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The Effect of Defaults and Task Difficulty on Consumer Satisfaction - Implications for Value Co-Creation Processes

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Abstract. Companies increasingly involve consumers in product design and development, e.g. through built-to-order and mass customization or by integrating data generated at the point of sale into product development and production processes. The latter approach requires that companies provide online tools and interfaces like product configurators for consumer participation in value co-creation. Our research addresses the question how to design such tools to i) obtain reliable data and ii) keep customers happy with both products and value co-creation processes. In a lab experiment, we show how two interface elements, default values and task difficulty, affect consumers' product satisfaction, and satisfaction with the configuration process. Results indicate that product satisfaction is influenced by default values while process satisfaction is not, and task difficulty influences neither.

Keywords: E-Commerce, Product Configuration, Defaults, Reference Points, Co-Creation

1 Introduction

Consumers today increasingly demand individualized products and are less willing to make compromises regarding their product requirements. Accordingly, many companies provide mass customization services or built-to-order services [1-2]. Customers are often involved in customization and creation processes with the help of online tools like product configurators [3-5]. Beyond offering consumers the opportunity to customize products according to their requirements, product configurators generate data uniquely valuable for companies' product development and production processes. Porsche, for instance, set up a crowdsourcing project with a product configurator at its core to collect information about consumer preferences for developing a new car model [6].

The quality of data generated with product configurators is, however, strongly dependent on how the interface and the configuration process are designed [3]. Design decisions can affect consumer preference-building and decision processes, thus intro-

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ducing noise into the data or distorting them (e.g. [3-4]). Our research aims at identifying those elements of the configuration process which influence consumer preferences and decisions systematically to help companies design better configuration processes and systems. In this paper, we focus on the effects of two basic elements, default product configurations and task difficulty. Higher task difficulty, displaying greater numbers of attributes and attribute combinations, makes the configuration and selection task more complex, thus potentially frustrating or confusing consumers [7-8]. Product configurators typically start with a default product configuration (i.e. attribute combination) and let consumers change attribute levels one at a time, informing them about corresponding changes in price and the availability of other attribute levels [9]. Prospect theory tells us that consumer preferences are influenced by reference points like default configurations [10]. Specifically, consumer preferences and their satisfaction with different products depend on whether they perceive these products as gains or losses relative to their reference points [11]. We therefore use a model of multi-attribute reference points [12] to explain why consumers react differently to configurators that transport identical marketplace information (in terms of attribute availability, prices etc.) but start the configuration process with different default configurations.

For practitioners, our results are of interest because they show how consumer choice predictions can be improved without requiring additional consumer input and shed light on the influence of decision aid design on consumer choice. Our research helps retailers and product manufacturers understand the implications of certain design decisions, thus helping them to design better interfaces and to interpret the data generated during product configuration. If data are to be used in product development, being able to assess the reliability and validity of these data is particularly important [13].

The paper is organized as follows. Section 2 outlines the theoretical background to our research. Section 3 presents our research model. Section 4 describes the experimental setting and the results of our empirical investigation. Section 5 discusses the implications and limitations of our study.

2 Theoretical Background

2.1 Effects of Default Configurations on Consumer Decision Processes

Product configurators are interactive decision aids that display available attribute combinations to consumers (Figure 1[1]) [4]. Product configurators are particularly useful for providing consumers with insights into attribute trade-offs. When a consumer specifies a certain attribute level, the configurator gives feedback on how this change affects the decision space in terms of available levels in other attribute dimensions. When trade-offs exist between attributes, i.e. good performance in one attribute implies bad performance in another attribute, choosing one attribute level during con-

[1] More examples are available at www.configurator-database.com.

figuration may bar consumers from choosing certain levels of another attribute [14]. For instance, choosing the level “15-16in” for the attribute “screen size” may make low levels for the attribute “price” unavailable (Figure 1).

Product configurators usually start with a default product configuration with default values for every attribute. Default values are pre-set attribute levels that the consumer can change during the configuration process [15-17]. Because consumers are cognitive misers [18] they often leave defaults unchanged [19-21]. Consumers who are presented with a default configuration set to the best and most expensive available attribute levels in as many attribute dimensions as possible are more likely to choose a more expensive version of the product than consumers who are presented with a lower-performance and cheaper default configuration [17], [22].

