Preference stability belief as a determinant of response to personalized recommendations

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ABSTRACT

Preference stability refers to the objectively measured choice consistency among options with different attribute values in the same product category. We suggest that a consumer’s subjectively held belief of preference stability may be an important determinant of response to personalized recommendations. Experimental results confirm that preference stability belief moderates the effect of customization on the evaluation of recommendation accuracy and receptiveness to the learning relationship. Customization will produce stronger effects on accuracy evaluation and receptiveness for subjects with high preference stability belief than for subjects with low preference stability belief. Customers who believe their preferences are stable appreciate customized recommendations more, notice more acutely whether recommendations are customized or not, and are more receptive to the learning relationship when recommendations are customized than when not. Customers who believe their own preferences are less stable do not appreciate customized recommendations as much, are less sensitive to whether recommendations are customized or not, and are not more receptive to the learning relationship even when recommendations are customized. Theoretical and managerial implications of our findings are discussed.

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INTRODUCTION

Companies have deployed recommendation systems to learn customer preferences and recommend personalized products. For instance, Netflix customers are encouraged to disclose their movie preferences by rating movies. Customers rate about 2 million movies online each day and, when returning to the website, they are recommended movies tailored to their individual preferences based on their movie ratings. Netflix CEO Reed Hastings (2007) observes: “The more we learn about the preferences of Netflix subscribers, the easier it is to satisfy and keep them.”

This underlying assumption of personalized recommendations – that customers have stable preferences marketers can reveal by building a learning relationship (e.g., Pine et al., 1995) – is seen as a challenge to the notion of constructed preferences (e.g., Bettman et al., 1998; Lichtenstein and Slovic, 2006), which maintains that customers often do not have stable, well-defined preferences for marketers to learn and, as a result, customers may fail to recognize or appreciate recommendations customized to their measured preferences (Simonson, 2005: p. 32). With personalized recommendation services such as those of Netflix and Amazon gaining more customer acceptance (e.g., Flynn, 2006), the challenge to constructive preferences may become more real and more credible. Already, the challenge has triggered some kind of “debate” in the field of behavioral decision theories on whether customers have more stable inherent preferences (e.g., Bettman et al., 2008; Simonson, 2008).

Preference stability often refers to the objectively measured choice consistency among options with different attribute values in the same product category (e.g., Hoeffler and Ariely, 1999; Simonson, 2005: p. 33; Amir and Levav, 2008). While we do not object to the notion of constructed preferences, we suggest that the operational definition of preference stability may be too restrictive for exploring customer response to personalized recommendations. For example, research in consumer choices has indicated that the context in which choices are made plays a dominant role in preference formation. When making a choice between option a and option c, a is more likely to be preferred when a and c are presented with option a’ which a dominates (When a dominates a’, a is superior to a’ in one or more attributes and not inferior to a’ in any other attributes) than when a and c are presented without a’ (Huber et al., 1982). The implication is that preference (1) is largely determined by the decision context, (2) is unstable, and (3) is not something marketers can learn or customize to.

We suggest that this operational definition of preference stability can be usefully supplemented by other definitions of preference stability. Most customers will probably accept that, as they gain experience in a product domain, they may discover or develop “stable preferences” – patterns of interest (i.e., subjective values) at the category, subcategory, and/or attribute levels – and that such preference patterns can be learned by marketers and usefully applied to personalized recommendations. They may believe this even if objective measurement of their choices would reveal inconsistencies. For example, a customer may honestly believe that he or she has “stable preferences” at the category level (e.g., “I prefer wine to beer or whiskey”), the subcategory level (e.g., “I prefer red wine to white wine”), the sub-subcategory level (e.g., “I prefer cabernet sauvignon to merlot”), and/or at the attribute level (e.g., “With cabernet sauvignon, I prefer full-bodied to medium-bodied, tobacco flavor to ripe berry or...
green pepper flavors, and Bordeaux to Napa Valley”). Most customers also will probably agree that knowledge of and recommendations customized to such stable preference patterns may be valuable to customers and, ultimately, to marketers.

