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Increasingly, firms allow consumers to mass customize their products. In this study, the authors investigate consumers' evaluations of different mass customization configurations when they are asked to mass customize a product. For example, mass customization configurations may differ in the number of modules that can be mass customized. In the context of mass customization of personal computers, the authors find that mass customization configuration affects the product utility that consumers can achieve in mass customization as well as their perception of mass customization complexity. In turn, product utility and complexity affect the utility that consumers derive from using a certain mass customization configuration. More specifically, product utility has a positive effect and complexity has a negative effect on mass customization utility. The effect of complexity is direct as well as indirect because complexity also lowers product utility. The authors also find that consumers with high levels of product expertise consider mass customization configurations less complex than do consumers with low levels of product expertise and that for more-expert consumers, complexity has a less-negative impact on product utility. The study has important managerial implications for how companies can design their mass customization configuration to increase utility and decrease complexity.

Marketing Mass-Customized Products: Striking a Balance Between Utility and Complexity

The combination of advanced engineering and information technology enables firms to be highly flexible and responsive in providing product variety through mass customization (e.g., Pine, Victor, and Boyton 1993). However, marketing researchers are just beginning to explore the effectiveness of mass customization strategies from a consumer perspective (Huffman and Kahn 1998; Wind and Rangaswamy 2001). Liechty, Ramaswamy, and Cohen (2001) model the product choices that consumers make in a mass customization configuration. However, little is known about how different mass customization configurations differentially affect the utility that a consumer derives from mass customization, which is the focus of the current article. For example, the Web sites of different personal computer (PC) manufacturers may have different mass customization configurations that may affect consumers' preferences for mass customization in different ways.

The objective of this article is not to explain why consumers choose to mass customize a product rather than to buy a standard alternative but to explain why consumers, when mass customizing a product, prefer one mass customization configuration over another. Mass customization configuration refers to the outline or arrangement of the different product components that can be mass customized. For example, mass customization configurations may differ in the number and levels of product modules that a consumer may customize.

We explain consumers' evaluations of mass customization configurations by building on choice task complexity theory (e.g., Bettman, Johnson, and Payne 1990; Johnson

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and Payne 1985), consumer choice theory (McFadden 1986), and loss aversion theory (Tversky and Kahneman 1991). Our central premise is that consumers' latent utility for a certain mass customization configuration (i.e., mass customization utility) is simultaneously affected by (1) the product utility that consumers can achieve by using the mass customization configuration (i.e., product utility) and (2) consumers' perception of the complexity of composing their product when using the mass customization configuration (i.e., complexity). We also identify mass customization configuration factors that may differentially affect both product utility and complexity. To test the developed theory, we use data from an experiment of mass-customized PC purchases. The extended logit model (Ashok, Dillon, and Yuan 2002) that we specify estimates simultaneously both measurement equations and structural equations for the hypothesized effects. It also allows for differences between consumers based on consumer expertise (e.g., Alba and Hutchinson 1987) and unobserved factors (through a random coefficient specification).

Thus, this article contributes to the marketing literature by addressing the novel and relevant question, Why do consumers evaluate one mass customization configuration differently from another? This question is relevant for companies such as Dell or Hewlett-Packard when they (re)design their mass customization configuration. We find empirical support for the developed theory through the estimation of a random coefficient specification of the extended logit model, and we derive recommendations for companies that offer mass customization.

RESEARCH HYPOTHESES

The Effect of Product Utility and Complexity on Mass Customization Utility

First, we expect that consumers attach a higher utility to a mass customization configuration when it allows them to achieve a higher product utility. Second, we expect that consumers attach a higher utility to more simple rather than more complex mass-customization configurations. The reason is that increased complexity requires greater consumer effort to generate the same mass-customized product (Johnson and Payne 1985) and that consumers want to minimize decision effort (Wright 1975).

> H_1: (a) The product utility that a consumer can achieve by using a mass customization configuration has a positive effect on mass customization utility, whereas (b) the complexity of using a mass customization configuration has a negative effect on mass customization utility.

We also expect that complexity may directly affect product utility. As mass customization becomes more complex, it becomes more likely that consumers need to resort to simplifying decision heuristics (e.g., Newell and Simon 1972). In turn, the use of heuristics makes it less likely that consumers select the product with the highest possible product utility, because heuristics force consumers to take into account only a subset of all module trade-offs, and therefore the product they compose may be suboptimal.

> H_2: The complexity of using a mass customization configuration has a negative effect on the product utility that a consumer can achieve by using a mass customization configuration.