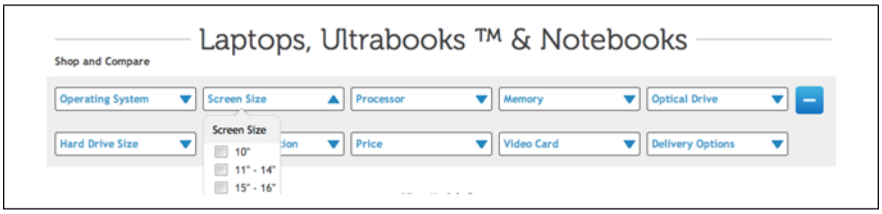

Figure 1. Dell’s notebook configurator

Consumer acceptance of default values is thought to depend on their “marketplace metacognition” [23] that is how well consumers are able to judge whether a default configuration will lead them to make a good purchase decision or whether they believe that a default configuration is merely in the seller’s best interest [24]. High default levels in the attribute “price” in particular can increase consumer skepticism and encourage them to think about reasons against buying the default product, thus reducing or even reversing the intended effect. To maximize sales, for instance, Hermann et al. [4] recommend setting the default value for price not to the highest possible level but between median and maximum levels.

2.2 Default Configurations as Reference Points

Default configurations also affect purchase decisions because consumers often use them as reference points to compare other products with [9-10]. Product, or prospect, evaluation being reference-dependent is one of the major tenets of prospect theory: (1) Decision-makers judge the attractiveness of prospects relative to a reference point in terms of changes of their wealth (gains or losses). (2) Decision-makers are loss-averse. (3) Decision-makers display diminishing sensitivity to both gains and losses [25-26]. These three tenets are reflected in the shape of prospect theory’s value function (Figure 2).

A reference point is any one stimulus which “other stimuli are seen in relation to” [27]. Reference points are dynamic [10-11], [28] and when reference points are adapted, they shift in the direction of a realized outcome. Because the value function is concave in the domain of gains (Figure 2), a gain following a previous gain is enjoyed more when the reference point is adapted after the preceding gain. If the reference point is not adapted, the following gain will be enjoyed less due to diminishing sensitivity - again, as expressed by value function's concavity in the gains domain. Conversely, if the reference point is adapted after a loss is realized, a subsequent loss will be more painful than if the original reference point is maintained: the value function is convex in the domain of losses (Figure 2). In the case of product configurators, changing a default value to a lower-utility attribute level (e.g. higher price or lower processor speed for notebooks as in Figure 1) represents a loss for the consumer in that attribute; changing a default value to a higher-utility attribute level represents a gain in that attribute [10], [29].

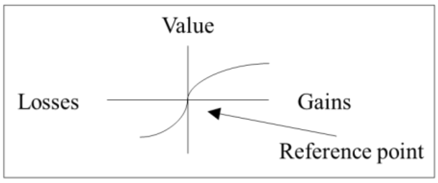

Figure 2. Value function in prospect theory

Although above definition of reference points implies that consumers must have reference points – or construct them during product evaluation – for all attribute dimensions, most prior research has focused on one single attribute, usually price (e.g. [30]) or value (e.g. [31]). With the exception of [28] and [12] few studies pick up on Tverksy and Kahneman's [29] multi-attribute theoretical framework which extends the simple single-attribute prospects considered in their original research. Multiple-attribute prospects are (1) split into their attributes, (2) each attribute is described by a value function, and (3) each prospect and attribute is evaluated relative to a reference point. Prospects may therefore resemble different compositions of gains and losses on different attribute dimensions [29]. Even [28] used only two attributes, aggregating all attributes aside from price into a "quality" dimension.

With a view to using product configurators as tools to inform co-creation and sales processes, the information loss from aggregations across attributes is undesirable. We therefore use a new method [12] to compute gains and losses which takes into account reference points on all attribute dimensions (section 4.2). This permits us to determine, for each consumer, which attribute levels constitute gains and losses, and also to compute overall product utilities in terms of prospect values. In other words, if consumers use default configurations as reference points, the effect of different default configurations can be predicted for each attribute as well as for overall product preferences.

