KEITH WILCOX and SANGYOUNG SONG*

This research demonstrates that during self-customization, consumers use their experiences from prior feature decisions to form expectations about subsequent decisions. When the difficulty experienced during decisions later in the process deviates from that which occurs earlier in the process, consumer preference is affected by the discrepancy between actual and expected difficulty. Specifically, the results show that when the difficulty experienced during feature decisions deviates from expectations, consumers may spend more or less money on product features as a result of discrepant fluency than when they perform the same task and the level of difficulty is expected. The results demonstrate that discrepant fluency effects are not limited to sequential decisions but can influence a single feature decision, which was accomplished by altering consumers' expectations before the decision. These discrepant fluency effects emerge even when the attributes of the alternatives and the composition of the focal decision settings remain the same.

*Keywords*: fluency, customization, decision framing, sequential choice, expectations

# Discrepant Fluency in Self-Customization

Consumers base their product judgments on a variety of factors. To illustrate, consider a consumer's decision to upgrade the hard drive on a computer while customizing it online. The decision will likely involve comparing the amount of additional memory to the cost of the upgrade relative to his or her needs. During this process, however, several other factors could influence the consumer's decision. Research on fluency, for example, suggests that the level of difficulty experienced during the feature's evaluation may affect whether it is chosen because consumers often like products more when they are easy to process than when they are difficult to process (Labroo, Dhar, and Schwarz 2008; Lee and Labroo 2004). Although many types of fluency exist, a common finding is that people often misattribute the ease experienced at the time of judgment with more favorable product evaluations. Thus, the consumer may be more likely to upgrade the hard drive if he or she experiences ease while evaluating the feature.

Although such fluency effects are well documented in marketing (see Schwarz 2004), previous research has focused on the effect of fluency on a single product evaluation in which the level of difficulty is changed at the time of judgment. However, many purchasing situations, especially those that entail self-product-customization (Valenzuela, Dhar, and Zettlemeyer 2009) involve multiple, related evaluations. For example, to customize a laptop computer online, consumers make a series of feature decisions that often vary in difficulty before completing their purchase. Although previous research has suggested that the ease or difficulty experienced during such decisions can affect the choice of features, researchers have not considered whether differences in the difficulty experienced during feature decisions influence subsequent customization preferences. Could the level of difficulty experienced while evaluating features in a customization process affect the outcome of subsequent decisions? Considering the prevalence of self-customization as a strategic tool—which appears in industries as diverse as computers, apparel, and automobiles—an answer to this question holds great significance for marketers.

In this research, we focus on fluency effects that influence feature preference during self-customization. We define discrepant fluency as a fluency effect that emerges when there is a discrepancy between the expected and the actual difficulty experienced at the time of judgment. We

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demonstrate that when the difficulty experienced later in the customization process deviates from the difficulty experienced earlier, this discrepancy influences consumer preference. Specifically, we show that discrepant fluency can lead consumers to spend more, and in some cases less, money on product options than when they perform the same task when the level of difficulty is expected. Importantly, we also demonstrate that discrepant fluency effects are not limited to sequential decisions but can also emerge in a single feature decision by misaligning consumers' expectations with the difficulty experienced during the decision.

As a result, this research offers several contributions. Although prior research has shown the effects of a previous decision on consumer preference, much of this research has focused on how the content (e.g., prices) of previous decisions affects preference during a current decision (see Simonson and Tversky 1992). To the best of our knowledge, our study is the first to demonstrate that a current decision can be influenced by the level of difficulty experienced during a previous decision without changing the content of the previous decision. In addition, by demonstrating that discrepant fluency effects can materialize by altering consumers' expectations for a single decision, our findings should be applicable to a large array of situations in which expectations can be manipulated before choice. This research has important implications for managers as well. Specifically, while it is generally assumed that managers should make it easy for consumers to make decisions (Novemsky et al. 2007), our findings indicate that, in some situations, managers may be able to increase sales by increasing the difficulty experienced during a decision to affect the fluency of subsequent product judgments.

## *FLUENCY AND CONSUMER JUDGMENT*

While content-focused models of judgment suggest that decisions derive from the substance of information considered, the subjective experiences that accompany thought processes can also serve as a basis for judgment (Janiszewski 1993; Labroo and Lee 2006; Reber, Wurtz, and Zimmerman 2004; Schwarz 2004; Shapiro 1999). The processing fluency/attribution model adopts a cognitive perspective and suggests that people generate inferences according to the level of difficulty experienced at the time of judgment and often misattribute fluency to evaluations of stimuli. For example, people conclude that they like a product more when they must recall two as opposed to eight attributes because they misattribute the ease of retrieving fewer attributes to their more positive feelings toward the product (Menon and Raghubir 2003). In addition, consumers evaluate products that are easy to process, both conceptually (Lee and Labroo 2004) and visually (Labroo, Dhar, and Schwarz 2008), more favorably than they do those that are difficult to recognize because they mistake the ease of processing for greater liking. Consumers also infer that the price difference between two products is larger if they find it easy to compute the difference (Thomas and Morwitz 2009). Although this literature has identified many types of fluency (e.g., ease of processing, ease of computation) that produce different inferences (e.g., greater product liking, larger price differences), all these studies suggest that consumer evaluation can be influenced by the difficulty experienced at the time of judgment.

## *DISCREPANT FLUENCY AND SELF-CUSTOMIZATION*

### *The Discrepancy Hypothesis*

We propose that the ease or difficulty experienced during self-customization decisions may not influence judgment unless the level of difficulty deviates from expectations. That is, the effect of fluency on judgment may have less to do with the level of difficulty per se than with the perceived discrepancy between the actual and the expected level of difficulty at the time of judgment. For example, if a consumer expects to experience difficulty while making a product feature decision but then finds the decision to be easy, the unexpected ease of the experience should have a greater impact on judgment than if he or she had expected the evaluation to be easy. Support for this prediction comes from research (Whittlesea and Williams 1998, 2000) finding that people experience greater familiarity when they observe nonwords that are easy to pronounce (e.g., hension) compared with actual words (e.g., station) or difficult-to-pronounce nonwords (e.g., lictpub). If feelings of familiarity depend on the ease of processing alone, people should judge the actual words as more familiar. However, because people anticipate the processing of nonwords to be difficult, when processing is unexpectedly easy, they attribute the discrepancy to their greater familiarity (i.e., the fluency of the experience influences their judgment). Recent studies have also shown that perceptual fluency influences judgments of truth when the fluency level deviates from a previous level (Hansen, Dechene, and Wanke 2008). Although little is known about the marketing variables that may lead to the formation of baseline fluency expectations (Schwarz 2004) and its impact on consumer preference, research suggests that previous experiences have a direct influence on expectations. This research has strong implications for discrepant fluency in self-customization.

### *Prior Decisions and Expectations*

Consumers' expectations for an experience are often based on their prior knowledge and information that is stored in memory (Goode, Dahl, and Moreau 2010). For example, consumers learn that higher prices often are positively correlated with greater quality, so they expect expensive products to be more enjoyable than inexpensive ones (Plassmann et al. 2008). In addition, receiving information that a movie is good produces favorable expectations, which can serve as comparison standards for judging the experience (Klaaren, Hodges, and Wilson 1994). Although much of the prior research has focused on how presenting information regarding benefits, attributes, and functionality can shape consumer expectations, a growing body of evidence indicates that past experiences also can serve as a standard for judging a present experience. For example, Tversky and Griffin (1991) find that people contrast their experiences when they happen sequentially and that any given experience can serve as a standard for comparing future experiences (see also Novemsky and Ratner 2003). Biswas, Grewal, and Roggeveen (2010) demonstrate that when consumers sequentially sample experiential products (e.g., music), the experiences earlier in the sequence serve as comparison standards for judging subsequent experiences. Finally, Goode, Dahl, and Moreau (2010) argue that previous disparate experiences may serve as baseline expectations for judging new experiences.