The Effect of Mass Customization Configuration Factors on Product Utility and Complexity

We discern four factors on which mass customization configurations may differ and that may have differential effects on the product utility that is obtained through the use of a mass customization configuration as well as on the complexity of this configuration. The first factor is the extent of mass customization. A configuration that is low in the extent of mass customization may offer fewer modules for mass customization (e.g., only the memory and processor of a PC) or fewer levels among which to choose per mass customizable module (e.g., for mass customization of the processor, only two processing speeds are available) than a configuration that is high in the extent of mass customization. The second factor is the heterogeneity in the levels that are available for a mass customizable module. A configuration that is low in level heterogeneity may offer only very similar module levels among which a consumer can choose (e.g., a 17-inch or 18-inch screen), whereas a configuration that is high in level heterogeneity may offer very different module levels among which a consumer can choose (e.g., a 15-inch or 21-inch screen). The third factor is the individual pricing of mass customizable modules within a mass customization configuration. Mass customizable modules may be individually priced (e.g., the price of the different processors is shown) and shown along with the total product price, or they may be such that only the total product price is shown (e.g., the price of the different processors is not shown, but only the computer's total price is shown). The fourth factor is the presence and level of a default version. A mass customization configuration may show a default version (e.g., for the processor, the configuration contains a preselected processing speed) or it may not, and when a default version is shown, it may be a high-end (e.g., the highest processing speed is preselected) or a low-end (e.g., the lowest processing speed is preselected) default version.

We identified these four mass customization configuration factors for two main reasons. First, when we examined existing mass customization configurations in the context of PC purchasing, we found that differences between mass customization configurations were strongly pronounced on these four factors. Second, these four factors have a consistent theoretical background. They all affect complexity through the number of trade-offs that consumers must make while composing their mass-customized product. In addition, they all affect product utility through the extent to which consumers are able to select a product that is close to their ideal product (i.e., the product that has the most attractive combination of product module levels for that consumer).

Extent of mass customization. Increases in the extent of mass customization lead to a greater number of possible products that a consumer can compose through the mass customization configuration. On the one hand, such increases likely reduce the average distance between the mass-customized product that a consumer may compose and his or her ideal product, thereby increasing product utility. On the other hand, consumers must trade-off a greater number of possible module levels. In turn, this increases the number of cognitive steps in the consumer decision-making process, which increases perceived complexity (Bettman, Johnson, and Payne 1990).

H_3: The extent to which consumers can mass customize products increases (a) the product utility that can be achieved by using a mass customization configuration and (b) the complexity of using a mass customization configuration.

Level heterogeneity. An important determinant of product utility may be whether consumers can find their most preferred module level, which is consistent with research on consumer perceptions of retail assortments (Broniarczyk, Hoyer, and McAlister 1998). Given a certain extent of mass customization, a mass customization configuration that offers module levels that are relatively close to the mean (low level heterogeneity) enables a larger number of consumers to select their most preferred module levels than does a configuration with levels that are more dispersed (high level heterogeneity). Thus, we hypothesize that increasing level heterogeneity (for a given extent of mass customization) has a negative effect on product utility.

H_{4a}: Increasing heterogeneity in mass customizable module levels decreases the product utility that a consumer can achieve by using a mass customization configuration.

Note that this hypothesis assumes that consumer module-level preferences are heterogeneous and concentrated around the mean (e.g., following a normal distribution; see Allenby, Arora, and Ginter 1999).

We also expect that greater level heterogeneity increases complexity, assuming that decision complexity increases as the differences in the trade-offs between different module levels increase. Bettman, Johnson, and Payne (1990) highlight the effect of the number of cognitive steps on consumer decision complexity, and others have shown that a larger variance in trade-offs also increases choice complexity (e.g., Chatterjee and Heath 1996). As module levels become more heterogeneous, trade-off variance increases. Thus, we expect complexity to increase as well.

H_{4b}: Increasing heterogeneity in mass customizable module levels increases the complexity of using a mass customization configuration.

Individual pricing of mass customizable modules. Individual pricing of mass customizable modules may affect product utility for several reasons. In particular, we expect that the inclusion of individual prices of mass customizable modules makes price more salient to consumers because it more clearly expresses the prices associated with each module, and consumers tend to focus on information that is explicitly displayed (e.g., Slovic 1972). Individual pricing may also lead to a more disaggregate perception of monetary losses and thus a higher perceived total price (e.g., Tversky and Kahneman 1991). For these reasons, we expect that individual pricing leads consumers to select less expensive module levels, thereby obtaining a lower-quality product when higher-quality module levels have higher prices.

