=1.68, p=0.012; Figure 3 Up). Similarly, we found support to the proposition that recommendations consultation upholds choice quality as perceived overload increases because the interaction between perceived overload and recommendations consultation was significant (F=1.61, p=0.036; Figure 3 down).

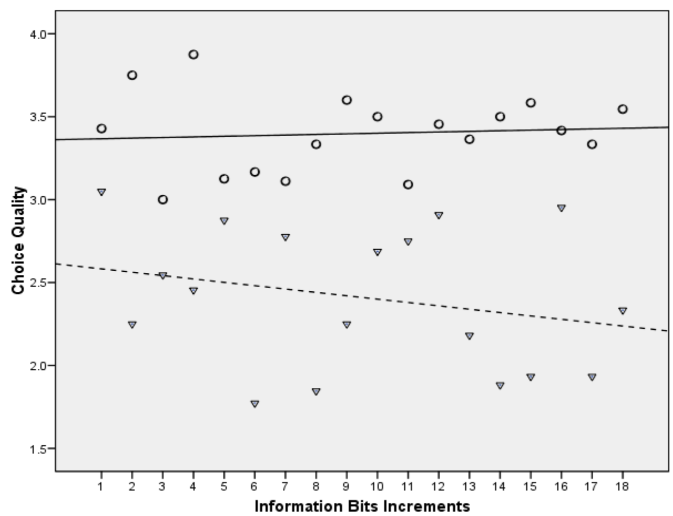

Figure 3a. Recommendations effect on choice quality (upper line: RA consulted).

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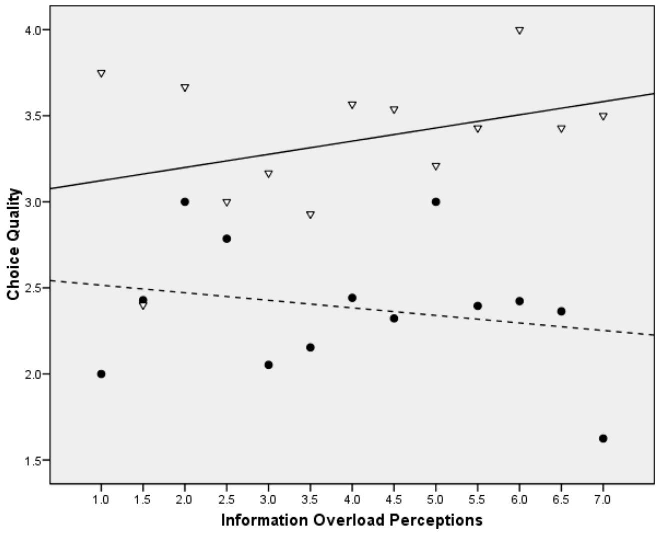

Figure 3b. Recommendations effect on choice quality (upper line: RA consulted).

We then tested the proposition that product recommendations effect on choice quality is salient for choice sets with proportional attribute distribution (P7). We found support to this proposition by means of a three way interaction (Number of Attributes x attribute distribution x recommendations consultation; F=2.47, $p<0.05$; Figure 4). This interaction shows the recommendations to enhance choice quality for choice sets with proportional distribution of attribute levels across the alternatives at all attribute levels (Appendix for means). The interaction also highlights that recommendations consultation improved choice for all choice sets only when the number of attributes became high. We finally tested and found support to the proposition that consumers consulting and conforming to recommendations will have higher choice confidence than consumers consulting and reacting to recommendations (5.13 vs. 4.41, F=8.55, p=.004).