Together, these findings suggest that in a self-customization process, the difficulty experienced during a previous decision can serve as an expected standard for comparing the difficulty experienced subsequently. Therefore, if the difficulty experienced subsequently deviates from that standard, it may result in a fluency effect on judgment. Our central premise holds that in self-customization, consumers may experience fluency when the difficulty experienced while making feature decisions later in a sequence deviates from a previous level of difficulty. Thus, discrepant fluency is a fluency effect that depends less on the actual level of difficulty experienced than the discrepancy between actual and expected difficulty. Importantly, we argue that because the discrepancy is due to a divergence from expectations, the fluency effect can be enhanced or reduced by altering consumers' expectations without changing the level of difficulty at the time of judgment. This suggests that discrepant fluency effects should not only emerge in sequential decisions but also influence single feature decisions when consumers' expectations for the difficulty to be experienced are misaligned with the actual difficulty. As we discuss next, however, the outcome of discrepant fluency on customization preferences depends on the inferences generated by the discrepancy.

### *Discrepant Fluency and Self-Customization Preference*

Although there are numerous types of fluency, which can produce different inferences that have distinct effects on consumer judgment, one of the most common inferences generated by fluency is greater liking. Numerous studies demonstrate that when consumers experience ease while evaluating a product or brand, they infer that they like it more (Labroo, Dhar, and Schwarz 2008; Lee and Labroo 2004; Menon and Raghubir 2003), which can increase the likelihood that they will select it (Ferraro, Bettman, and Chartrand 2009). In Studies 1 and 2, we rely on decision framing (i.e., rejecting or adding features) to show that the effect of the experience of ease on preference is strongest when the level of difficulty deviates from a previous level of difficulty. Previous customization studies (Levin et al. 2002; Park, Jun, and MacInnis 2000) indicate that participants retain more optional features when they reject than they do when they add because consumers are more loss averse for quality than for money (Park, Jun, and MacInnis 2000). Importantly, this research also finds that decisions to reject are more difficult than those to add (Novemsky and Kahneman 2005; Park, Jun, and MacInnis 2000). Drawing on these findings, in Study 1, we presented participants with two sets of optional features for a product and created a discrepancy by altering the framing of the decisions. Specifically, participants customized a laptop computer that required them to either add or reject an initial set of features before deciding whether to add a subsequent set of features. We demonstrate that consumers add more features when they previously rejected features (a more difficult decision) than when the same decisions are preceded by a task of similar difficulty (i.e., an adding task). We also show that the discrepant fluency effect is reduced by manipulating consumers' expectations that the second task will be easier. Study 2 replicates these findings in a different category (i.e., cars) and demonstrates that inferences of liking mediate the effect of the discrepancy on preference.

Study 3 shows that the inferences generated by discrepant fluency during self-customization are not limited to judgments of liking. Thomas and Morwitz (2009) find evidence for an ease-of-computation effect whereby consumers' naive belief that it is easier to judge the size of larger price differences than smaller price differences systematically biases judgment. Specifically, they demonstrate that when people are presented with two alternatives with price differences that are easy to compute, they infer the difference to be larger, which decreases their preferences for the higher-priced alternative compared with when the price differences are easy to compute. In Study 3, we show that the ease or difficulty experienced while computing price differences during customization may only affect preference when the difficulty deviates from expectations. Specifically, we show that consumers infer a price difference to be smaller (larger) when the prices are more difficult (easier) to compute than those in a previous customization decision, which increases (decreases) their preference for the higher-priced option in the current decision. That is, we show that discrepant fluency can influence customization preference by making price differences seem smaller or larger without changing the difficulty experienced during the decision. In Study 4, we replicate the findings from Study 3 in a different product category (i.e., digital cameras) and create the discrepancy by manipulating participants' expectations before having them make only one feature decision.

## *STUDY 1*

In Study 1, participants added or rejected an initial set of features for a laptop computer before adding a subsequent set of features. We expected participants to add more features in the subsequent set when it was preceded by a more difficult rejection task than when it was preceded by an adding task of similar difficulty. Furthermore, we predicted that the effect would be mitigated by aligning participants' expectations with the difficulty of the subsequent set.

### *Method*

*Pretest of set composition.* Forty pretest participants drawn from the same population as the main study rated the features of a laptop computer according to how likely they would be to add a premium upgrade of the feature (1 = "not likely at all," and 7 = "very likely") and how important it would be to add the feature upgrade (1 = "not important at all," and 7 = "very important"). On the basis of the pretest results, the main study contained 14 features, divided into two equivalent groups that were comparable in terms of the cost to upgrade ($M_{Initial}$ = \$85.71, $M_{Subsequent}$ = \$85.71), likelihood of upgrading ($M_{Initial}$ = 4.55, $M_{Subsequent}$ = 4.62), and importance ($M_{Initial}$ = 5.13, $M_{Subsequent}$ = 5.16).

*Participants and design.* One hundred thirteen undergraduate students at a large northeastern U.S. university participated in the main study. The experiment employed a 2 (discrepancy: high vs. low) × 2 (expectations: control vs. easier) between-subjects design.

*Procedure.* We randomly assigned participants to one of the four conditions. In all conditions, we told participants that they would be customizing a laptop computer and gave them a starting price, which varied by condition. Then, they considered the initial feature set and either rejected or added premium features depending on the discrepancy condition. After making the initial set of decisions, approximately half the participants received consensus information that was designed to manipulate expectations regarding the difficulty of the subsequent set (adapted from Menon and Raghubir 2003). Specifically, we told respondents that they would be customizing another set of features on the computer and that the majority of students that had participated in the study previously found the decisions to be easier than those for the initial set (easier conditions). The remaining participants were not given consensus information (control conditions). All participants then decided whether to add premium features in the subsequent set. We counterbalanced the presentation order of the features within each feature set.

In the high-discrepancy conditions, participants were purchasing a laptop computer with a starting price of $1,200, but because they could add or reject features, the final price would be between $600 and $1,800. We then sequentially presented two versions of each feature (a lower-priced, basic version and a higher-priced, premium version) in the initial feature set in which they were endowed with the premium versions and asked participants whether they would like to reject them. After the participants made their decisions about the initial feature set, they made decisions about the subsequent feature set, except that they were endowed with the lower-priced, basic versions and were asked whether they would like to add the premium upgrades. In the low-discrepancy conditions, participants were instructed that the model they were customizing started at $600 but that the final price could be as high as $1,800 after adding features. The decision framing remained constant in both the initial and the subsequent sets. That is, participants were endowed with the basic version of each feature and considered whether they wanted to add the premium versions of each feature.

*Measures*. We recorded the number of premium features selected in each feature set (features selected), how much was spent on features (spending), and the time to make a decision about each feature (decision time) as a measure of decision difficulty. We created a measure of discrepancy by subtracting the time to complete the initial set from the time to complete the subsequent set, with negative numbers corresponding to easier subsequent decisions.