H_{5a}: Individual pricing of mass customizable modules decreases the product utility that consumers achieve when using a mass customization configuration.

We also expect that individual pricing of mass customizable modules increases complexity because of the greater cognitive effort that is involved in processing the separate price information. Presenting individual prices for each mass customizable module along with the total price emphasizes more clearly the separate cost–benefit trade-offs that consumers must make for each module. Therefore, we expect that, on average, consumers are likely to be more aware of the number of trade-offs (i.e., cognitive steps) they must make and that this in turn leads to a greater perceived effort in the decision and a higher perceived complexity (e.g., Bettman, Johnson, and Payne 1990; Johnson and Payne 1985).

H_{5b}: Individual pricing of mass customizable modules increases the complexity of using a mass customization configuration.

Default version. A final mass customization configuration factor that we address is the default version of the mass customizable product that may be offered. Prior research suggests that across many different applications, consumers are more willing to switch "up" to higher-priced, higher-quality products than to switch "down" to lower-priced, lower-quality products (e.g., Simonson, Kramer, and Young 2003). A possible explanation for this effect is that there is an asymmetry in price and quality loss aversion that makes the quality loss relatively more difficult to compensate for in monetary terms (Park, Jun, and MacInnis 2000; Tversky and Kahneman 1991). On the basis of these previous findings, we expect that when a base default is offered that is relatively unattractive in terms of its module levels, consumers select a product that is closer to their ideal product. Furthermore, consumers who are presented with an advanced default are more willing to switch up than the latter are to switch down.

H_6: Offering a base default version leads to a higher product utility when using a mass customization configuration than does offering an advanced default version.

We also expect that providing a default version may affect complexity, because a default version that is closer to a consumer's ideal product may allow him or her to go through a smaller number of module-level comparisons than a default that is farther from the consumer's ideal product. Depending on a consumer's preferences, a base default version or an advanced default version may be closer to his or her ideal product, and therefore complexity may be greater or smaller. We include a control variable for complexity and heterogeneity in our model to allow for this effect.

The Role of Consumer Expertise

Prior research has shown that consumer expertise plays a central role in consumers' ability to deal with task complexity (e.g., Alba and Hutchinson 1987; Spence and Brucks 1997). Therefore, we expect that consumers with high consumer expertise experience less complexity when participating in mass customization than do consumers with low consumer expertise (see Huffman and Kahn 1998).

H_7: Consumer expertise decreases the complexity of using a mass customization configuration.

Furthermore, we expect that even if consumers perceive a certain mass customization configuration to be complex, consumers with high expertise are relatively less likely to need to resort to the use of decision heuristics, and if they do use heuristics, the heuristics are more effective (see H_2). For example, Alba and Hutchinson (1987) argue that higher consumer expertise leads to a greater ability to analyze information and to select information that is most important and relevant to the task. Therefore, we expect that complexity has less of an effect on the product utility that experts can achieve in mass customization than on the product utility that nonexperts can achieve.

H_8: The negative effect of complexity on product utility in using a mass customization configuration is weaker for consumers with high expertise than for consumers with low expertise.