In this paper, we suggest that a consumer’s belief that he or she has context-free preferences for marketers to learn and usefully apply to personalized recommendations (hereafter referred to as preference stability belief as opposed to objectively measured preference stability) may be an important but underexplored determinant of customer response to personalized recommendations. Although previous research (e.g., Simonson, 2005; Kramer, 2007) has discussed how stability or clarity of preferences may affect response to personalized recommendations, their focal interest was to explore its role as a moderator on the effects of seemingly irrelevant contextual factors (e.g., transparency of the preference measurement task). The emphasis on contextual effects is consistent with the assumption that customer preferences are often undeveloped and unstable and customers tend to have limited insight into their own preferences (Simonson, 2005: pp. 34–35). However, while preferences may be unstable when objectively measured, customers may still hold fairly strong belief in the stability of their own preferences and such subjectively held belief might have consequences of interest for personalized recommendations. With preference stability belief, our focal interest here is to explore its role in reinforcing the effects of customization on customer response to personalized recommendations.

Preference stability belief may vary among individuals and product domains. Most customers may believe that they have “stable preferences” in at least a few product domains. In the leisure-reading domain, for example, a customer may say, “I don’t read mysteries, romances, or horror novels, but I do read historical fiction and adventure,” and thereby believes that he or she has “stable preferences.” Similarly, most product domains claim the “stable preferences” of at least some customers. From chocolate bars to laundry detergents, from music CDs to recipe books, “stable preferences” can be observed among experienced customers of these product categories. This variation among individuals and product domains may be appropriately utilized to the advantage of marketers in serving ever smaller market segments or even individual customers.

Preference stability belief is often prevalent and persistent, and likely to be consequential to customer response to personalized recommendations. While repeatedly testifying to the absence of stable, well-defined preferences, decision researchers do not deny that consumers may hold beliefs of stable preferences, as prescribed in the rational choice theory in the economics tradition (Bettman et al., 1998: pp. 187–188). Preferences tend to be more stable for certain objects (e.g., chocolate, coffee), for products with which we are familiar or experienced (Hoeffler and Ariely, 1999), or for product categories (Bettman et al., 1998; Simonson, 2005). Simonson (2008) suggests that customers may have more stable inherent preferences that are not determined by context. Researchers also persistently explored whether constructed preferences stabilize and transcend contexts (Haubl and Murray, 2003; Amir and Levav, 2008). With its prevalence and persistence, preference stability belief is likely to influence customer response to personalized recommendations.

In this research, we explore whether preference stability belief will interact with customization to influence customer evaluation of recommendation accuracy and customer receptiveness to the learning relationship. In the rest of the paper, we discuss the theoretical basis to develop research hypotheses. We then describe the experiment we conducted to test our research hypotheses empirically. Finally, we will discuss our research findings and implications for the theories and practice of individual marketing.

CONCEPTUAL BASIS AND RESEARCH HYPOTHESES

Customer response to personalized recommendations
Customer response to personalized recommendations is a research priority in individual marketing (Murthi and Sarker, 2003; Simonson, 2005; Zhang and Wedel, 2009). We are interested in two basic types of customer response: (1) customer evaluation of recommendation accuracy and (2) customer receptiveness to the “learning relationship,” a metaphor used in the individual marketing literature to describe how the focal company can use its information technology applications to engage the customer in an ongoing dialog, learn his or her preferences, and make customized offers (e.g., Pine et al., 1995; Winer, 2001; Simonson, 2005). Accuracy evaluation is fundamentally related to the expected benefit from personalized recommendations whereas receptiveness reflects a predisposition critically relevant to the long-term success of personalized recommendations.

Customer evaluation of recommendation accuracy refers to the extent to which a customer perceives that system recommendations closely meet his or her own needs, interests, and preferences during multiple interaction episodes. For instance, for the customer who says, “I don’t read mysteries, romances, or horror novels, but I do read historical fiction and adventure,” recommending historical fiction and adventure may lead to higher accuracy evaluation whereas recommending mysteries, romances, or horror novels may lead to lower accuracy evaluations. Accuracy evaluation of online agents may be influenced by overall and extreme agreement and disagreement between recommendations and the customer’s needs, interests, and preferences (Gershoff et al., 2003).

We define customer receptiveness to the learning relationship as the extent to which a customer is willing to accept the focal company’s personalized recommendation services, the essence of which is a learning relationship in which the focal company creates an ongoing dialog via technology media to learn customer preferences and provide customized offers (e.g., Pine et al., 1995). We suggest that receptiveness reflects a customer’s evaluative response to the specific company offering personalized recommendation.
services, rather than a customer’s personality trait that predisposes him or her to respond to personalized recommendation services more positively regardless of whichever company offering such services (e.g., propensity to “receive market information” in Mowen et al., 2007). This distinction is necessary as it enables us to see receptiveness as a dependent variable subject to the influence of the independent variables. For instance, for the customer who reads historical fiction and adventure but not mysteries, romances, or horror novels, customized recommendations (i.e., recommending historical fiction and adventure and not recommending mysteries, romances, or horror novels) and easy-to-use system interface from the focal company may hopefully lead to higher receptiveness to the learning relationship (i.e., more favorable response to the focal company’s business practice of using a computer-based system to delve into his or her leisure reading preferences and recommend what might be his or her next reading selection), although we know very little about how much the difference can be.