2.3 Task Difficulty

Large choice sets are, on the one hand, more satisfactory for consumers than small choice sets because the chances to find a product which fits consumer needs and requirements are higher [32]. On the other hand, larger choice sets tend to make consumers feel more uncertain whether their assessment of the best product is reliable

[33]. Large choice sets increase the complexity of the decision task. This can result in information overload due to consumers' limited cognitive abilities, and have adverse effects on consumer satisfaction and decision quality [32], [34].

Considering that some studies found evidence that most people are not able to process more than around 7 facts at any one time (e.g. [35]) and that many products possess at least 7 relevant attributes, it seems safe to conclude that consumers often find themselves in cognitively demanding situations. Being cognitive misers [18], consumers use simplification strategies to reduce cognitive effort [33]. In situations of excessive cognitive demand, consumers tend to make only the effort necessary to arrive at an acceptable rather than a fully satisfactory decision [18].

Thus it is not surprising that products which are more difficult to evaluate are chosen less frequently than products which are easier to evaluate [36]. Similarly, consumers prefer to base their decision on attributes which are easy to evaluate than on attributes which are difficult to evaluate [37].

Product configurators can make the decision process less effortful. Consumers change one attribute level at a time, which means that they effectively compare two products (pre-change and post-change) that differ in only two attribute dimensions, assuming that the price also changes. Changes in one attribute level (e.g. higher processor speed) can make some other attributes' levels unavailable (e.g. low prices): consumers also need to remember trade-off relationships between attributes during configuration. The level of cognitive effort during product configuration thus depends mainly on three factors: the number of attributes, the number of levels per attribute [38] and the number of trade-off relationships between attributes.

3 Research Model

The default configuration can act as a reference point for consumers. High-utility default values (i.e. set to attribute levels which yield high utility) require that the consumer initially accept a loss in at least one attribute if she wishes to change the default value. The more attributes are set to high-utility default values, the greater the chance is that changing them will lead to a number of losses. We call this case "loss-inducing default".

Low-utility default values (i.e. set to attribute levels which yield low utility) initially permit consumers to realize gains by changing the default value to a higher-utility level. We call this case "gain-inducing default". Because reference points are less likely to be (fully) adapted after losses than after gains [11] consecutive losses will be felt less acutely or, in other words, will register on a less steep part of the loss curve than a loss following a gain (Figure 2). Assuming that the consumer had already updated her reference point to reflect a gain in one attribute, changing this attribute level downwards (because she realizes that in another attribute dimension higher-utility levels have become unavailable) will cause her a greater loss than before the update. We therefore suggest that consumers will be more satisfied with the configured product in the presence of loss-inducing defaults.

Consumers judge decision aids based on the effort they save in the decision process [38]. Because different default configurations do not affect effort levels, we do not expect that consumer satisfaction with the configuration process will be affected by them.

H_1: Consumer product satisfaction will be higher in the presence of loss-inducing defaults (high-utility default values).
H_2: Consumer satisfaction with the configuration process will not vary depending on gain-inducing and loss-inducing defaults.

Product satisfaction depends on the fit between consumer preferences and configured (i.e. available) products. If products are evaluated on the same attributes, and those attributes only, that were used for product configuration, we would not expect the number of attributes to affect product satisfaction.

The greater the number of configurable attributes, the higher the cognitive demand that the configuration process imposes on consumers [39], particularly if the number of trade-offs also rises [14]. Therefore we suggest that satisfaction with the configuration process will decrease with the number of configurable attributes.

H_3: Consumer product satisfaction will not vary with greater numbers of configurable attributes.
H_4: Consumer satisfaction with the configuration process will be lower for greater numbers of configurable attributes.

Figure 3 summarizes the research model for consumer satisfaction.