Model

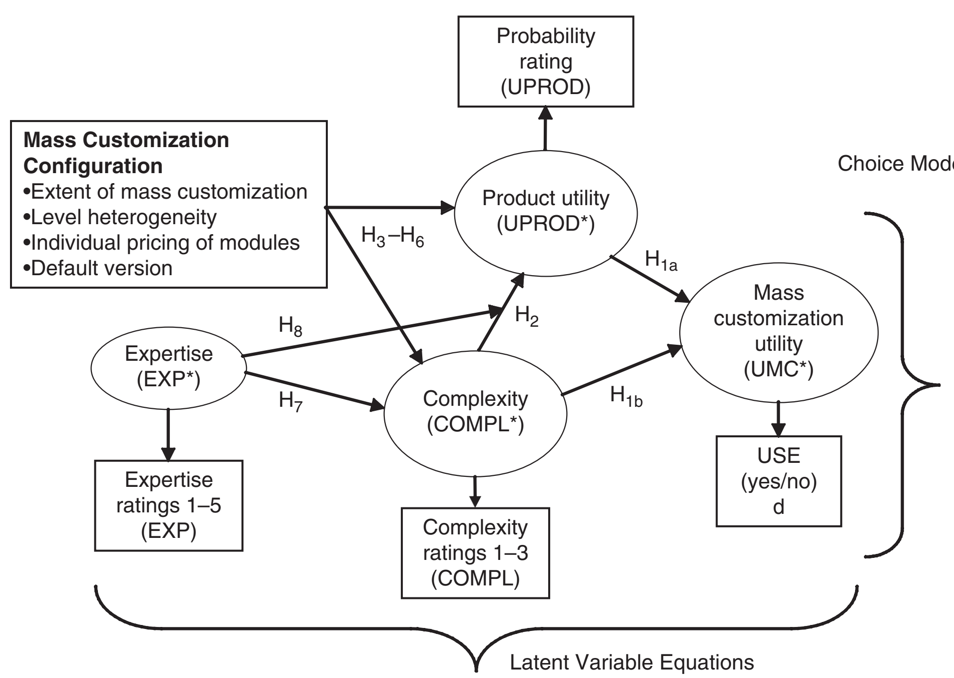
We develop a model that captures how mass customization configuration and consumer expertise affect product utility and complexity and how these latter two constructs in turn affect mass customization utility (for a graphic summary, see Figure 1; a technical appendix is available on request). We express the utility of mass customization configuration c to consumer i (UMC^*_{ci}) as a function of product utility ($UPROD^*_{ci}$), complexity ($COMPL^*_{ci}$), and an individual and mass customization configuration specific error term (ε_{MCci}) that captures unexplained variation in consumers' utility due to measurement error and unobserved explanatory variables. To allow for differences among consumers, we model the parameters (β) in the model as random coefficients with their own error terms (ν). We allow for different variances for the error terms in the equation and assume that they are independent and normally distributed.[1] In our estimation, this utility function drives the probability that a consumer chooses to use a given mass customization configuration or not, and we assume that the error terms ε_{MCci} are independently and identically Gumbel distributed to obtain the binary logit specification.

$$UMC^*_{ci} = \alpha^{MC} + \left(\beta^{MC}_{PROD} + \nu^{MC}_{PRODi}\right)UPROD^*_{ci} + \left(\beta^{MC}_{COMPL} + \nu^{MC}_{COMPLi}\right)COMPL^*_{ci} + \varepsilon_{MCci}. \quad (1)$$

Next, we express both product utility and complexity as a function of consumer expertise (EXP^*_i) and a vector of mass customization configuration factors $\mathbf{CONF}_c$. In the product utility model, we add to this specification the effect of complexity and allow for an interaction with consumer expertise. To control for further remaining heterogeneity, we also include (1) a variable that represents progress through the experiment (PRO); (2) random coefficient parameters for the effects of the latent factors, mass customization configuration, and progress; and (3) interactions of expertise with experimental variables (i.e., extent of mass customization).

[1]Equations 2 and 3 follow the same structure and notation. We tested the assumption of independent errors in our application, and it could not be rejected.

Figure 1
MASS CUSTOMIZATION UTILITY MODEL



Notes: Boxes represent the observed measures and the factors manipulated in the experimental study, and circles represent the underlying latent constructs. Arrows running from boxes to circles and from circle to circle represent hypothesized main effects, arrows pointing at other arrows represent hypothesized interaction effects, and vertical arrows (from circles to boxes) represent measurement relationships.

$$(2)\ \mathrm{UPROD}^*_{ci} = \alpha^{PROD} + (\beta^{PROD}_{COMPL} + \beta^{PROD}_{EXPCOMPL}\mathrm{EXP}^*_i + \nu^{PROD}_{COMPLi})\mathrm{COMPL}^*_{ci} + (\beta^{PROD}_{EXP} + \nu^{PROD}_{EXPi})\mathrm{EXP}^*_i + (\boldsymbol{\beta^{PROD}_{CONF}} + \boldsymbol{\beta^{PROD}_{EXPCONF}}\mathrm{EXP}^*_i + \boldsymbol{\nu^{PROD}_{CONFi}})\mathbf{CONF}_c + \gamma^{PROD}\mathrm{PRO} + \varepsilon_{PRODci}.$$

$$(3)\ \mathrm{COMPL}^*_{ci} = \alpha^{COMPL} + (\beta^{COMPL}_{EXP} + \nu^{COMPL}_{EXPi})\mathrm{EXP}^*_i + (\boldsymbol{\beta^{COMPL}_{CONF}} + \boldsymbol{\beta^{COMPL}_{EXPCONF}}\mathrm{EXP}^*_i + \boldsymbol{\nu^{COMPL}_{CONFi}})\mathbf{CONF}_c + \gamma^{COMPL}\mathrm{PRO} + \varepsilon_{COMPLci}.$$