Determinants of response to personalized recommendations
We expect that customer response to personalized recommendations may be influenced by three major variables: (1) customization of recommendations; (2) ease-of-use of the system interface; and (3) preference stability belief. While customization and ease-of-use, respectively, pertain to the outcome and process of personalized recommendation service, preference stability belief is an individual difference variable that may have an interaction effect with customization of recommendations as we will discuss below.

Customization of recommendations
Customization refers to the extent to which recommendations are tailored to the measured individual preferences. Recommendation systems are designed to approximate individual preferences (Gershoff and West, 1998; Iacobucci et al., 2000): in the face of product proliferation and information overload, the closer the match between recommendations and preferences, the more benefit (e.g., in the forms of reduced search effort, increased quality of purchase decisions, and reduced price) customers may reap from using the system (Haubl and Thrifts, 2000; Diehl et al., 2003; Aksoy et al., 2006). When recommendations are not related to preferences, they become a random list of products and services available in the firm’s inventory and customers will benefit little from using recommendation systems. When recommendations are in violation of customer preferences, e.g., recommending products of which customers have explicitly stated they have no interest, they become a nuisance.

**H1:** Customization of recommendations will positively affect (a) the evaluation of recommendation accuracy and (b) receptiveness to the learning relationship.

Ease-of-use
Technology adoption research suggests that customer acceptance is predicted by instrumental process benefits such as perceived ease-of-use, over and beyond outcome benefits such as perceived usefulness (Davis, 1989; Dabhoklar and Baggozi, 2002) during interactions with the system. Ease-of-use is largely instrumental to achieving the outcome and, therefore, will probably not affect accuracy evaluation. However, ease-of-use may enhance the overall experience of the interaction interface, e.g., by saving customer time and effort, being more efficient, and, therefore, affording instrumental benefit of its own. In other words, ease-of-use may have an effect, over and beyond that of customization, on customer receptiveness.

**H2:** Ease-of-use in personalized recommendation service (a) will not affect the evaluation of recommendation accuracy but (b) will positively affect receptiveness to the learning relationship.

We expect that customization and ease-of-use may have an interaction effect on receptiveness to the learning relationship, but not on recommendation accuracy evaluation. In this research, however, it is not our focal interest to formulate hypotheses on those constructs.

Preference stability belief
The major thrust of the paper is to examine the effects, if any, of preference stability belief. We suspect that, in the context of personalized recommendations, preference stability belief may provide customers with different levels of motivation for processing personalized recommendations. Previous research has found that the intensity of information processing is directly related to the need for information, expectancy (i.e., the cognitive association between information processing and the expected goal attainment), and value of the information (e.g., Burnkrant, 1976; Wilton and Myers, 1986). Customers with high preference stability belief may have a stronger need for and expect more benefit from customized recommendations and, therefore, are more likely to process information concerning recommended movies. Consequently, there is a higher likelihood for them to respond to personalized recommendations based on the level of customization. In contrast, customers who do not believe that they have stable preferences probably expect much less benefit from customization and, therefore, are less likely to process information of recommended movies. As a result, their response is less likely to be influenced by the level of the customization.

Based on the above discussion, we argue that preference stability belief as an individual difference variable will probably interact with customization: strong belief in stable preferences may reinforce the effects of customization whereas weak belief in stable preferences may diminish the effects of customization. For instance, a customer who strongly believes in his or her preferences in leisure reading (e.g., “I like historical fiction and adventure but not mysteries, romances, or horror novels.”) will feel strongly about the customization quality of recommendations (e.g.,
“Why do they recommend me romances I will never read?”). In contrast, if a customer does not believe that he or she has stable preferences (e.g., “I am not very particular about leisure readings.”), then he or she probably does not care about whether recommendations are customized or not (e.g., “Everything is fine for me.”). In other words, customization will be more effective for customers with high preference stability belief than for customers with low preference stability belief.

**H3a:** Preference stability belief will interact with customization to affect the evaluation of recommendation accuracy. Specifically, the effect of customization on accuracy evaluation will be greater when preference stability belief is high than when preference stability belief is low.

