THE EFFECTS OF MALFUNCTIONING PERSONALIZED SERVICES ON USERS’ TRUST AND BEHAVIORS

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Abstract

Online merchants adopt web personalization to customize web content to match online users’ needs. Prior research has only looked at the “success” side of web personalization. Little research examines the “problematic” side of web personalization. The objective of this research is to explore how “malfunctioning” personalized web services influence an online user’s trust in the personalization agent and the behavioral intention of that user. In particular, this research looks at two types of malfunctioning personalization: irrelevant recommendations and biased recommendations. We draw on trust theories to develop seven hypotheses to predict the effects of malfunctioning personalized web services. We conducted a study with a personalized music download website. We found that irrelevant recommendations led to low trust in the personalization agent’s competence and integrity, and biased recommendations led to low trust in the integrity of the personalization agent. These findings provide empirical evidence of the possible problems of malfunctioning personalization and help firms understand and quantify the challenges and limitations of incorporating web personalization in their websites.

Keywords: Web Personalization, Malfunctioning Personalization, Trust, Recommendations.
1 INTRODUCTION

Hundreds of thousands of online merchants worldwide are using the web as a major channel to interact with online users for brand promotion and product marketing. This leads to fierce competition as online merchants try their very best to attract and retain every online user. One strategy that online merchants adopt is to differentiate their services for each individual user. In the process of producing a differentiated service, online merchants first identify each user, and then acquire more information about that user’s interests by having him or her provide information to online merchants either directly through tracking devices on the site (Mobasher et al. 2000). Ultimately, highly-focused and relevant services are delivered to each user. This entire process is generally termed “personalization”. The technology enabler is referred to as “a personalization agent”, a collection of software modules that deploys tools to collect and analyze the browsing behavior and purchase transactions of online users (Ardissono et al. 2002). The objective of personalization is to treat each user in a unique way to fit marketing and advertising with his or her needs. Personalization technologies help online merchants better communicate with their customers and generate more business opportunities (Ho 2006; Tam & Ho 2005, 2006).

The use of personalized services by online merchants is growing at a phenomenal rate. In practice, many business-to-consumer websites have adopted personalization technologies. One often-cited successful example is Amazon.com, which uses personalized book recommendations for each of its 31 million customers. Other commercial websites that have adopted personalization technologies include ebay.com, shopping.com, and audible.com. The success of this strategy makes it a desirable area of study for information systems (IS) researchers. One area of prior research has looked at the effectiveness of personalization. For example, one group of studies compare personalized websites with general websites and examine the effects of personalization on attracting an online user’s attention and influencing his or her decision to purchase a personalized recommendation. For instance, Tam and Ho (2005) adopt the Elaboration Likelihood Model to examine the effects of personalization on the extent of users’ sampling of personalized recommendations. They find that the recommendations attract more clicks and are often selected as the final choice for purchase. Te’eni (2001) finds that as a personalized website often filters irrelevant content and puts the relevant content on the topmost page of a website, this can shorten an online user’s searching time. Tam and Ho (2006) conduct an experimental study showing that online users have a tendency to explore (and even select) personalized recommendations during their shopping process. Liang et al. (2006) empirically demonstrate that users are more satisfied with a personalized website than a general website.

The findings of prior work on personalization rest on an assumption that personalization technologies function well. However, this is not necessarily the case, as online merchants have to make a huge investment in technologies such as data mining, collaborative technology, click stream analysis components and pattern recognition in order to produce high-quality personalized services (Ardissono et al. 2002). It is unlikely that small companies who lack resources can afford to deliver the “best” personalized services. Moreover, some online merchants may attempt to present a product with a higher profit margin as a personalized recommendation. In these situations, personalization cannot fulfil its obligation, i.e., to provide personalized recommendations matched to an online user’s preferences and needs. We consider these problems to be malfunctions in web personalization. The current research aims to look at the problems of malfunctioning web personalization.

Specifically, the current research focuses on two kinds of malfunctioning personalized services. The first is the generation of recommendations irrelevant to an online user’s preferences and needs. The second malfunctioning service is dishonest recommendations that are biased to benefit the online merchant. Apart from online users’ privacy concerns, the above two problems have been reported as online users’ major worries when using personalized services (Ho 2006). The current research will look at the effects of these problems on online users’ trust and behavior. We are particularly interested in whether and how online users trust in a personalization agent. This issue of trust has been central in
the personalization literature (e.g., Komiak & Benbasat 2006; Wang & Benbasat 2007). We formulate the research question as follows: *How do “malfunctioning” web personalized services influence an online user’s trust in the personalization agent and behavioral intention of the user?*

We address our research problem using an online study. We developed a personalized music website which was capable of collecting online users’ music preferences and generating personalized recommendations. The website generated irrelevant or biased recommendations. We invited 143 students who often downloaded digital music online to visit our personalized music website. At the end of the study, they completed a post-task questionnaire to report their perceptions of, and their experience with, personalized services. The questionnaire items are shown in Appendix 1.