### *Results*

We analyzed features selected in the initial and subsequent feature sets and spending using analysis of variance (ANOVA). We used discrepancy, expectation, and their interaction as independent factors.

*Manipulation check*. Participants took longer to make their decisions about the initial feature set when they rejected than when they added features ($M_{Add}$ = 7.4 seconds, $M_{Reject}$ = 11.1 seconds; t = 8.03, $p < .001$). An ANOVA with the discrepancy measure as the dependent variable revealed a main effect of discrepancy ($F(1, 109) = 16.70$, $p < .001$) and no significant interaction ($F(1, 109) = .01$, n.s.). As we expected, participants took less time to complete the subsequent set than the initial set when they added features following a rejection task (M = –13.1 seconds); a t-test confirmed that the discrepancy was significantly less than zero (t = –4.39, $p < .001$). The discrepancy was smaller when participants added features following an adding task (M = .7 seconds; t = .42, n.s.) and was not significantly different from zero. These results validate the discrepancy manipulation.

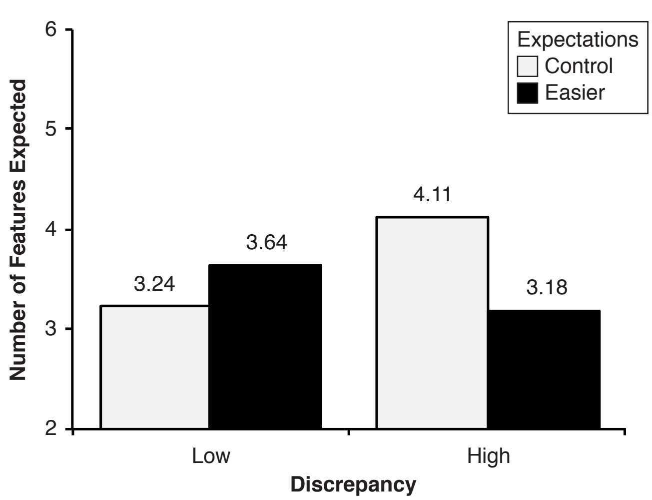
*Initial feature set decisions*. When participants customized the initial feature set, they lacked any decisions against which to contrast their experiences. Therefore, preference should have depended less on fluency and more on loss aversion due to differences in the framing of the alternatives (Park, Jun, and MacInnis 2000). Consistent with this prediction, we found a main effect of discrepancy on features selected ($M_{Low}$ = 3.39, $M_{High}$ = 4.09; $F(1, 109) = 5.41$, $p < .05$) and no significant interaction ($F(1, 109) = 1.30$, n.s.). That is, participants who rejected features retained more features than those who added them in the initial set, consistent with prior research on option framing in product customization (Levin et al. 2002; Park, Jun, and MacInnis 2000).

*Subsequent feature set decisions*. As we illustrate in Figure 1, the interaction between discrepancy and expectations was significant for the features selected in the subsequent set ($F(1, 109) = 4.82$, $p < .05$). Participants in the control condition selected more features in the high-discrepancy condition than in the low-discrepancy condition ($M_{Low}$ = 3.24, $M_{High}$ = 4.11; $F(1, 109) = 4.12$, $p < .05$). However, we found no significant difference in the features selected between the low- and high-discrepancy conditions when participants expected the subsequent set to be easier ($M_{Low}$ = 3.64, $M_{High}$ = 3.18; $F(1, 109) = 1.16$, n.s.). Furthermore, participants selected more features in the high-discrepancy condition when they did not have consensus information than when they believed the subsequent task would be easier ($M_{Control}$ = 4.11, $M_{Easier}$ = 3.18; $F(1, 109) = 4.66$, $p < .05$). Together, these results support our prediction that the experience of unexpected ease during feature decisions increases preference for the features.

*Spending*. Because of its relevance to managers, we also analyzed spending in the subsequent feature set. The interaction between discrepancy and expectation on spending was

Figure 1

STUDY 1: THE EFFECT OF DISCREPANCY ON SUBSEQUENT SET PREFERENCE



significant ($F(1, 109) = 5.33$, $p < .05$). Participants in the control condition spent more on features in the high-discrepancy condition than in the low-discrepancy condition ($M_{Low}$ = \$272, $M_{High}$ = \$353; $F(1, 109) = 4.29$, $p < .05$). However, we found no significant difference in the features selected between the low- and the high-discrepancy conditions when participants expected the subsequent set to be easier ($M_{Low}$ = \$313, $M_{High}$ = \$266; $F(1, 109) = 1.43$, n.s.). Furthermore, participants selected more features in the high-discrepancy condition when they did not have consensus information than when they believed the subsequent task would be easier ($M_{Control}$ = \$353, $M_{Easier}$ = \$266; $F(1, 109) = 4.94$, $p < .05$).

*Alternative hypotheses tests*. Although the results are consistent with our theory, we also acknowledge possible alternative explanations. Research on self-regulation suggests that when people engage in mentally challenging tasks, they may deplete key resources needed to exert self-control in subsequent tasks (Vohs et al. 2008). Therefore, more difficult initial decisions may decrease the resources available to exert self-control, which would lead people to select more expensive features in the subsequent task. To rule this out, we conducted an additional analysis of the choices in the subsequent set when participants had no consensus information. If the increase in preferences for features in the subsequent set in the high-discrepancy condition results from resource depletion, the effect should be strongest at the end of the subsequent set, after participants have made most of their choices. Specifically, the difference in the percentage of participants selecting the premium option between the high- and the low-discrepancy conditions should be greatest for the last feature selected (i.e., the 14th option). However, an analysis of each choice in the subsequent set (features 8–14) revealed that the difference was greatest for the 8th feature (high = 79%, low = 45%; Wald's $\chi^2 = 6.46$, $p < .05$). Other than a marginally significant difference pertaining to the 9th option (high = 68%, low = 45%; Wald's $\chi^2 = 3.01$; $p < .10$), we found no other significant differences between the high- and the low-discrepancy conditions. Thus, the effect of the initial set difficulty on feature preference was strongest immediately after the initial set, consistent with the discrepant fluency hypothesis, because the discrepancy should be greatest right after a shift from a difficult decision to one that is easier.

Another potential explanation for the results in the control condition is that people may have used the number of features selected in the initial set as an anchor. Thus, because people selected more options in the initial set when they rejected features, the greater number of options selected in the initial set may have influenced the number of features selected in the subsequent set. Although there was a positive correlation between the number of features selected in the initial and the subsequent sets ($r = .39$, $p < .01$), the correlation was significant in the low-discrepancy condition ($r = .37$, $p < .05$) but not in the high-discrepancy condition ($r = .31$, n.s.). A supplemental analysis of the number of features selected in the subsequent set using analysis of covariance with discrepancy, expectation, and their interaction as independent factors and the number of features selected in the initial feature set as a covariate produced equivalent results to those we reported previously. Thus, it is unlikely that the results are due to anchoring on the number of features selected in the initial set.

### *Discussion*

The results of Study 1 support our hypothesis that the discrepancy between the actual and the expected difficulty associated with the subsequent set leads to customization preferences that reflect the unexpected ease experienced during those decisions. When participants rejected features before subsequently adding features, they selected more features in the subsequent set than when the subsequent set was preceded by an adding task of similar difficulty. We also demonstrated that the effect was mitigated when participants expected the subsequent feature set to be easy.