Finally, we define three measurement equations to estimate parameters (λ) that relate the observed measures of product utility, complexity, and consumer expertise to their underlying latent constructs. We allow for different error variances (η) for the different measures of each construct and assume independent normal distributions for each equation conditional on the latent constructs.

$$(4a)\quad \mathrm{UPROD}_{ci} = \lambda_{PROD}\mathrm{UPROD}^*_{ci} + \eta_{PRODci}.$$

$$(4b)\quad \mathbf{COMPL}_{ci} = \boldsymbol{\lambda_{COMPL}}\mathrm{COMPL}^*_{ci} + \boldsymbol{\eta_{COMPLci}}.$$

$$(4c)\quad \mathbf{EXP}_i = \boldsymbol{\lambda_{EXP}}\mathrm{EXP}^*_i + \boldsymbol{\eta_{EXPi}}.$$

Estimation

We estimate the model using a smooth simulated maximum likelihood procedure (Train 2003). Note that in our application, we have several observations for each respondent and that the individual random components in the random coefficients remain constant for the simulations for all observations from the same respondent. We multiply the individual-level probabilities to obtain the total simulated maximum likelihood for all respondents. In our estimation, we based the simulated mean per individual for each of the random coefficients and the three latent constructs on 100 Halton draws. We tested our estimation procedure using synthetic data and different numbers of draws, and we concluded that the estimation procedure worked well but that the random coefficient standard deviation parameters could be recovered well only if we used starting values that were close to the original values. Therefore, in our application, they may need to be interpreted with caution.

DATA

We tested our hypotheses with an experiment in which we asked consumers to mass customize PCs under different experimental conditions that mimicked real-world mass customization configurations and to choose whether they would use the mass customization configuration if it were to become available.

Respondents

Respondents in the experiment were real-life consumers who are members of an ongoing consumer panel of approximately 2000 people at Tilburg University. We collected data in 2001. The panel is Internet based and is used to collect a variety of data. Respondents participated in the experiment in their own home using the Internet. Participants in the panel are randomly selected from the total population of the Netherlands and are provided with Internet access by the panel management if necessary. After we eliminated respondents (1) under 16 years of age, (2) with no interest in purchasing a PC in the next two years or who had not purchased a PC in the past four years, and (3) with missing values or invalid responses, 409 respondents remained. The average age of the respondents was 43.7 years; 37.2% of the respondents were female, and 52.6% held a bachelor's degree or higher.

Procedures

We went through several steps to ensure the credibility and validity of our experimental task. A few weeks before the actual data collection, we explored several offerings of PC vendors and conducted a pretest with the panel to validate that the range of levels we selected were realistic for respondents. We also measured the panel members' self-reported level of expertise regarding PCs. Furthermore, we developed an experimental Web site that approximated a consumer's experience when buying a mass-customized PC online. The experimental interface allowed consumers to choose their most preferred level from different modules, and as one of the manipulations, the interface included a base default version. We pretested the experimental mass customization interface offline with several consumers, and we discussed it with some PC experts and the consumer panel management. On the basis of the pretest and discussions, we added a click-through "help" option that was accessible at any stage of the experiment.

In the experiment, an introduction page explained the respondent's task and the various components of the PC that could be mass customized. This was followed by a practice task that all respondents needed to complete. Next, each respondent mass customized a PC in eight different experimental conditions that we presented on different Web pages. These eight conditions differed on the four mass customization factors (we summarize these in Table 1). A pull-down menu showed all levels within each mass customizable PC module. To confront respondents with the different aspects of the mass customization configuration in each of the eight conditions, we asked respondents to select a PC in all the scenarios they faced. This task situation is similar to a consumer's using a Web site, for example, to find out what PC he or she could configure and how much it would cost. If a default was present, respondents could choose the default immediately, but they could also choose the default after having "tried" different mass customization configurations. However, they could not revert to a standard default option once they had tried other options. That is, after trying different configurations, respondents could still select the default option, but only by composing this configuration themselves. The initial default settings were not "stored," and the respondent would need to select the appropriate levels. In this case, they needed to compose the default version themselves. Prices were shown for the default (when available) and then for each alternative the respondent composed. After respondents selected their preferred PC, we measured their product utility, complexity, and mass customization utility.