5. DISCUSSION

The experimental results lend support to research propositions. Results suggest a curvilinear relation between information load and perceived overload, which indicates that the impact of additional increments in product information after some levels (condition 7 shown in the Appendix) are not as influential in driving overload perceptions. The consumer use of decision heuristics at high levels of information overload helps explaining this finding. Findings lend support to the notion that the utility of consulting product recommendations increases as the information load and as perceived overload increases. Consumers did use an information-processing heuristic by consulting product recommendations more as information overload increases. Moreover, this tendency was higher for consumers low on the need for cognition. Importantly, consumers appear to conform (vs. react) to recommendations more at high levels of perceived overload. Further, the lower the need for cognition was, the less the consumer reacted to recommendations at higher levels of information overload.

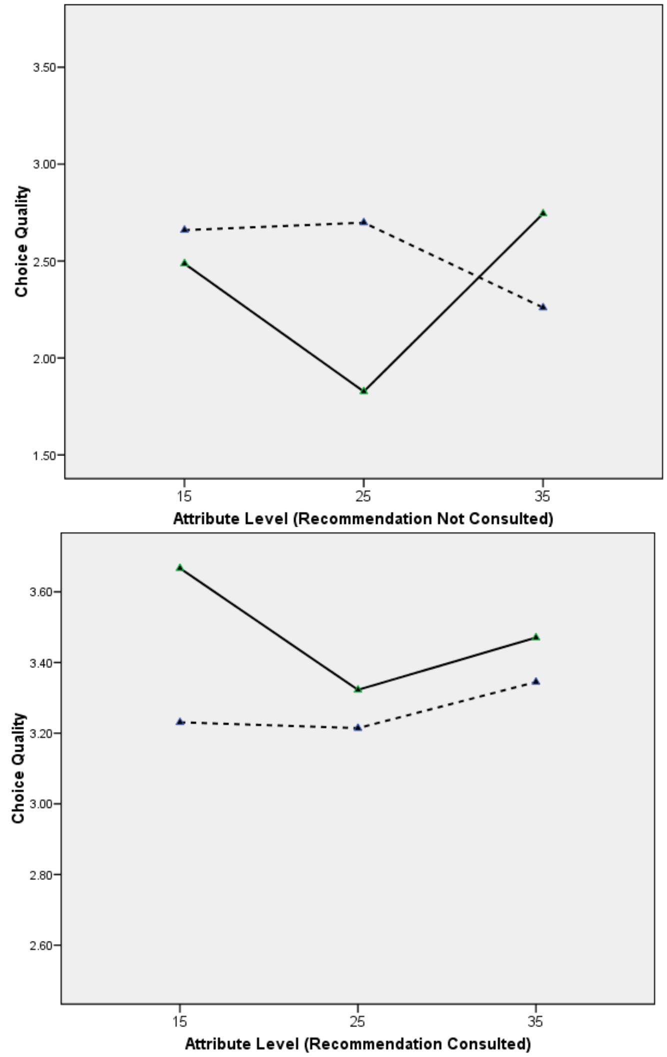

Figure 4. Recommendations effect on choice quality for choice sets with proportional versus disproportional distribution of attribute levels across the alternatives.

— = Proportional attribute distribution.

- - - = Disproportional attribute distribution.

The findings show the positive effects of product recommendations on choice quality at high levels of information loads and overload perceptions. The positive impact of recommendations on choice quality was particularly salient for choice sets with proportional distribution of attribute levels across the alternatives. Finally, choice confidence improved for consumers who consulted and conformed (vs. reacted) to recommendations. In effect, the recommendations might have made the accuracy feedback as immediate and tangible as the effort feedback by signaling to consumers that a product in the choice set is more optimal than the initially considered one [5], which might have triggered consumers to have lower levels of confidence in their choice if they reacted to the recommendations.

This research contributes to theory by studying the relation between information loads and overload perceptions over a wide range for three factors deemed to determine the information load

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and by showing that consumers indeed do employ decision heuristics in response to information overload. People appear to regard the use of product recommendation agent as information-processing reduction heuristic. This research further established a link between information overload and reactance to recommendations and underlined the role of need for cognition. It contributes to the recommendation agents' literature by showing the impact of recommendations on choice at different information overload levels and by showing the salient effect of recommendations on choice quality for sets with proportional distribution of attribute levels across the alternatives.