## *STUDY 2*

The primary objectives of Study 2 were to replicate the findings in a different product category (automobiles) and to provide evidence that the findings were the result of increased liking. To enhance the external validity of our findings, we conducted the study on an online panel comprised of nonstudent participants. Furthermore, we simplified the design so that participants only made a decision on two features (an initial feature and a subsequent feature) during the customization task. Finally, we manipulated expectations differently. Previous research has shown that priming the concept of ease can alter expectations and serve as a comparison standard for judging the fluency of a subsequent experience (Hansen and Wanke 2008). Thus, we primed or did not prime the concept "easy" before the subsequent decision.

### *Method*

*Participants and design*. One hundred twenty-one people in an online panel (aged 21–63 years) participated in the study. The experiment used a 2 (discrepancy: high vs. low) × 2 (expectations: neutral prime vs. easy prime) between-subjects design.

*Procedure*. The procedure was similar to that of Study 1 with a few notable exceptions. First, participants were instructed that they would be customizing a new car by the Mode Motor Company, a fictional carmaker. Then, they were given one initial feature to reject or add depending on the condition. Specifically, participants in the high-discrepancy condition were initially endowed with the feature and asked if they wanted to remove it from their car configuration. Participants in the low-discrepancy condition were not endowed with the feature and were asked if they wanted to add it. Afterward, we primed or did not prime the concept "easy." Specifically, after participants made their first feature selection, there was a brief interruption while the next option was being loaded. During the interruption, approximately half of the participants saw the words "Mode Motor Company" (neutral condition). The remaining participants saw the words "Customization Made Easy" (easy prime condition). The words remained on the screen for five seconds before participants were presented with the subsequent feature and asked whether they wanted to add the option. The two features used in this study were GPS navigation (\$1,500) and leather seats (\$1,400). We counterbalanced the presentation order of the features so that half the participants decided on the GPS navigation initially. After making their subsequent feature decision, participants indicated how much their liked the subsequent feature.

*Measures*. We recorded preference for the initial and subsequent feature (preference) and the time required to make a decision about each feature (decision time). We measured discrepancy by subtracting the time to make the initial decision from the time to make the subsequent decision. We measured liking with a three-item, seven-point semantic differential scale (1 = "dislike," and 7 = "like"; 1 = "not enjoy," and 7 = "enjoy"; and 1 = "not pleasing," and 7 = "pleasing"; $\alpha = .98$).

### *Results*

We analyzed preference for the initial and subsequent feature using logistic regression, with discrepancy, expectation, and their interaction as independent variables. A separate logistic regression analysis that added the presentation order of the features to the current analysis revealed that the presentation order did not interact with any other factor in our model and produced equivalent results.

*Manipulation check*. As we anticipated, it took longer for participants to reject the feature than to add it ($M_{Reject}$ = 18.5 seconds, $M_{Add}$ = 15.1 seconds; t = 2.35, $p < .05$). An ANOVA with the discrepancy measure as the dependent variable revealed a main effect of discrepancy ($F(1, 117) = 7.27$, $p < .001$) and no significant interaction ($F(1, 117) = .06$, n.s.). Participants took less time to make the subsequent decision than the initial decision when they added the feature following a rejection task (M = –4.0 seconds; t = –4.21, $p < .001$). The discrepancy was smaller when participants added features following an adding task (M = –.8 seconds; t = –1.00, n.s.) and was not significantly different from zero. These results validate the discrepancy manipulation.

*Initial feature decision*. As in Study 1, we found a main effect of discrepancy on preference for the initial feature (low = 38.6%, high = 57.8%; Wald's $\chi^2 = 4.57$, $p < .05$). However, we found no significant interaction (Wald's $\chi^2$ = 1.62, n.s.).

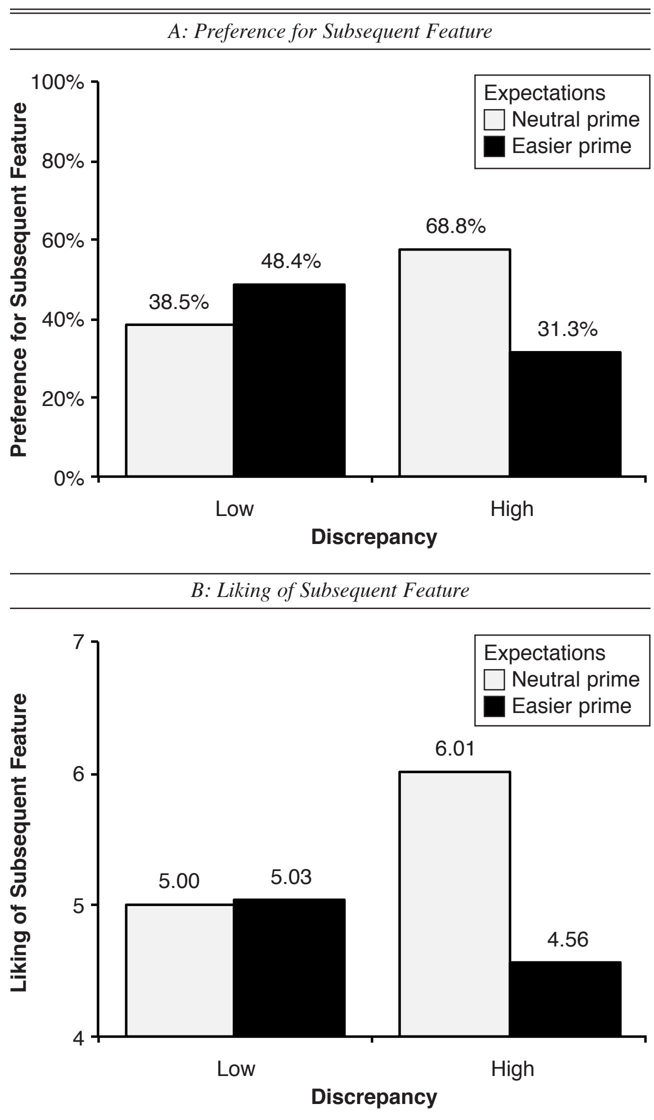
*Subsequent feature set decisions*. As we illustrate in Figure 2, we obtained a significant expectations × discrepancy interaction effect on preference for the subsequent feature ($\beta = -1.98$; Wald's $\chi^2 = 5.14$, $p < .05$). Consistent with our prior findings, participants were more likely to select the subsequent feature in the high-discrepancy condition (68.8%) than in the low-discrepancy condition (38.5%) when there was a neutral prime (Wald's $\chi^2 = 5.14$, $p < .05$). However, we found no significant difference between high-discrepancy (31.3%) and low-discrepancy (48.4%) conditions when there was an easy prime (Wald's $\chi^2$ = 1.91, n.s.). Finally, participants were more likely to select the subsequent feature when there was a neutral prime (68.8%) than when there was an easy prime (31.3%) in the discrepancy conditions (Wald's $\chi^2 = 8.55$, $p < .01$).