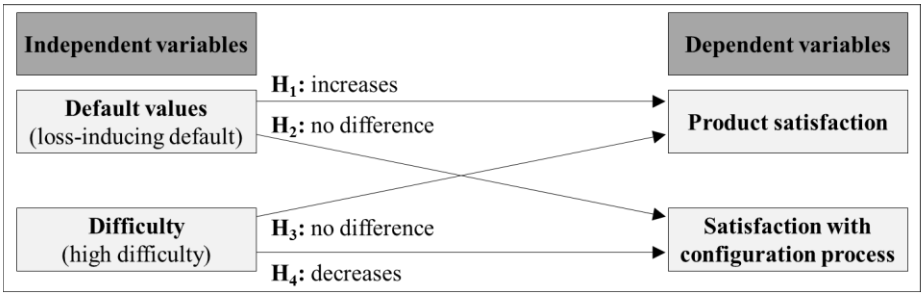

Figure 3. Research model

4 Empirical Investigation

4.1 Procedure and Treatments

We tested our research model in a laboratory experiment with a 2x2 within-subject design to control for individual-level differences in information processing. The treatment variables were default values and task difficulty.

In treatments with gain-inducing defaults, all default values were set to the worst possible attribute levels such that in the first configuration step any change in attribute levels would lead to a gain and subsequent attribute level changes would be more likely to be gains than losses. In treatments with loss-inducing defaults, all default values were set to the best possible attribute levels such that in the first configuration step any change in attribute levels would lead to a loss and subsequent attribute level changes would be more likely to be losses than gains.

Task difficulty was operationalized as the number of attributes available for configuration. In low-difficulty treatments, three attributes were displayed, and in high-difficulty treatments, four attributes were displayed. Each attribute had 5 levels. For the high-difficulty treatments, we doubled the number of available product combinations, which also added two trade-off relationships compared to the low-difficulty treatments. Conducting pairwise comparisons between attribute configurations and keeping in mind possible (attractive) attribute combinations thus became much harder in the high-difficulty treatments.

As experimental products, we used notebooks and digital cameras. Notebooks were described with battery life, weight, price (low-difficulty treatment) and hard drive (high-difficulty treatment); digital camera with resolution, zoom, price (low-difficulty treatment) and weight (high-difficulty treatment). The relationships between the attribute levels were defined such that it was not possible to configure a product with more than one attribute level set to “best”.

The experimental procedure required participants to carry out 4 configuration tasks, two with notebooks and two with digital cameras (Figure 4). Participants were given detailed instructions before each configuration task. The instructions provided situational framing in order to accommodate the possibility that not all participants might have specific initial reference points with regard to the relevant product attributes. Participants were instructed that a friend of theirs had asked for help in choosing a new product to buy after her favored product (described with three or four attributes depending on the task difficulty treatment) had become unavailable in the store she wanted to shop at. The instructions emphasized that all attributes were equally important for their friend to make sure that participants had to take market information in the form of trade-offs between attributes into account.

Tasks 1 and 3 doubled as training tasks, in which participants could familiarize themselves with configurator and product. To control for product-related effects, we varied product order. Groups A and C were shown notebooks first, Group B was shown digital cameras first. We also controlled for treatment order effects. Groups A and B received the two treatments with gain-inducing defaults first, group C the two treatments with loss-inducing defaults (Figure 4).

After each task, participants filled in a product- and process-related questionnaire (QP in Figure 4) on their product satisfaction and satisfaction with the configuration process and rated a set of pre-defined products. After the final task 4, an additional questionnaire (QA in Figure 4) was handed out which contained questions for various personality-related constructs that have been found to influence decision-making (see 4.4) and some socio-demographic variables (e.g. age, gender).