Several practical implications emerge. Integrating a recommendation agent based on consumer preferences appears to be beneficial for consumers and retailers (by helping consumers make quality choices at high levels of information overload). Recommendations enhance choice, particularly as information load and perceived overload increases. In addition, recommendation agents appear to have particular influence on choice when product information is less diagnostic (attribute levels are proportionally distributed across the alternatives in the choice set). Finally, the outcome of recommendation agents can be optimized as consumers in general show less reactance to recommendations at higher levels of information overload.

This work has limitations. Although the study sample comprised actual consumers randomly selected from large consumer panel, the sample was self-selected. Nonetheless, the sample distribution across the consumer population was satisfactory. The research considered only one product category and did not examine whether similar effects are obtainable for less complex and for experience products. Further, this research did not investigate the effects of information overload and product recommendations on shopping enjoyment and long term performance measures such as consumer loyalty and retention. These topics are potential extensions to this line of research.

6. APPENDIX

6.1 Experimental conditions (Information Load*)

Information load Increment (condition)	*Attribute Levels Distribution*	*Number of Alternatives*	*Number of Attributes*	*Participants in condition (% of total)*
1	Disproportional	6	15	27(5.8)
2	Proportional	6	15	20(4.3)
3	Disproportional	18	15	25(5.4)
4	Proportional	18	15	19(4.1)
5	Disproportional	6	25	32(7.3)
6	Proportional	6	25	34(7.3)
7	Disproportional	18	25	27(5.8)
8	Proportional	18	25	22(4.7)
9	Disproportional	30	15	21(4.5)
10	Proportional	30	15	30(6.4)
11	Disproportional	6	35	31(6.7)
12	Proportional	6	35	22(4.7)
13	Disproportional	30	25	22(4.7)
14	Proportional	30	25	27(5.8)
15	Disproportional	18	35	27(5.8)
16	Proportional	18	35	33(7.1)
17	Disproportional	30	35	21(4.5)
18	Proportional	30	35	26(5.6)

* Information load increments are determined following Lee and Lee (2004) and Lurie (2004); also fulfilling the approximation: Information Load=No. of Alternatives + 2(No. of Attributes)

6.2 Pretest and Manipulation Checks

A pretest was performed to ensure task and measure comprehensibility [8], to check the manipulation of independent variables and to inspect the distribution of control variables. The pretest ensured that an increment from six (and eighteen) to thirty alternatives resulted in a noticeable change in information load. The pretest included three sections: The first contained the manipulation checks, the second examined product experience level and where the product category was relevant for the participant pool (e.g., manipulating the attributes level would be realistic and meaningful). The third section helped determining the 35 most important attributes (of 45 attributes identified using two retailing websites) to be included in experiment (each attribute was evaluated using a Very Important/Not Important at All seven-point item).

Six questionnaire versions were created for the pretest, all sharing the items of product experience and involvement, as well as attribute importance evaluation (the versions differed only in the first section). The first two versions were developed to check the manipulation of number of alternatives (6, 18, and 30). The two versions differed in the order the three levels were presented to each participant (i.e., while the order was 6-18-30 in the first version, the order was reversed in second version). This eliminated the possibility that a respondent rated level one as having fewer alternatives than levels two and three because it was displayed first. Similar steps were taken in versions three and four, which checked the manipulation for number of attributes. Versions five and six examined the manipulation for attribute distribution (proportional vs. disproportional). Version five (six) assessed the manipulation for a proportional (disproportional) distribution of attribute levels across the alternatives (both for the price attribute).

An invitation to participate in the pretest was emailed to 116 consumers (convenience sample). 77 useable responses were received. Because the measure (for both the alternatives level and attributes level) was within-subjects, ANOVA with repeated measures was used to analyze the input. For attribute distribution, a chi-square test was used. The 32 participants that evaluated alternatives level had to respond to a seven-point bipolar item (What do you think of the quantity of laptops offered: Not enough to make a choice/too much to make a choice) (item repeated for each of the three levels presented to the respondent).