*Liking*. As we illustrate in Figure 2, we obtained a significant expectations × discrepancy interaction effect on liking of the subsequent feature ($F(1, 117) = 5.76$, $p < .05$). As we expected, participants liked the subsequent feature more in the high-discrepancy condition than in the low-discrepancy condition when there was a neutral prime ($M_{Low}$ = 5.00, $M_{High}$ = 6.01; $F(1, 117) = 5.13$, $p < .05$). However, we find no significant difference between high- and low-discrepancy conditions when there was an easy prime ($M_{Low}$ = 5.03, $M_{High}$ = 4.56; $F(1, 117) = 1.22$, n.s.). Finally, participants liked the subsequent feature more when there was a neutral prime than when there was an easy prime in the discrepancy conditions ($M_{NeutralPrime}$ = 6.01, $M_{EasyPrime}$ = 4.56; $F(1, 117) = 11.74$, $p = .001$).

*Mediation*. We conducted a test for mediated moderation using the three models suggested by Muller, Judd, and Yzerbyt (2005) to assess whether the interaction effect of discrepancy and expectations on preference was mediated by liking. The first model is the previously discussed analysis of preference, which establishes the discrepancy by expectations interaction on preference. The second model is a regression analysis with liking as the dependent variable and discrepancy, expectations, and their interaction as the independent variables, which demonstrates a significant discrepancy × expectations interaction on liking ($\beta = -1.40$; t = –2.25, $p < .05$). The third model adds liking and the interaction between liking and expectations as independent pre-

Figure 2

STUDY 2: THE EFFECT OF DISCREPANCY ON SUBSEQUENT FEATURE PREFERENCE AND JUDGMENTS OF LIKING



dictors to the first model. There is a significant effect of liking on preference ($\beta = .65$; Wald's $\chi^2 = 6.91$, $p < .01$) and the discrepancy × expectations interaction was reduced from $\beta = -1.98$ (Wald's $\chi^2 = 5.14$, $p < .05$) to $\beta = -1.33$ (Wald's $\chi^2 = 2.33$, n.s.). This pattern of results supports liking as a mediator of the discrepancy × expectations interaction effect on preference.

### *Discussion*

The results of Study 2 provide further support for our model of discrepant fluency in sequential customization. Specifically, we demonstrated that when consumers experience unexpected ease while evaluating a product feature, they infer that they like it more, which increases preference for the feature. In the next study, we demonstrate that discrepant fluency is not limited to judgments of liking but can also affect customization preference by influencing consumers' inferences regarding the magnitude of the difference in prices between two product options. In doing so, we show that discrepant fluency can lead consumers to spend more or less money on features during self-customization.

## *STUDY 3*

Recent research has demonstrated that consumers believe that it is more difficult to judge the size of smaller price differences than larger price differences (Thomas and Morwitz 2009). As a result, they often misattribute the ease or difficulty experienced while computing a price difference to the size of the difference. When consumers experience ease computing a price difference, they infer that the difference between prices is larger. In a recent study, Thomas and Morwitz (2009) gave participants six different price points and asked them, at each price point, whether they would choose to purchase their favorite brand of memory stick over a less expensive brand. The price differences were easy (e.g., \$41.00 vs. \$35.00) or difficult to compute (\$41.56 vs. \$35.00). They found that easy-to-compute price differences decreased the likelihood of selecting the more expensive brand because participants incorrectly judged the price differences to be larger than when the prices were difficult to compute. Their research also suggests that when consumers experience difficulty computing a price difference between two options, they infer that the price difference is smaller, which should increase their preference for the higher-priced option.

In Study 3, we sought to replicate these findings by having participants choose between two versions of product features in a sequential customization task (i.e., an initial decision and subsequent decision). However, we wanted to show that the ease or difficulty of price difference computations only affects customization preference when it deviates from an expected standard. In most of their studies, Thomas and Morwitz (2009) used prices that were relatively small (most price differences under \$10), so participants were more likely to expect the differences to be relatively difficult to compute, and the ease-of-computation effect emerged. In Study 3, we used larger price differences (more than \$10) because we predicted that participants initially would expect such differences to be easy to compute, thus mitigating the ease-of-computation effect on participants' initial decisions. However, after participants made their initial decision, actually experiencing ease or difficulty, we expected preference in the subsequent decision to be determined by the extent to which the price computation difficulty deviated from that of the initial decision. Specifically, we predicted that participants would infer that easy-to-compute price differences were larger when they previously experienced difficulty computing price differences. This should decrease their preference for the higher-priced option compared with participants who did not experience a discrepancy (i.e., those who made easy price difference computations in each decision). However, when participants previously experienced ease in computing the price difference, we expected them to infer that difficult-to-compute price differences were smaller. Thus, we expected a reversal in preference when the price computations were more difficult than those in the previous decision such that participants would be more likely to select the higher-priced option compared with those who did not experience a discrepancy (i.e., those who made difficult price difference computations in each decision).

### *Method*

*Pretest*. To ensure that participants expected larger price differences to be easier to compute than smaller price differences, we conducted a pretest on 46 undergraduate students from the same population as the main study. We told all participants that they were deciding between two brands that differed in price. We further instructed approximately half of the participants that the difference in the prices was between \$1 and \$10. We instructed the remaining participants that the difference was between \$10 and \$100. All participants then indicated how difficult they expected it would be to compute the price difference between the two brands (1 = "difficult," and 9 = "easy"). As we anticipated, participants indicated that they would expect the larger price difference to be easier to compute than the smaller price difference ($M_{Smaller} = 5.87$, $M_{Larger} = 7.79$; $t = -2.76$, $p < .01$).

*Participants and design*. One hundred sixty-four undergraduate students participated in the study. The experiment used a 2 (discrepancy: high vs. low) × 2 (computation difficulty: easy vs. difficult) between-subjects design.

*Procedure*. We instructed participants that they were participating in a study designed to examine how much people would be willing to pay for options during product customization. We then told them that they were purchasing a laptop computer online and had to decide on some optional features to add to their purchase. Next, we presented them with an initial feature and asked them to choose between two fictional brands: a high-priced brand and a low-priced brand. The price difference between the two brands was either easy or difficult to compute depending on the condition. We then presented them with a subsequent feature and asked them to choose between two brands (a high-priced and a low-priced brand); the price differences were either easy or difficult to compute. Thus, there were two low-discrepancy conditions in which participants made easy or difficult computations in both decisions and two high-discrepancy conditions in which participants either made easy computations followed by difficult computations, or vice versa. After making their choices, participants indicated how large or small they perceived the price difference to be between the two brands in the subsequent feature decision.

The accessories were a wireless mouse and a memory stick. We counterbalanced their presentation order so that half the participants made a decision about the memory stick first. The two brands of wireless mouse were Brand A, which was a high-priced wireless laser mouse, and Brand B, which was a less expensive optical mouse. The two brands of memory sticks were Brand C, which was a high-priced version with 8 GB of memory, and Brand D, which was a less expensive version with 4 GB of memory. The price difference between the two brands of wireless mouse was either $58.00 and $24.00 (easy to compute) or $58.94 and $24.36 (difficult to compute). The price difference between the two brands of memory sticks was either $29.00 and $15.00 (easy to compute) or $29.47 and $15.13 (difficult to compute). Note that for both features, the actual difference in prices between the two brands was always larger in the difficult to compute conditions.

*Measures*. We used the same measures as in Studies 1 and 2: preferences, time, and discrepancy. In addition, we measured the perceived size of the price difference on a single-item 11-point scale (1 = "small," and 11 = "large"; Thomas and Morwitz 2009).

### *Results*

We analyzed preference for the initial and subsequent feature using logistic regression, with discrepancy, computation difficulty, and their interaction as independent variables. A separate regression analysis that added the presentation order of the features to the current analysis revealed that the presentation order did not interact with any other factor in our model and produced equivalent results.