Table 1

MASS CUSTOMIZATION CONFIGURATION FACTORS AS MANIPULATED IN THE EXPERIMENT

Characteristic	*Levels*	*Description*
Extent of Mass Customization		
Number of mass customizable modules	Low	4 (processor, monitor, memory, and hard drive)
	High	8 (processor, monitor, memory, hard drive, mouse, keyboard, video card, and speakers)
Number of levels per mass customizable module[a]	Low	4 (for first four modules); 2 (for second four modules)
	High	8 (for first four modules); 4 (for second four modules)
		Module levels included (ranked from 1 to 15)
Level Heterogeneity[a]	Low	4, 5, 6, 7
		4, 5, 6, 7, 8, 9, 10, 11
		4, 5, 6, 7, and 2, 3
		4, 5, 6, 7, 8, 9, 10, 11 and 2, 3, 4, 5
	High	3, 5, 7, 9
		1, 3, 5, 7, 9, 11, 13, 15
		3, 5, 7, 9 and 1, 3
		1, 3, 5, 7, 9, 11, 13, 15 and 1, 3, 5, 7
Individual Pricing of Mass Customizable Modules	Individual	Price is given per module level and at the product level.
	Combined	Price is given only at the product level.
Default Version		
Default present	Yes	
	No	
Base versus advanced default	Base	Lowest quality level is given as default.
	Advanced	Highest quality level is given as default.

[a]We always included the first four modules in the mass customization configuration; the second four modules were fixed in the "low" number of mass customizable modules condition and could be mass customized in the "high" number of mass customizable modules condition.

Independent Variables

In the experimental conditions, we manipulated four factors based on our hypotheses development (H_3–H_6): (1) the extent of mass customization (number of modules and number of levels per module), (2) the level heterogeneity, (3) the individual pricing of modules, and (4) the type and availability of a default version (for an overview of these factors and their levels, see Table 1). We also included a predefined part in the experiment that served as a baseline evaluation in the model. We measured consumer expertise using five aspects of consumer expertise about PCs (i.e., knowledgeable, competent, expert, trained, and experienced) on a seven-point scale (e.g., the measure for knowledge ranged from "not at all knowledgeable" to "very knowledgeable"). We adapted these measures of consumer expertise from Netemeyer and Bearden's (1992) work, and the coefficient alpha showed high reliability (.97).

Design

A fractional factorial design prescribed the variations over experimental conditions. The design was a 32-profile fraction of a 4.2^5 full factorial that represented all mass customization configuration variables at two levels, each of which, with the exception of the default variable, varied on four levels (two of the four levels represented "no default," and the other two represented "base default" and "advanced default," respectively). We divided the 32 total profiles systematically into four versions of eight profiles, using an additional free four-level factor that was also available in the 32-profile fraction. Each level of this factor represented one version of the survey. This procedure ensured that there was no confounding between versions and the other variables in the design, but it did not allow for the estimation of separate parameters for each version in the analysis. We randomized the profiles in each of the four versions, and we added one practice task. We randomly assigned each respondent to one of the four versions of eight profiles.

Dependent Variables

Our central variable of interest was the respondent's choice of whether or not to use a certain mass customization configuration. Therefore, we asked respondents to choose whether they would use the mass customization configuration they had just used if it was really available to them. This choice is explained on the basis of the underlying latent utility that the respondent associates with using the mass customization configuration. This approach is common in consumer choice modeling (e.g., Ashok, Dillon, and Yuan 2002; McFadden 1986). As an indicator for product utility, we asked respondents to express the likelihood that they would purchase the product they selected if it was really available to them and was priced at the level presented in the scenario. This approach is common in previous research in conjoint analysis (e.g., Huber et al. 1993). The response was given on a scale that ranged from 0% to 100%. To measure complexity, we used three ratings of the complexity of the configurations used to compose the PC—"complicated," "difficult," and "effortful"—which we measured on a seven-point scale. The coefficient alpha of this measure showed a high reliability of .91. Confirmatory factor analysis showed that our measures of expertise, product utility, and complexity fit well with three distinct factors.

RESULTS

On our seven-point scales of expertise (five items) and complexity (three items), on average, respondents rated themselves close to the midpoint of the scale. The average reported product utility as measured by the likelihood of buying the PC was 32.3%. The average number of responses per scenario was 75.7, and across all experimental scenarios, respondents chose to use the mass customization configuration in 25.8% of the cases. The number of yes responses for each scenario ranged between 12 (of 80) for the least attractive scenario and 29 (of 85) for the most attractive scenario.