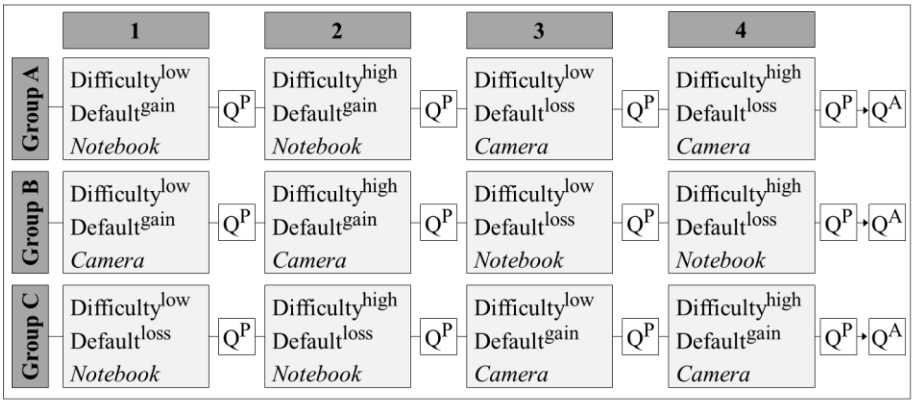

Figure 4. Experimental procedure

4.2 Measurement of Variables

Dependent variables. The dependent variables were product satisfaction and satisfaction with the configuration process. Both were measured repeatedly (after each task) with three items on a 7-point scale (1-"strongly disagree" to 7-"strongly agree").

Control variables. We controlled for product and configurator experience, price sensitivity and gender. Participants with high levels of product experience understand product-related information better and faster, which could make it easier for them to get used to the product configurator [40-41]. Similarly, participants without product but with configurator experience are likely to feel comfortable using the configurator faster. Since the experimental products were high-price items between 400 and 800 euros [42], price-sensitive participants might show lower overall levels of product satisfaction [25], [42]. We measured participants' price sensitivity with four items (7-point scale). Prior studies found gender-related differences in experience and purchasing behavior for technical products [43-44].

Measurement of reference points and product utilities. For each available product, we computed gains and losses as the differences between the reference points (default values) and the product's attribute levels. After normalizing them with the maximally available gain or loss in the respective attribute dimension, we computed the single-attribute prospect value. Overall product utilities (prospect values) were computed by integrating single-attribute utilities in a simple weighted additive function [12].

4.3 Sample

We conducted a pretest with 15 participants who did not take part in the final experiment. All suggestions made unanimously by at least 2 participants for improving configurator usability and treatment comprehensibility were adopted. For the final experiment, 95 students from the University of Passau were invited to a lab and given instructions how to proceed. Groups A, B and C contained 40, 37, and 18 participants respectively. Each participant received 7 euros. 68% of the participants were female and average age was 23 years, ranging from 19 to 53. On average, participants were experienced but not experts in using product configurators (3.221, SD=1.07). Product experience was higher for notebooks (3.803, SD=1.444) than for cameras (3.612, SD=1.444); again, participants were on average knowledgeable but not experts on both products.

4.4 Results

In task 1, a learning effect was clearly visible: in all groups, participants explored the "market situation", i.e. available products, and familiarized themselves with the configurator, using many more clicks per attribute (on average) than in any subsequent task (see Table 1 for group A as an example). Task 3 was the training task for the new product type: participants were again given the chance to explore the market situation. They used, on average, slightly more clicks than in task 4, although task 3 involved only three attributes (compared to four attributes in task 4). The gain-loss ratio indicates how many attribute-level gains and losses participants incurred on average in each treatment (Table 1). It is computed as the number of changes in attribute levels which correspond to a gain (positive difference to the default value in that attribute) divided by those corresponding to a loss (negative difference to the default value in that attribute). As intended, the gain-loss ratio was higher in treatments with gain-inducing defaults than in treatments with loss-inducing defaults. For group A, for instance, the gain-loss ratio decreased by 26.3% and 16.7% respectively between tasks 1 and 3 (low-difficulty) and tasks 2 and 4 (high-difficulty treatments).

Table 1. Attribute level changes during configuration tasks (Group A)

Task	*Number of clicks per attribute [mean (sd)]*	*Gain-loss ratio to default [mean (sd)]*
1	10.958 (7.651)	0.746 (0.222)
2	5.875 (4.080)	0.640 (0.202)
3	4.742 (4.691)	0.483 (0.323)
4	3.475 (2.508)	0.472 (0.249)

Descriptive statistics show that participants' product satisfaction was higher in the low-difficulty than in the high-difficulty treatments, and higher in the loss-inducing defaults treatments than in the gain-inducing default treatments. Participants' satisfaction with the configuration process was also higher in the low-difficulty treatments. For cameras, it was slightly higher in the loss-inducing defaults treatments, for notebooks in the gain-inducing treatments (Table 2).