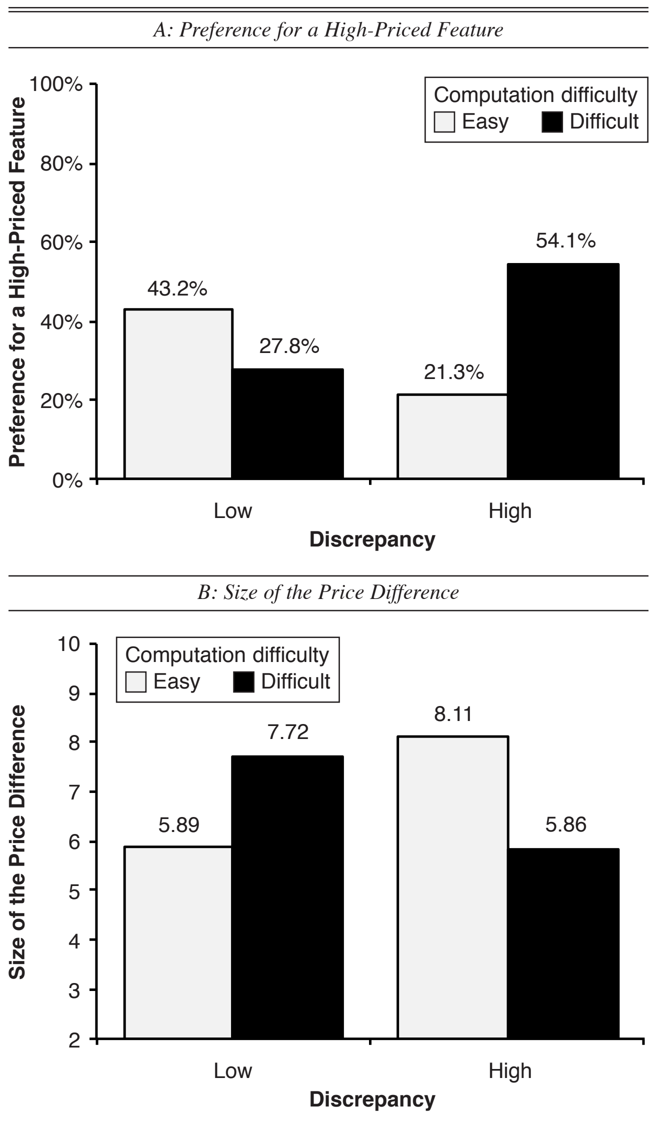
*Manipulation check*. Participants took marginally significantly less time to make a decision when the price difference was easy to compute in both the initial feature decision ($M_{Hard}$ = 13.6 seconds, $M_{Easy}$ = 11.2 seconds; t = 1.91, $p <$ .10) and the subsequent feature decision ($M_{Hard}$ = 11.6 seconds, $M_{Easy}$ = 10.2 seconds; t = 1.70, $p < .10$). An ANOVA with the discrepancy measure as the dependent variable revealed a significant interaction ($F(1, 160) = 14.40$, $p <$ .001). As we expected, participants took longer to make the subsequent decision when difficult-to-compute prices were preceded by easy-to-compute prices (M = 3.1 seconds; t = –4.63, $p < .001$). Participants took less time to make the subsequent decision when easy-to-compute prices were preceded by difficult-to-compute prices (M = –6.3 seconds; t = 3.64, $p = .001$). In the low-discrepancy conditions, participants took less time to make the subsequent decision when prices were easy (M = –.6 seconds; t = .94, n.s.) and difficult (M = –1.2 seconds; t = 1.63, n.s.) to compute, but neither was significantly smaller than zero.

*Initial feature decision*. As we expected, there was no significant difference in preference for the high-priced brand when the price difference was easy to compute (39.5%) compared with when it was difficult to compute (27.7%; Wald's $\chi^2 = 1.53$, n.s.).

*Subsequent feature decision*. As we illustrate in Figure 3, we obtained a significant discrepancy × computation difficulty interaction effect on preference for the high-priced feature ($\beta = .54$; Wald's $\chi^2 = 9.92$, $p < .01$). In the low-discrepancy conditions, there was no significant difference in preference for the high-priced brand between the difficult-to-compute condition (27.8%) and the easy-to-compute condition (43.2%; Wald's $\chi^2 = 2.01$, n.s.). As we expected, when the price difference was difficult to compute, participants were more likely to select the high-priced feature in the high-discrepancy condition (54.1%) than in the low-discrepancy condition (27.8%; Wald's $\chi^2 = 5.05$, $p < .05$). When prices were easy to compute, participants were less likely to select the high-priced feature in the high-discrepancy condition (21.3%) than in the low-discrepancy condition (43.2%; Wald's $\chi^2 =$ 4.87, $p < .05$). Thus, the same price differences may result in different brand preferences depending on the extent to which the difficulty computing the price differences deviates from previous standards.

*Size of price difference*. As we illustrate in Figure 3, we obtain a significant discrepancy × computation difficulty interaction on the size of the price difference ($F(1, 160) = 15.76$, $p < .001$). When discrepancy was low, participants perceived the price difference to be larger when it was diffi-

Figure 3
STUDY 3: THE EFFECT OF DISCREPANCY ON SUBSEQUENT FEATURE PREFERENCE AND PERCEIVED PRICE DIFFERENCE



cult to compute ($M_{Easy}$ = 6.89, $M_{Difficult}$ = 7.72; $F(1, 160) = 3.62$, $p < .05$). This result is not surprising, because the difference is actually larger in the difficult-to-compute conditions than in the easy-to-compute conditions. As we expected, when prices were easy to compute, the size of the price difference was larger in the high-discrepancy condition than in the low-discrepancy condition ($M_{High}$ = 8.11, $M_{Low}$ = 5.89; $F(1, 160) = 7.38$, $p < .01$). In addition, when prices were difficult to compute, the size of the price difference was smaller in the high-discrepancy condition than in the low-discrepancy condition ($M_{High}$ = 5.86, $M_{Low}$ = 7.72; $F(1, 160) = 8.39$, $p < .01$).

*Mediation*. We conducted a test for mediated moderation (Muller, Judd, and Yzerbyt 2005) to assess whether the discrepancy × computation difficulty interaction effect on preference is mediated by the size of the price difference. The previous analysis of preference establishes the interaction effect of discrepancy and expectations on preference. A regression analysis with the size of the price difference as the dependent variable and discrepancy, computation difficulty, and their interaction as the independent variables demonstrates a significant discrepancy × computation difficulty interaction effect on the size of the price difference ($\beta$ = 3.37; t = 3.97, $p < .001$). Adding the size of price difference and the interaction between the size of the price difference and discrepancy to the first model demonstrates a significant effect of the size of the price difference on preference ($\beta$ = –.74; Wald's $\chi^2$ = 20.00, $p < .001$), and the magnitude of the discrepancy × computation difficulty interaction is reduced from $\beta$ = .54 (Wald's $\chi^2$ = 9.92, $p < .01$) to $\beta$ = –.80 (Wald's $\chi^2$ = .89, n.s.). This pattern of results supports the size of the price difference as a mediator of the discrepancy by computation difficulty interaction effect on preference.