**H3b:** Preference stability belief will interact with customization to affect receptiveness to the learning relationship. Specifically, the effect of customization on receptiveness will be greater when preference stability belief is high than when preference stability belief is low.

### EMPIRICAL TESTS OF THE RESEARCH HYPOTHESES

**Method**

**Subjects and design**

Subjects were 267 undergraduate students taking business courses on two university campuses who participated in exchange for extra credits. We used a 2 × 2 factorial design to manipulate customization of recommendations and ease-of-use at low and high levels. Subjects were randomly assigned to one of the four cells. The 228 subjects who completed the experiment were about equally distributed in the four cells. For the distribution of subjects in the four conditions, see Table 1. We measured preference stability belief of subjects with a six-item scale (Shen and Ball, 2009; see Appendix for the measurements).

**Procedures**

The experiment was ostensibly to test drive new movie recommendation software programs provided by developers outside university campuses. Participating subjects would receive personalized recommendations of new movies showing in local theaters, which would be generated by their randomly designated recommendation software program. Subjects had no obligation to view any of the recommended movies. Participation was strictly defined in the experimental schedule: (1) in the first week (mid-February of 2008), subjects completed a survey designed to collect their movie preferences; (2) every Thursday during the next 6 weeks, subjects were e-mailed recommendations of new movies showing in local theaters during the weekend (“new” is defined as first appearing that weekend or the previous two weekends); (3) during the 6-week period, subjects were asked twice to provide feedback so as to improve the quality of recommendations; and (4) in the eighth week, subjects completed a survey questionnaire with approximately 60 items.

First, subjects completed a questionnaire of 56 movie preference items. These items allowed the subjects to rate 20 popular movies that had shown in the past year (from widely different genres), 16 movie genre types (“Action,” “Horror,” “Romantic Comedy,” etc.), 10 prominent actresses, and 10 prominent actors. Each subject rated each of the 56 items on a −2 to +2 scale regarding how much he or she liked the movie (liked very much = +2), how much he or she liked the genre, or how much he or she liked the actor or actress. Care was taken so that these movies, genres, actresses, and actors represented a wide sampling of available types. For example, actors ranged from the classic leading-man type (George Clooney) to ones who were familiar in more idiosyncratic roles (Johnny Depp).

A few days before each new movie appeared in local theaters, the movie was rated by one of the researchers on those same 56 items, representing the extent to which it was similar in terms of the 20 past movies, the 16 genres, and the 20 actors and actresses. At least 50 of the 56 ratings for a movie were “0,” but if a new movie was somewhat similar to one of the 20 past movies rated by the subjects, it would get a rating of “1” for that past movie, and if it was very similar, it would get a rating of “4.” For example, a movie that was a sequel to one of the previous 20 movies that subjects rated would get a “4” for that item. Fit within the definition of movie genres was likewise used in the similarity score. For example, if the new movie was clearly both in the “general comedy” and “action” genres, then it would get a “1” for each of those items. If it was so clearly a horror movie that no other category fit, it received a “4” for the “horror” category. Finally, the actors and actresses were used in calculating the similarity score for each new movie. If the lead actress in the movie was a prominent actress, similar in terms of roles played and public persona to Meryl Streep, then the movie would get a “1” for the “Meryl Streep” item; if Streep actually appeared in the new movie, the similarity rating would be a “4.”

A desirability score could thus be generated for each subject for each new movie playing in his or her local theaters that weekend. This was done by taking a vector product of the subject’s 56 preference values with the 56 similarity ratings for the new movie. Thus, if a subject had a “−2” for the horror movie genre (indicating dislike of the genre), and the movie in question was definitely a horror movie, then its similarity rating to horror movies was “4,” and the product of the subject preference by similarity to the horror genre would contribute −8 to the desirability score.

### Table 1. Subjects distribution in four conditions

<table>
<thead>
<tr>
<th>Ease-of-use</th>
<th>Customization of recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>58</td>
</tr>
<tr>
<td>High</td>
<td>59</td>
</tr>
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</table>
for that subject. Since the movie was definitely not a romantic comedy (i.e., 0 similarity to romantic comedy), the subject’s preference for romantic comedy was irrelevant in the desirability score calculation. The resulting score for each movie, for each subject, could then range from −48 to +48, but typically ranged from −5 to +15. This algorithm was developed over two pre-tests, in which various similarity values and algorithmic approaches were tried, and feedback from the pre-test subjects indicated that the final algorithm seemed to produce the strongest manipulation of customization of recommendations.