Table 2. Product satisfaction and satisfaction with the configuration process

product	*difficulty*	*default*	Product satisfaction [mean (sd)]	Satisfaction with configurator [mean (sd)]
camera	low	gain	3.515 (1.196)	4.127 (1.188)
camera	low	loss	4.117 (1.372)	4.350 (1.097)
camera	high	gain	3.273 (1.181)	3.845 (1.133)
camera	high	loss	3.758 (1.294)	3.956 (0.753)
notebook	low	gain	3.633 (1.307)	4.250 (1.105)
notebook	low	loss	3.661 (1.226)	4.186 (1.121)
notebook	high	gain	3.117 (1.101)	4.013 (1.233)
notebook	high	loss	3.133 (1.139)	3.836 (0.983)

We used mixed effects regression to account for potential individual effects across treatments [43-44]. We conducted model comparisons to examine the effects of product experience, configurator experience, price sensitivity, and gender on product satisfaction (Table 3) and satisfaction with the configuration process (Table 4). For the regression on product satisfaction, Anovas indicate that models with random intercepts for individuals fitted best ($\chi(1)=12.374$, $p= 0.0004$).

Table 3. Regression results for dependent variable product satisfaction

	Model 1	Model 2	Model 3
Intercept	0.399 (0.074)	0.165 (0.594)	0.403 (0.072)
Default	0.374* (0.022)	0.359* (0.029)	0.373* (0.022)
Difficulty	-0.106 (0.467)	-0.106 (0.467)	-0.106 (0.467)
Product	0.136 (0.393)	0.150 (0.350)	0.132 (0.408)
Default x Difficulty	-0.058 (0.801)	-0.057 (0.802)	-0.057 (0.801)
Default x Product	-0.413 (0.071)	-0.422 (0.065)	-0.402 (0.075)
Difficulty x Product	-0.200 (0.372)	-0.200 (0.372)	-0.200 (0.372)
Default x Difficulty x Product	0.055 (0.861)	0.056 (0.862)	0.055 (0.862)
Product experience	0.002 (0.937)	0.010 (0.745)	0.006 (0.853)
Configurator experience	-0.133** (0.002)	-0.127** (0.003)	-0.135** (0.002)
Price sensitivity	-	0.037 (0.280)	-
Gender	-	-	-0.035 (0.750)
AIC	1249.9	1250.7	1251.8

**p<0.05 **p<0.01 ***p<0.001; Estimate (SD)*

Anovas indicate that including gender ($\chi(1)= 0.0284$, $p= 0.8662$) or price sensitivity ($\chi(1)=1.07$, $p=0.3009$) do not lead to improvements over model 1. Marginal R^2 for model 1 is 0.01 and conditional R^2 is 0.243. The treatment effect for loss-inducing defaults and the effect of the control variable "configurator experience" are robust across all models.[2] Loss-inducing defaults had a positive effect on participants' product satisfaction. H1 is supported. Task difficulty did not affect participants' product satisfaction. H3 is supported. Across all treatments, participants with higher levels of configurator experience were less satisfied with the product. Product experience did not influence participants' product satisfaction.

Finally, we conducted mixed effects regression on satisfaction with the configuration process (Table 4). Again, the model with random intercepts for individual effects fits the data best ($\chi(1)=4.2115$, $p=0.0401$).