### *Discussion*

The results of Study 3 demonstrate that the effect of discrepant fluency is not limited to judgments of liking but can also affect price perceptions during self-customization. Specifically, we showed that when it is easier to compute the price difference in a current decision than that in a previous decision, consumers perceive the price difference to be larger, which reduces preference for the higher-priced brand. Similarly, when the price difference is more difficult to compute, it seems smaller, which increases preference for the higher-priced brand.

In the studies so far, we created a discrepancy by altering the difficulty of an initial and subsequent task. This raises the possibility that our findings could be due to differences in the difficulty experienced between the two tasks instead of deviations from expectations, as we propose. Although we provided evidence for our theory by manipulating expectations to reduce the effects observed in Studies 1 and 2, in the next study, we provide direct evidence that expectations underlie our findings. Specifically, we replicated the results of Study 3 by having participants make only one choice and manipulating expectations before the decision.

## *STUDY 4*

In Study 4, participants made one feature decision in which the price difference between options was easy or difficult to compute. We created a discrepancy by manipulating their expectations before the decision. When it is easy to compute the price difference, we predicted that participants would perceive the price difference to be larger when they expected to experience difficulty than when they expected to experience ease, which should reduce preference for the high-priced option. Similarly, when it is difficult to compute the price difference, we predicted that participants would perceive the difference to be smaller when they expected to experience ease than when they expected to experience difficulty, which should increase preference for the high-priced option.

### *Method*

*Participants and design*. Seventy-eight undergraduate students participated in the study. The experiment used a 2 (discrepancy: high vs. low) × 2 (computation difficulty: easy vs. difficult) between-subjects design.

*Procedure*. We instructed participants that they were purchasing a digital camera at a local retailer and must decide which type of memory card they would like to add to their purchase. To prime difficult expectations, we gave them the following instructions: "The salesperson that is helping you is called away, but before he leaves he tells you that you may find it hard to make a decision and have trouble. If so you should let him know." To prime easy expectations participants were given the following instructions: "The salesperson that is helping you is called away, but before he leaves he tells you that you should not find it hard to make a decision or have trouble so just let him know." We then presented participants with two memory cards to choose between: a high-priced version with 16 GB of memory and a low-priced version with 8 GB of memory. The price difference between the two brands was either easy to compute ($54.00 vs. $28.00) or difficult to compute ($54.63 vs. $28.15). Thus, there were two high-discrepancy conditions in which participants expected to experience difficulty (ease) but then made a decision between options for which the prices were easy (difficult) to compute. In addition, there were two low-discrepancy conditions in which participants expected to experience difficulty (ease) and then made difficult (easy) price computations. Participants then indicated their perceptions regarding the magnitude of the price difference and completed a manipulation check for the expectations manipulation.

*Measures*. We recorded preference for the high-priced memory card (preference) and the time needed to make a decision (decision time). We measured the perceived size of the price difference on the same scale as the previous study. We measured expected difficulty on a three-item, seven-point semantic differential scale (1 = "difficult," and 7 = "not difficult"; 1 = "hard," and 7 = "easy"; 1 = "effortful," and 7 = "effortless"; $\alpha$ = .97).

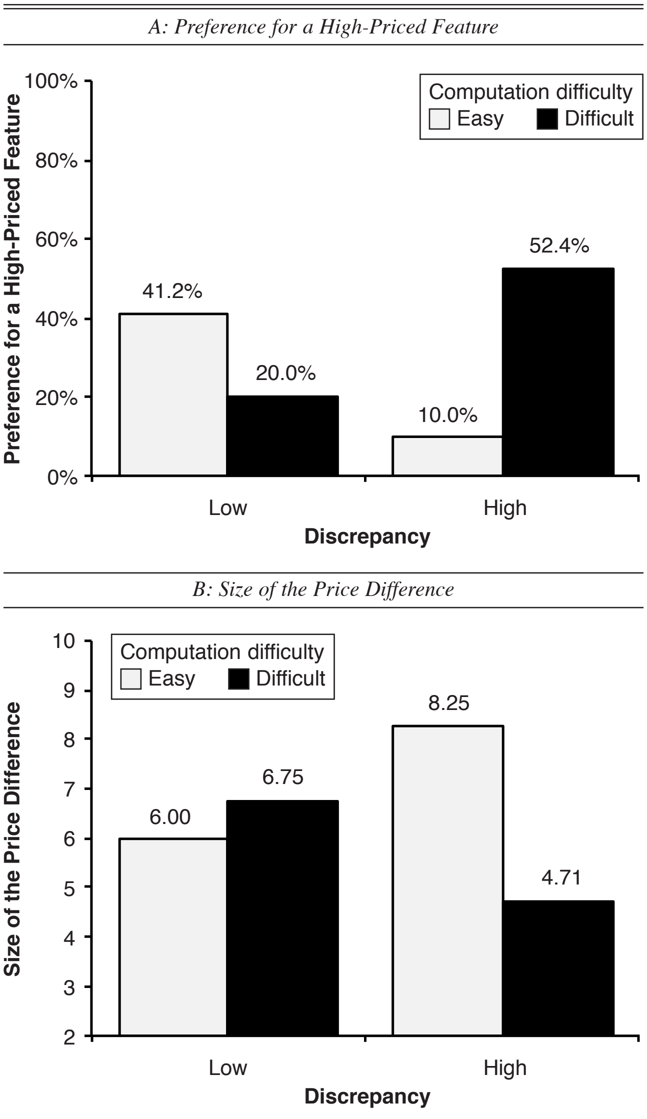
### *Results*

*Manipulation check*. As we expected, participants indicated that they expected the memory card decision to be easier when they were presented with the easy prime than with the difficult prime ($M_{Easy}$ = 5.45, $M_{Difficult}$ = 4.69; $F(1, 74) = 4.24$, $p < .05$). As in the previous study, participants took marginally significantly longer to make a decision when the prices were difficult to compute ($M_{Easy}$ = 10.8 seconds, $M_{Difficult}$ = 13.9 seconds; $F(1, 74) = 3.16$, $p < .10$).

*Preference*. We analyzed preference using logistic regression, with discrepancy, computation difficulty, and their interaction as independent variables. As we illustrate in Figure 4, we obtain a significant discrepancy × computation difficulty interaction effect on preference for the high-priced feature ($\beta = -3.32$; Wald's $\chi^2 = 8.48$, $p < .01$). When discrepancy was low, there was no significant effect of computation difficulty on preference for the high-priced brand in the difficult-to-compute condition (20.0%) and easy-to-compute condition (41.2%; Wald's $\chi^2 = 1.91$, n.s.). As we expected, when the price difference was difficult to compute, participants were more likely to select the high-priced feature in the high-discrepancy condition (52.4%) than in the low-discrepancy condition (10.0%; Wald's $\chi^2 = 4.36$, $p < .05$). When prices were easy to compute, participants were less likely to select the high-priced feature in the high-discrepancy condition (10.0%) than in the low-discrepancy condition (41.2%; Wald's $\chi^2 = 4.24$, $p < .05$).