**Manipulations**

To manipulate customization of recommendations into “low” and “high” conditions, we used the desirability ratings of all new movies for a given subject, and then chose either the highest-rated choice to recommend each week (“high customization” condition), or a random or poorly-rated one (“low customization” condition). If the subject was in the “high customization” condition, the movie with the highest score not previously recommended to that subject was chosen to be recommended. For the subjects in the “low customization” condition, a randomly drawn movie (first four recommendations) or the lowest-scored movie (last two recommendations) was selected from the pool of previously un-recommended movies. It was necessary to switch from “randomly-drawn” to “lowest-scored” part-way through the experiment, because manipulation checks run every 2 weeks indicated that the “low customization” condition was not generating sufficiently low perceptions of recommendation accuracy. We attribute this to the fact that late winter is a time when studios seldom release their blockbuster movies; thus, the movie offerings available did not generate strong preference reactions in many subjects. It should be noted that the researchers were not trying to develop a new movie recommendation algorithm for this research, but merely to produce recommendations that achieved the desired manipulations. There undoubtedly are, or will be, proprietary algorithms that are or will be far superior at providing recommendations for just-released movies. This ad hoc algorithm was satisfactory for our purposes.

To manipulate ease-of-use into “low” and “high” conditions, we varied the amount of effort subjects had to expend in order to access the basic information of recommended movies. Subjects in the “low ease-of-use” condition, after receiving recommended movies, would be asked to copy and paste an included link that took them to the homepage of Internet Movie Database (via the university survey website for tracking purposes). At the IMDB website, subjects could perform further search to locate information regarding the recommended movie and its stars and reviews, to view trailers, and, if they were interested, to perform more search to find show times at local theaters. In contrast, subjects in the “high ease-of-use” condition expended much less effort in search. Their recommendation e-mails contained, along with recommended movies, clickable links that took them (via the university survey website for tracking purposes) to the webpage of (1) show times of the recommended movie in local theaters; (2) information about the recommended movie and its stars and reviews at IMDB; and (3) a trailer of the recommended movie that plays automatically at YouTube.

**Measurements**

We used scales developed in our previous research on personalized recommendation services (Shen and Ball, 2009) to measure preference stability belief and the two dependent variables: evaluation of recommendation accuracy and receptiveness to the learning relationship (see the Appendix for the measurements). In our previous research, we followed the recommended procedures for scale development to establish the reliability and validity of the measurements (e.g., Nunnally, 1978; Churchill, 1979; Fornell and Larcker, 1981; Anderson and Gerbing, 1988).

In the current research, these scales continue to display adequate psychometric properties with only slight modifications of the items based on the results of two pretests and the final experiment. Composite scores were calculated by averaging the scores of all items of a measurement. For descriptive statistics, see Table 2. Note that preference stability belief was fairly strong (\(m = 4.83, SD = 0.86\)) in our research, suggesting that our subjects believed, to some degree, that they had stable preferences in movies.

**Table 2. Descriptive statistics**

<table>
<thead>
<tr>
<th>Manipulations</th>
<th>Ease-of-Access</th>
<th>N</th>
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<th>ACE</th>
<th>RLR</th>
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<td></td>
<td></td>
<td></td>
<td>Mean</td>
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<td>Mean</td>
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<td>4.13</td>
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<tr>
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<tr>
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<td>Total</td>
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<td>4.83</td>
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<td>4.61</td>
</tr>
</tbody>
</table>

PSB, preference stability belief; ACE, accuracy evaluation; RLR, receptiveness to the learning relationship.

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Test results

We tested the interaction effects of preference stability belief and customization with multiple regression (as opposed to ANOVA) models because preference stability belief, one of the independent variables, was measured as a continuous variable. We mean-centered it and created its interaction term with customization. We followed a stepwise approach by adding the following predictors: (1) customization; (2) ease-of-use; and (3) the centered preference stability belief and its interaction term with customization. We did not find any suppressor effects.

In the regression model in which recommendation accuracy evaluation was the criterion \( R^2 = 0.18, F(4, 223) = 12.12, p < 0.001 \), we found that, consistent with H1a, customization had a significant impact on the evaluation of recommendation accuracy \[ b = 0.98, \beta = 0.34, t = 5.53, p < 0.001 \]. We also obtained support for H2a: ease-of-use did not have a significant effect on recommendation accuracy evaluation \[ b = 0.23, \beta = 0.08, t = 1.30, p = 0.20 \]. These results show that our manipulation of customization produced the desired effect on perceived accuracy, and that ease-of-use had no halo effects on perceived accuracy.