Table 2 presents the estimation results for our model and summarizes the results in terms of the hypotheses. The relevant parameter notation from Equations 1–3 is also provided. With the exception of H_{3b} and H_{4b}, the null hypothesis was rejected ($p < .05$) for all hypotheses. We do not report the estimates of the measurement equations, but all were significant and had acceptable levels (these results are available on request). We also estimated standard deviations for the random coefficients in the model. Here, we found significant heterogeneity on all parameters in the mass customization utility model (Equation 1) and on the parameters of the latent variables in the product utility and complexity models (Equations 2 and 3). For the mass customization factors, we find only one parameter with significant heterogeneity for the product utility model and three for the complexity model. In the context of our experiment, there is relatively little difference in the impact of mass customization configuration factors among consumers. Finally, we controlled for respondents' progress through the experiment. We found that as respondents progressed, both product utility and complexity decreased, the former possibly due to boredom or fatigue and the latter more likely due to learning.

FURTHER ANALYSES

We compared the proposed model with two nested model specifications (a model without random coefficients and a model in which the effect of consumer expertise was not included) and two nonnested specifications (a model that did not include complexity and a model in which neither complexity nor product utility was included). We found that in all specifications, parameter estimates were identical in sign and had effects similar to the proposed model. A log-likelihood ratio test revealed that the proposed model outperformed both nested alternatives ($p < .01$), and a comparison of consistent Akaike information criterion scores showed that it also outperformed the two nonnested alternatives. We also investigated whether an alternative explanation for the observed effect of complexity on product utility could be a moderating effect of complexity on the relationship between product utility and mass customization utility. We estimated a model that included both effects and found our previous results to be robust to the additional moderating effect. The moderating effect itself was also significant.

Table 2

MASS CUSTOMIZATION PREFERENCES: RANDOM COEFFICIENT EXTENDED LOGIT MODEL[a]

	Effect on Mass Customization Utility		
	Parameter	*t-Value*	*Hypothesis*
Intercept (α^{MC})	–4.32	–22.67[b]	
Product utility (β^{MC}_{PROD})	6.10	14.65[b]	**H_{1a}**
Random coefficient (s.d.)	8.60	18.76[b]	
Complexity (β^{MC}_{COMPL})	–.43	–7.70[b]	**H_{1b}**
Random coefficient (s.d.)	.21	21.02[b]	

	Effect on Product Utility			*Effect on Complexity*		
	Parameter	*t-Value*	*Hypothesis*	*Parameter*	*t-Value*	*Hypothesis*
Variable level intercept (α^{PROD} and α^{COMPL})	.39	64.22[b]		–.45	–19.36[b]	
Random coefficient (s.d.)	.20	63.93[b]		1.44	45.58[b]	
Complexity (β^{PROD}_{COMPL})	–.02	–9.67[b]	**H_2**			
Random coefficient (s.d.)	.04	21.02[b]				
Complexity × consumer expertise ($\beta^{PROD}_{EXPCOMPL}$)	.01	5.66[b]	**H_8**			
Consumer expertise (β^{PROD}_{EXP}) and (β^{COMPL}_{EXP})	.04	12.06[b]	N.A.	–.74	–42.75[b]	**H_7**
Random coefficient (s.d.)	.09	32.15[b]		.04	4.45[b]	
Mass Customization Configuration Factors[c]						
Number of mass customizable modules	.02	4.77[b]	**H_{3a}**	.01	.84	H_{3b}
Random coefficient (s.d.)	.01	2.28[b]		.03	1.97[b]	
Number of levels	.01	1.51	H_{3a}	–.02	–1.25	H_{3b}
Random coefficient (s.d.)	.01	1.62		.01	.46	
Level heterogeneity	–.01	–3.45[b]	**H_{4a}**	.01	.76	H_{4b}
Random coefficient (s.d.)	.00	.35		.04	2.10[b]	
Individual pricing of mass customizable modules	–.01	–2.06[b]	**H_{5a}**	.05	3.57[b]	**H_{5b}**
Random coefficient (s.d.)	.00	.33		.05	3.43[b]	
Default present	–.01	–2.66	N.A.	.00	.27	N.A.
Random coefficient (s.d.)	.00	.75		.00	.22	
Base versus advanced default	.03	4.46[b]	**H_6**	–.01	–.70	N.A.
Random coefficient (s.d.)	.00	.39		.01	.54	

[a]N = 409 (total number of observations is 2427). Hypotheses that were confirmed are bold. For expositional clarity and in the interest of space, only hypothesized effects and intercepts are reported. Full estimation results are available on request.

[b]Significant at the 95% confidence level.

[c]The vectors $\boldsymbol{\beta}^{PROD}_{CONF}$ and $\boldsymbol{\beta}^{COMPL}_{CONF}$ capture the effects of all mass customization configuration factors.