The analysis showed that participants perceived significantly different information loads between each of the three levels ($M6=2.66$, $M18=4.81$, $M30=4.94$; $F6\text{-}18\ (1, 31)=69.65$, $F6\text{-}30(1, 31)=139.7$, $F18\text{-}30(1, 31)=27.59$, all p-values<0.001). Similarly, the 23 participants evaluating the attributes level had to respond to the seven-point bipolar item (What do you think of the quantity of attributes offered: Not enough to make a choice/too much to make a choice; item was repeated for each of the three levels presented to the participant). The analysis showed that participants reported significantly different information loads between each of the three levels ($M15=2.87$, $M25=4.30$, $M35=4.87$; $F15\text{-}25(1, 22)=77.85$, $F25\text{-}35(1, 22)=10.33$, $F15\text{-}35(1, 22)= 97.32$, all p-values<0.01). The 22 participants evaluating the success of attribute distribution manipulation responded to a binary item (Was the number of laptops priced at \$600 different or similar to the number of laptops priced at \$750 and \$900?). For (dis)proportional structure, the number was (not) equal. Participants in the (dis)proportional structure condition reported (un)equal distribution of the price attribute across alternatives ((1, 22) = 12.32, $p < 0.01$).

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The second section (shared for all participants) showed that the laptop computer is a product bought and used frequently by participants (87 percent of participants indicated using or to have used a laptop regularly; 75 percent of participants have already bought a laptop). This section also showed the internal consistency for product experience items (α=0.96) and product involvement items (α=0.87) and clarified the sample distribution according to these variables.

Attributes were assigned to experimental conditions using the pretest input. Attributes that have higher weights appeared more often in conditions with fewer attributes. This was done because the inclusion of an attribute in a choice set renders the attribute more important for the decision maker [9]. Consequently, including less important attributes in a choice set made up of few attributes would inflate the attribute's importance. In effect, choice sets containing only less relevant attributes for the alternative (choice sets that do not provide basic and important attributes such as price, processing speed, or memory size) are unrealistic and would reduce ecological validity.

6.3 Sample Demographics (n=466; 56.9% females)

Age: 11.6% ages 18-24, 26.4% 25-34, 20.0% 35-44, 19.7% 45-54, 9.9% 55-64, 12.4% 65+. Education level: 19.6% Primary/secondary education level, 70.8% Undergraduate degree, 9.7% Graduate degree. Income: 14.2% less than $15K, 18.9% 15-29K, 29.0% 30-44K, 19.7% 45-59K, 9.7% 60-74K, 7.5% 75K or higher. Marital status: 28.8% single, 57.9% married/common law partner, 13.3 other status. Employment: 9.5% students, 78.6% working full-time, 7.1% working part-time, 4% searching.

6.4 Choice Quality Means

Attribute Level	*Recommendation Consulted*	*Attribute Distribution*	*M*	*SE*	*95% Confidence (Lower/Upper)*	
15	No	Disproportional	2.660	.154	2.357	2.963
		Proportional	*2.487*	*.169*	*2.155*	*2.820*
	Yes	Disproportional	3.231	.207	2.823	3.638
		Proportional	*3.667*	*.193*	*3.287*	*4.046*
25	No	Disproportional	2.698	.145	2.413	2.983
		Proportional	*1.827*	*.147*	*1.539*	*2.115*
	Yes	Disproportional	3.214	.200	2.822	3.607
		Proportional	*3.323*	*.190*	*2.949*	*3.696*
35	No	Disproportional	2.260	.149	1.966	2.554
		Proportional	*2.745*	*.154*	*2.442*	*3.048*
	Yes	Disproportional	3.345	.196	2.959	3.731
		Proportional	*3.471*	*.181*	*3.114*	*3.827*

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