The centered preference stability belief did not have a significant effect \[ b = -0.21, \beta = -0.13, t = -1.53, p = 0.13 \], as expected. However, H3a was supported: the interaction term of preference stability belief with customization had a significant effect on the evaluation of recommendation accuracy \[ b = 0.74, \beta = 0.30, t = 3.59, p < 0.001 \]. We plotted the interaction effects on recommendation accuracy evaluation in Figure 1. As is graphically represented, the relationship between preference stability belief and the evaluation of recommendation accuracy is strong and positive in the high customization group while this relationship is weak and slightly negative in the low customization group. Put it in other terms, there is a strong effect of customization on recommendation accuracy evaluations, but only in the case of those customers who believe that their preferences are stable. There is a small negative effect of customization on recommendation accuracy evaluations when customers do not believe that their preferences are stable. These results suggest that customization was more effective in increasing accuracy evaluations for subjects with high preference stability belief.

For subjects with low preference stability belief, randomly drawn or lowest-scored movies were seen as slightly more accurate than customized recommendations.

In the regression model in which receptiveness was the criterion \( R^2 = 0.10, F(4, 223) = 6.02, p < 0.001 \), we found that receptiveness was significantly influenced by customization \[ b = 0.23, \beta = 0.13, t = 2.00, p < 0.05 \] and ease-of-use \[ b = 0.24, \beta = 0.13, t = 2.05, p < 0.05 \], as we hypothesized in H1b and H2b, respectively. The centered preference stability belief did not have a significant impact \[ b = -0.07, \beta = -0.06, t = -0.73, p = 0.47 \]. We found support for H3b: the interaction term of preference stability belief with customization had a significant impact on receptiveness \[ b = 0.43, \beta = 0.28, t = 3.18, p < 0.01 \]. We plotted the interaction effects on receptiveness to the learning relationship in Figure 2. The pattern is similar to that for the evaluation of recommendation accuracy in Figure 1: the relationship between preference stability belief and receptiveness to the learning relationship is strong and positive in the high customization group and weak and slightly negative in the low customization group. Or alternatively, there is a strong effect of customization on receptiveness, but only in the case of those customers who believe that their preferences are stable. There is a small negative effect of customization on receptiveness when customers do not believe that their preferences are stable. These results suggest that customization was more effective in increasing receptiveness for subjects with high preference stability belief. For subjects with low preference stability belief, randomly drawn or lowest-scored movies slightly outperformed customized recommendations in increasing receptiveness.

Conclusions

Test results confirmed that subjectively held preference stability belief moderates the effect of customization on the evaluation of recommendation accuracy and receptiveness to the learning relationship: for subjects with high preference stability belief, customization will have strong positive effects on accuracy evaluation and receptiveness whereas, for subjects with low preference stability belief, customization will have weak negative effects on accuracy evaluation and receptiveness. Customers who believe their preferences are stable appreciate customized recommendations more and
respond more acutely to whether recommendations are customized or not. Customers who believe their own preferences are less stable do not appreciate customized recommendations as much, and are less sensitive to whether recommendations are customized or not. While justifying for these interaction effects in H3a and H3b, we suggest that customers with different levels of preference stability belief may have different levels of motivation for processing recommended information. We tracked the number of times subjects clicked on the links to recommended movies we included in the emails. Our suggestion would find support if subjects with high preference stability belief had clicked on the movie links more often. Test results indicated that subjects with high preference stability belief recorded a higher number of clicks \( m = 2.43 \) on the links than subjects with low preference stability belief \( m = 1.66 \): \( \Delta m = 0.77, t = 2.04, df = 221.87 \) (equal variances not assumed), \( p < 0.05 \). These results were consistent with our suggestion that the interaction effects could be attributed to the different levels of motivation for information processing.

To explain this further, consider the case of a customer of an on-line restaurant recommendation service, which delivers recommendations through a GPS unit when the customer is traveling. Assume that the customer is willing to try any kind of ethnic or non-ethnic food that presents itself in a new city, and is not particular about price or ambience. In fact, the customer will try anything, and is well aware that there is, at present, no pattern to what he likes. He is unlikely to ask the GPS unit to provide more than a list of restaurants within a certain distance of his route, without recommendations. Suppose the GPS unit offers two options: (1) a random list of restaurants in this area and (2) a list of recommended restaurants in this area based on whatever patterns it believes it has found in his past choices. The customer may \textit{a priori} believe that the recommended list is not relevant to his need, is not as useful, and will probably choose to ignore the recommendation option. By ignoring the proffered recommendations, the customer will never discover whether or not the recommendations are accurate to his food preferences. On the other hand, if the customer believes that he does have stable preferences (e.g., when traveling, always likes to try well-made Szechwan Chinese food and Northern Indian cuisine), then he will probably find that customized recommendations are more relevant to his need, offer more helpful tips and, in turn, he may pay more attention to the recommendations and discover quickly if they are accurate or not.