Notes: s.d. = standard deviation; N.A. = not applicable.

A more detailed investigation of this effect suggested that consumers are more willing to accept the complexity of a mass customization configuration if the configuration allows them to achieve a higher product utility. Heath and colleagues' (2000) residual-desire effect could explain this finding. The authors suggest that when consumers trade off product quality loss and price, they are more concerned about forgone product quality than increased monetary costs. A similar effect could occur in the trade-off of product utility and effort, and consumers could be more willing to trade off effort for product utility than vice versa, making them less sensitive to complexity when product utility is high.

A restriction of our experimental design was that in configurations with a default version, we provided respondents with only one default, which was either a base or an advanced version. To test whether this approach may have affected our conclusions with respect to H_6, we ran an additional experiment with students at the first author's university. In this experiment, we copied the three default PC versions that were available through the Dell Web site at the time (i.e., base, intermediate, and advanced) as well as all modules and levels as they were available. This experiment had five versions. Versions 1, 2, and 3 had only the base, intermediate, and advanced default, respectively. In Version 4, all three defaults were first shown and briefly described on a separate screen, after which respondents could mass customize their PC, beginning with the default they preferred. Version 5 had no default. We randomly assigned respondents across versions. After composing a PC, respondents were asked about product utility, complexity, and mass customization utility. The number of respondents was 61, 46, 37, 41, and 39 for Versions 1 through 5, respectively.

From a multivariate analysis of variance that compared the mean scores for each of the factors across the versions, we found that respondents reported the highest product utility level when we presented them with a base default ($p <$ .05 for all versions, except the intermediate default), confirming our previous conclusion with respect to H_6. We also found that offering an intermediate default version led to the lowest perceived complexity, which was significantly lower than if multiple defaults or an advanced default was offered (both $p < .05$). We can explain this effect on complexity by the intermediate default being closest to most respondents' ideal product.

DISCUSSION

We found that within the rather large range of modules and module levels that we manipulated in this study, consumers did not perceive significant increases in complexity, and they were indeed able to achieve higher product utility. This is good news for firms that want to provide many options to consumers. We also found that the negative effects of complexity on mass customization utility are lower for expert consumers, making them a potentially attractive target segment for mass customization.

Thus, within the context of our experiment, we conclude that firms can benefit from the introduction of extensive mass customization by using a carefully designed mass customization configuration. Three features deserve more attention: First, level heterogeneity should not come at the expense of level availability in the most popular level range, because otherwise, product utility may be reduced. Second, pricing should be presented at the alternative rather than at the module level. This approach reduces complexity and increases product utility. Third, when consumers are presented with default versions, they obtain a higher product utility when presented with a base default than when presented with an advanced default.

Limitations and Further Research

Some limitations of our study are worth noting. Consumers in our experiment made hypothetical mass customization decisions and reported in terms of their intended use of a mass customization configuration in only one product context. Although we used real consumers in our study and took great care to develop realistic experimental conditions, consumers' decisions in the real world and/or for other product categories may differ. Moreover, we found evidence of learning as consumers progressed through the experiment. It would be worthwhile to test our model in other contexts to determine whether the effects we observed are generalizable.

Nevertheless, we hope that our research can be a starting point for further research in marketing on mass customization. We outline some promising areas for further research that also reveal additional limitations of our study. Because our research focuses on consumers' utility for different mass customization configurations, we do not address the question of how consumers choose between buying a mass-customized product and buying a standardized product. It would be relevant to study this latter question. In addition, we chose a setting in which consumers mass customized the product by choosing module levels to fit their most preferred product. However, in some cases, the supplier may take over this role on behalf of the consumer. It would be of interest to study the role of the supplier in such a mass customization choice process.

There also are aspects in our model that warrant more-detailed research, especially at the level of consumer information processing. Complexity may have the character of an individual trait rather than a task-specific effect, which could explain why the extent of mass customization has little impact on complexity. Further research could also investigate variations in consumers' decision strategies regarding different aspects of mass customization configurations. For example, different consumers may process individual prices and default suggestions differently. It would also be interesting to investigate whether consumers enjoy mass customizing a product. Research on self-service technology suggests that this is the case (Dabholkar and Bagozzi 2002). Finally, we believe that it would be worthwhile to establish an evaluation criterion that could be used to study whether consumers buy "better" or "worse" products when they mass customize than when they choose between standardized products. A possible candidate for such a criterion could be the measuring of consumers' product satisfaction after a certain period of use.

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