Figure 4

STUDY 4: THE EFFECT OF DISCREPANCY ON PREFERENCE AND PERCEIVED PRICE DIFFERENCE FOR A SINGLE DECISION




*Size of price difference*. We analyzed the size of the price difference using logistic regression, with discrepancy, computation difficulty, and their interaction as independent variables. As we illustrate in Figure 4, we obtained a significant discrepancy × computation difficulty interaction on the size of the price difference ($F(1, 74) = 13.39$, $p < .001$). When discrepancy was low, participants perceived the price difference to be larger when it was difficult to compute, but the difference was not significant ($M_{Easy} = 6.00$, $M_{Difficult} = 6.75$; $F(1, 74) = 3.88$, n.s.). As we expected, when it was easy to compute, the size of the price difference was larger in the high-discrepancy condition than in the low-discrepancy condition ($M_{High} = 8.25$, $M_{Low} = 6.00$; $F(1, 74) = 7.00$, $p < .05$). In addition, when it was difficult to compute, the size of the price difference was smaller in the high-discrepancy condition than in the low-discrepancy condition ($M_{High} = 4.71$, $M_{Low} = 6.75$; $F(1, 74) = 6.38$, $p < .05$).

*Mediation*. We conducted a test for mediated moderation (Muller, Judd, and Yzerbyt 2005) to establish the size of the price difference as a mediator. The previous analysis of preference establishes the interaction effect of discrepancy and computation difficulty on preference. A regression analysis with the size of the price difference as the dependent variable and discrepancy, computation difficulty, and their interaction as the independent variable demonstrates a significant discrepancy × computation difficulty interaction on the size of the price difference ($\beta = -1.46$; $t = -1.99$, $p = .05$). Adding the size of the price difference and the interaction between the size of the price difference and discrepancy to the first model reveals a significant effect of the size of the price difference on preference ($\beta = -.38$; Wald's $\chi^2 = 5.03$, $p < .05$), and the magnitude of the discrepancy × computation difficulty interaction was reduced from $\beta = -3.32$ (Wald's $\chi^2 = 8.48$, $p < .01$) to $\beta = -1.83$ (Wald's $\chi^2 = 1.86$, n.s.). This pattern of results supports the size of the price difference as a mediator of the discrepancy × computation difficulty interaction effect on preference.

## GENERAL DISCUSSION

Considerable evidence suggests that fluency affects a wide variety of consumer judgments (Schwarz 2004). In this research, we attempt to expand understanding of fluency by demonstrating that its effect on consumer judgment depends not only on the actual level of difficulty experienced at the time of a decision but also on the extent to which the experience deviates from an expected standard. The results of Study 1 confirm this point with an option framing manipulation; when participants rejected laptop features before upgrading features, which represents an easier task, they selected more premium upgrades in the subsequent set than when they only added features. Furthermore, we showed that the effect of discrepancy fluency on preference is due to a deviation from expectations by aligning participants' expectations with the difficulty of the subsequent set to reduce the effect. Study 2 replicates these findings in a different product category (automobiles) and demonstrates that greater liking (due to fluency) mediates the effect of discrepancy on preference. We then showed that discrepancy fluency is not limited to inferences of liking but can also influence price perceptions (Study 3). Specifically, we showed that when price differences are more difficult to compute than those in a previous decision, consumers perceive the differences to be smaller, which increases their preference for high-priced options. In addition, we demonstrated that when price differences are easier to compute, consumers perceive the differences to be larger, which reduces their preference for the high-priced options. We then replicated these findings in Study 4 by manipulating participants' expectations for a single feature decision, which provides strong support that expectations underlie discrepant fluency effects in sequential customization.

### *Contributions and Implications*

This research offers several theoretical contributions. Previous research in sequential decision making has indicated that consumer preferences depend on the content of prior decisions (Simonson and Tversky 1992); we further reveal that altering the difficulty experienced during previous decisions, while holding the content of those decisions constant, produces different decision outcomes. The difficulty experienced during a previous decision sets an expectation for the subsequent decision and acts as a standard for comparison. When the difficulty of the subsequent decisions is discrepant with the expected standard, people's preferences reflect the unexpected ease or difficulty experienced during the decision. Although we use the difficulty experienced during a previous decision to demonstrate discrepant fluency in most of our studies, our theory posits that any variable that alters expectations about the difficulty of a decision may result in discrepant fluency. Consistent with this prediction, we find that altering expectations can enhance or reduce the effects observed even for a single decision (Study 4). Further research should examine other ways to prime explicit or implicit standards for difficulty to extend our model beyond sequential judgments to individual decisions.

In addition, research in social psychology confirms that discrepant fluency affects judgments of familiarity (Whittlesea and Williams 1998, 2000), truth (Hansen, Dechene, and Wanke 2008), and attitude (Hansen and Wanke 2008), but its impact on product evaluation and preference has remained unclear. Extending these findings, we demonstrate that discrepant fluency can have a positive impact on feature evaluations and influence price perceptions, resulting in greater or lower preference for high-priced options. Our findings also complement research examining the effect of fluency on goal pursuit. In a recent study, Labroo and Kim (2009) demonstrate that when people hold an active goal, the experience of difficulty can make objects associated with the attainment of the goal more desirable. When the feelings of difficulty are attributed to an unrelated source, they are less likely to view the object as instrumental for goal attainment, which reduces preference for the object. Consistent with their findings, we show (Studies 1 and 2) that when consumers initially reject a feature, a task that is both difficult and makes people more focused on indulgence (Dhar and Wertenbroch 2000), they are more likely to select the higher-priced feature. However, we also demonstrate that when the initial task is difficult, it makes subsequent features more desirable through the unexpected ease of decision making. When the experience of ease was expected, the options were not as desirable.

This research also has important implications for marketing managers. First, our findings might help optimize customization design. Managers who want to gain a better understanding of consumer preferences should recognize the factors that influence decisions during the customization process. According to previous research, a key practical implication of fluency is that managers should make it as easy as possible for consumers to form preferences (Novemsky et al. 2007). Our research further suggests that fluency effects can be enhanced when consumers find their preference formation unexpectedly easy or more difficult. Second, our findings illustrate two practical ways to induce the discrepant fluency effects: decision framing and price computation difficulty. Marketers have long been interested in finding ways to sell higher-end products or additional accessories (i.e., "upselling" or "trading up"), and different methods of increasing upselling potential have been proposed (Andrews 1999; Wilkie, Mela, and Gundlach 1998). In this research, we showed that by creating an environment that is conducive to discrepant fluency, marketing managers can increase the likelihood of consumers upgrading to more expensive, higher-margin items—even without changing the actual set of choice alternatives presented to consumers.

### *Further Research*

This research points to some directions for additional studies. It would be worthwhile to examine the boundary conditions at which discrepancy still has an impact on fluency effects. Would discrepant fluency effects be observed across different product domains? For example, if participants customize their computers in their initial decision task with a rejection option framing, will they experience the unexpected ease of adding if their subsequent customization task pertains to an unrelated product? The findings also might extend into other domains that involve sequential decision making. Research on information processing (Saad 1999) conceptualizes consumer search strategies as sequential choice processes, in which people first decide which information to acquire, then whether to acquire additional information, and finally how to integrate the newly acquired information. It would be interesting to investigate how the ease or difficulty of acquiring initial information might influence consumers' decisions to search for new information, as well as their integration of the subsequent information. Research also might examine other ways to influence fluency outside a customization context. Similar effects might emerge when a previous decision is difficult because it seems costly or crucial, includes difficult-to-evaluate dimensions, or demands additional deliberation (Carmon, Wertenbroch, and Zeelenberg 2003). In summary, this research offers an initial step in examining discrepant fluency in marketing, but further work is needed to identify other antecedents and managerially relevant behavioral outcomes.

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