We can easily rule out the alternative explanation that the main effect of customization found in the experiment was due to subjects correctly guessing their group assignment. First, we used the same 56-item questionnaire to elicit movie preferences from all subjects. Second, preference measurement was not a very transparent task (e.g., Kramer, 2007): the number of questions would make it difficult, if not impossible, for subjects to remember their answers simply because they had taken the survey. Third, preference matching was not transparent at all because it was calculated with a mathematical formula. In other words, differences in the means of accuracy evaluation and receptiveness can only be attributed to customization treatment, not to subjects correctly guessing their group assignments.

Alternative explanations for the interaction effects of customization and preference stability belief can also be ruled out. First, we measured preference stability belief at the end of the experiment. Subjects could not have been alerted to its role in the experiment. Second, differences in preference stability belief cannot be attributed to preference elicitation and preference matching because of their relatively low transparency. Third, preference stability belief measured later could have been influenced by customization treatment. We examined this possibility and found that preference stability belief did not differ significantly between low and high customization groups: \( m_{low} = 4.78, SD = 0.88; m_{high} = 4.88, SD = 0.85; t(226) = 0.87, p = 0.39 \). The test results effectively rule out this possibility.

We can also rule out the possibility that involvement in movies, rather than preference stability belief, explains our results. We measured involvement in movies using a three-item scale adapted from previous research (Zaichkowsky, 1985): Cronbach’s \( \alpha = 0.95, \text{mean} = 5.21, \text{SD} = 1.27, \text{median} = 5.33 \). We found that: (1) involvement was not significantly related to preference stability belief \( r = 0.11, p = 0.11 \); and (2) we used the median point \( (=5.33) \) to code involvement into a binary variable (low and high), conducted a MANOVA analysis replacing preference stability belief with involvement, and found that involvement did not have an interaction effect (with customization) on accuracy assessment \( F(1, 219) = 1.55, p = 0.22 \) or receptiveness to the learning relationships \( F(1, 219) = 0.24, p = 0.63 \). Involvement was found to have a main effect on receptiveness to the learning relationship: \( F(1, 219) = 6.77, p = 0.01 \). We did not measure task involvement, so we are unable to rule out the possibility that difference in the levels of interest in our experiment can be an alternative explanation of our results.

Our research findings based on the experiment should be taken as preliminary. We echo Simonson (2005) in that customers may have very complex responses to personalized recommendations and individual marketing attempts. More research will be warranted. First, the relatively small \( R^2 \)s of the regression models indicate the limited predictive power of customization, ease-of-use, and preference stability belief as determinants of accuracy evaluation and, in particular, receptiveness to the learning relationship. We had to settle on these predicting variables given the purpose of our research. Future research may explore other key determinants of accuracy evaluation and receptiveness (e.g., privacy concerns). Second, we measured preference stability belief in the experiment. Although measuring preference stability belief does not necessarily invalidate its interaction effects, future research may consider directly manipulating preference stability belief and subject the interaction effects to more rigorous tests. Finally, we find initial evidence that preference stability belief may have important implications for the customization of services. More research may be warranted to better understand its antecedents and consequences.
THEORETICAL AND MANAGERIAL IMPLICATIONS

Our findings that preference stability belief may reinforce the effects of customization have both theoretical and managerial implications. Theoretically, we provided a reason to reconsider whether preference stability, often operationally defined as choice consistency among a set of options with different attribute values, is too restrictive to be considered the only useful way to conceptualize preference stability. While previous research emphasizes contextual effects and sees preference stability as a moderator of contextual effects, we supplement prior research with the effects of customization by suggesting that subjectively held belief of stable preferences may be a valuable basis for customization and may interact with customization to influence customer response to personalized recommendations. Our focus on customization effects rather than contextual effects does not necessarily contradict the notion of constructive preferences: it would be maladaptive for consumers to construct preferences from scratch each time they had to make a choice. Customized recommendations are often valuable not because they offer exactly what customers want (as hinted in the literature) but because customers believe they are closer to previously constructed stable preferences and, therefore, may be a better guide for preference construction in the current decision task (Amir and Levav, 2008: p. 146).