Table 4. Regression results for dependent variable satisfaction with configuration process

	Model 1	*Model 2*	*Model 3*
Intercept	0.226 (0.300)	-0.152 (0.619)	0.229 (0.295)
Default	0.244 (0.140)	0.221 (0.182)	0.243 (0.140)
Difficulty	-0.161 (0.272)	-0.160 (0.272)	-0.161 (0.273)
Product	0.133 (0.411)	0.156 (0.337)	0.130 (0.425)
Default x Difficulty	-0.034 (0.880)	-0.034 (0.880)	-0.034 (0.880)
Default x Product	-0.314 (0.172)	-0.332 (0.153)	-0.311 (0.181)
Difficulty x Product	0.011 (0.963)	0.010 (0.964)	0.010 (0.963)
Default x Difficulty x Product	-0.020 (0.951)	-0.019 (0.952)	-0.020 (0.952)
Product experience	0.093** (0.002)	0.106*** (0.001)	0.097** (0.003)
Configurator experience	-0.084* (0.044)	-0.073 (0.079)	-0.089* (0.041)
Price sensitivity	-	0.058 (0.081)	-
Gender	-	-	-0.037 (0.722)
AIC	1176.7	1175.7	1178.6
**p<0.05 **p<0.01 ***p<0.001; Estimate (SD)*			

Anovas indicate that including gender ($\chi(1)=0.3465$, $p=0.56$) or price sensitivity ($\chi(1)=1.1336$, $p=0.287$) do not lead to an improvement over model 1. Marginal R^2 for model 1 is 0.11 and conditional R^2 is 0.291. Results show that, across all treatments, participants with more product experience were more satisfied with the configuration process[3] (model 1 in Table 4). There was no treatment effect of gain-inducing / loss-inducing defaults on participants' satisfaction with the configuration process. H2 is supported. Task difficulty did not affect participants' satisfaction with the configuration process. H4 is not supported.

[2] We conducted additional model comparisons, systematically removing treatment variables and interaction effects. The effects of defaults and configurator experience on product satisfaction were robust across all models.

[3] As in the model for product satisfaction, we carried out additional model comparisons. The effects of product experience and configurator experience were robust.

5 Discussion

This study examines the effects of the design of product configurators, specifically task difficulty and default configurations, on consumers. How these design decisions affect consumers' decision processes is particularly important to know for those companies which use data generated during product configuration to inform co-creation or sales processes. Our results show that product satisfaction was higher for loss-inducing defaults, i.e. high-utility attribute levels, and did not change with task difficulty. Satisfaction with the configuration process was not affected by the default configuration or by task difficulty. Experience with product configurators had a negative effect on both product satisfaction and satisfaction with the configuration process; product experience had a positive effect on satisfaction with the configuration process but no effect on product satisfaction. Gender and price sensitivity had no significant effects on either dependent variable.

We contribute to recent research on the role of defaults in consumer decision processes. Our findings support the suggestion that, during product configuration, consumers use default configurations as reference points and therefore feel consecutive losses less acutely than a loss following a gain: reference points are less likely to be (fully) adapted after losses than after gains [11].

Some practical implications of our study are that the configuration process appears to be particularly difficult for consumers with little prior experience. This suggests that offering "beginner'" and "expert" configurators is advisable. Setting default values to higher rather than lower attribute levels increases not only sales [4] but also product satisfaction. However, this effect may not be persistent over time. If products can be returned, it may "wear off" and lead to higher return rates, suggesting that default configurations distort consumer preferences in the short run. In this case, basing co-creation or sales process on data generated from product configurators will have adverse effects unless interface design-related effects are accounted for.

We will address this question in future research. Specifically, we will examine how consumers react to default configurations in the presence of other reference points (e.g. status quo or aspiration levels) [31] to determine how strong the effect of default configurations on the decision process is in terms of utility differences, whether it persists after sales, and to find possible explanations for it. In the present study, participants were given a hypothetical shopping task rather than a real-effort task. Due to the expenses associated with buying digital cameras for our participants, we decided to consider only the first step towards a successful online purchase, i.e. consumers finding products they are sufficiently satisfied with to consider buying in the first place. Another limitation is that we used a student sample. Other user groups, e.g. older or less technology-savvy users, may show different reactions. Our results indicate that prior experience with products and configurators plays a role in how products and / or configuration processes are perceived; we would expect that in other samples with greater variability in these parameters (section 4.3), these effects will be more pronounced. Also, other factors are likely to play a role, e.g. income or risk aversion, which we did not examine in our current study but plan to address in future research.

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