Current managerial practices often assume stable preferences without asking whether customers really believe they have more stable patterns of preferences for marketers to learn. For instance, when a customer rates Legally Blonde with 4 stars (“really liked it” in Netflix’s 5-star rating system), there is no way to determine if this rating reflects more stable preferences of the customer or merely transient interests. Future recommendations based on unstable preferences may fail to connect even if the system makes the preference matching process more “transparent” by claiming that the recommendation was made “because you enjoyed Legally Blonde.” Similarly, purchases of gifts or textbooks from Amazon.com seldom indicate stable preferences. Recommendations based on such previous purchases often lead to customer dissatisfaction.

Our findings indicate that a customer’s perceived stability of his or her preferences should be integrated into preference learning processes so that learning relationships can be made more productive and more relevant to the customer. Managers may, for example, directly administer short surveys using items similar to our scale to identify customers with higher preference stability belief. Since customized recommendations matter more for customers with high preference stability belief than for customers with lower preference stability belief, a smarter recommendation strategy is to focus on delivering quality customized recommendations to customers with high preference stability belief who believe they can benefit more from customized recommendations, are more motivated to process customized information and, consequently, more receptive to learning relationships with the company. Being more focused will probably reduce much of the “noise” created by less interested customers because they do not believe they have stable preferences and, therefore, help the company build more credibility in individual learning relationships.

For customers who believe they have no stable preference patterns, managers may ask one interesting question: “Do they believe this because it is true, or do they just fail to see the patterns in their own preferences?” Since the development of a learning relationship with a profitable customer is to the strategic advantage of the firm, there would be reason to try to convince those with low preference stability beliefs that a recommendation system could uncover patterns they cannot see themselves. Those customers not using the recommendation system but yet showing a good statistical fit to some pattern might be individually approached via e-mail or through a personalized web page. The message could be: “You may believe that personalized recommendations won’t identify anything you’d really want. Well, we think you have patterns in your choices that you may not recognize, and we have prepared some recommendations for you based on that. Please give it a try and see what you think.” Once they try to like the recommendations, they may be led into believing that they have stable preference patterns and that they will benefit from personalized recommendations. In turn, they may assess recommendations as more accurate and may become more receptive to learning relationships. This may be a small fraction of customers, but their loyalty also helps increase profit margins.

BIOPGRAPHICAL NOTES

Dr Anyuan Shen earned his PhD from University of Nebraska-Lincoln in 2007. His research interests include consumer decision making, service personalization and loyalty, direct and database marketing, recommendation agents, and individualized learning relationships. Dr Shen has published in the Journal of Services Marketing, International Journal of Electronic Business, International Journal of Nonprofit and Voluntary Sector Marketing, the Proceedings of the American Marketing Association, and the Proceedings of the Academy of Marketing Science.

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REFERENCES

Recommendation Accuracy (Cronbach’s \( \alpha = 0.96 \))

1. Most of the recommendations that have been made were movies I really wanted to see.
2. The recommendations made were usually movies I think would be worth trying.
3. Recommendations frequently show that this system has understood the movie features or characteristics I particularly like.
4. This system usually fails to recommend what I’d really like to see.
5. Most of the recommendations connected poorly to my own interest.

Preference Stability Belief (Cronbach’s \( \alpha = 0.73 \))

1. If someone kept a record of movies I watch, he/she would probably be able to make a pretty good prediction of which movies I might be interested next.
2. The movies I like fit some sort of pattern.
3. Even someone who knows me well will not be able to make a good guess for the next movies that may interest me.
4. The movies I enjoy watching do not have a lot in common.
5. I can easily tell which movies I will really prefer and which I will not.
6. It is often difficult to predict which movies I will really enjoy and which I will not.

Receptiveness to the Learning Relationship (Cronbach’s \( \alpha = 0.82 \))

1. I would be willing to tell my movie preferences to this recommendation system if asked next time.
2. I would not want to reveal my real preferences about movies to the recommendation system in the future.
3. I would be ready to listen to the recommendations of this system.
4. I just do not want to use this recommendation service.
5. I will be checking for movie recommendations just about every time I use this service.
6. I do not intend to give any serious considerations to the movie recommendations provided by this company or organization.

“All constructs were measured with 7-point Likert scale anchored from “strongly disagree” to “strongly agree.”