The rest of this paper is organized as follows: The next section outlines the theoretical frame of the current work and presents the hypotheses. Sections 3 and 4 describe the online study and its findings. Section 5 discusses the implications of the work. Section 6 concludes the paper.

## 2 HYPOTHESES DEVELOPMENT

Research in social psychology often looks at the importance of trust in interpersonal dyads. In the last decade, trust has received a great deal of attention in information systems (IS) research. Prior IS research examines whether and why users trust in technologies, such as Internet shopping (Gefen et al. 2003), online firms (Bhattacherjee 2002) and Internet banking (Suh & Han 2002). As personalization agents work like an assistant to give recommendations to online users, prior research also looks at users’ trust in recommendation agents. Wang and Benbasat (2005) found that perceived ease of use of the agent influenced a user’s trust in the agent, which in turn influenced the perceived usefulness of the agent and a user’s intention to use. Ho and Bull (2010) found that, in the context of mobile personalization, the personalization agent’s capability to detect a mobile user’s location influenced his or her trust in personalized mobile services.

The current research looks at two aspects of trust, competence and integrity of a target of trust (Mayer et al. 1995). The first dimension of trust, competence, focuses on the trustor’s perception that the trustee is capable, and an expectancy that the trustee’s word or written statement can be relied on. The second dimension of trust, integrity, involves the trustor’s perception that the trustee adheres to a set of principles that the trustor finds acceptable. The current research examines the two major problems of personalization agents, i.e., irrelevant recommendations and biased recommendations, and their effects on a user’s trust in the competence and integrity of the agent.

Irrelevant recommendations are personalized offers that do not match a user’s preferences or needs. In the process of personalization, the agent explicitly asks a user’s preferences and/or implicitly collects the user’s past transactions, and then analyses the data to produce recommendations. If the recommendations are irrelevant, the user will perceive that some procedure in personalization has gone wrong, and the personalization agent is incapable of meeting its obligations (i.e., provision of personalized services to online users). As the agent is perceived to be incapable and unlikely to deliver on promises, a user loses his or her confidence in the performance of the agent. This will lead to a decrease in competence trust. Hence, we propose the following:

**H1:** Irrelevant personalized recommendations will negatively affect a user’s competence trust in the personalization agent.

Online users form “principles” to evaluate recommendations from a personalization agent based on their general Internet browsing experience. Presenting irrelevant recommendations as if they are generated from a careful personalization process is unlikely to align with the “principles” in users’ minds. Thus, the users are likely to perceive offering irrelevant recommendations to be unacceptable,

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1 This research references work by Komiak and Benbasat (2006). As their work did not examine benevolence trust in the recommendation agent, we did not include benevolence trust in this study.
and lose their integrity trust in the personalization agent (Mayer et al. 1995). Hence, we propose the following:

**H2:** Irrelevant personalized recommendations will negatively affect a user’s integrity trust in the personalization agent.

Biased recommendations are generated based on external factors, other than an online user’s preferences. Possible external factors include online merchants’ promotion strategies, and a high commission rate from certain product vendors to online merchants. In the study by Komiak and Benbasat (2008), biased recommendations were products from the same product vendor and influenced a user’s integrity attribution process. That is, the personalization agent ignored the indicated preferences and the past transactions of an online user, and provided limited information for his or her decision making process. As all personalized recommendations came from one single vendor, the recommendations were deemed to be biased towards that vendor. The current research anticipates that there is no effect of biased recommendations on a user’s competence trust in the agent. This is because displaying a list of products from the same product vendor involves using different criteria to generate recommendations. Using different criteria to generate recommendations is not an incompetence issue. Hence, we propose that biased recommendations will not affect an online user’s competence trust in the agent.

**H3:** Biased personalized recommendations will not affect a user’s competence trust in the personalization agent.

Presenting online users with biased recommendations from one single product vendor is different from an online user’s expectation of personalized services. The recommendations are not tailored to the user’s preferences and needs and the personalization agent seems to be profit oriented, rather than customer oriented. Hence, this practice is not considered to be acceptable. Online users are likely to think that the personalization agent fails to adhere to its principle to service online users. Hence, biased recommendations will lead to a decline in integrity trust.

**H4:** Biased personalized recommendations will negatively affect a user’s integrity trust in the personalization agent.

When relying on personalized recommendations to make a purchase decision, a user takes “risks”. Selecting an irrelevant recommendation or a biased recommendation as a choice may result in a loss of money or a waste of shopping time. There is also concerned about a user’s privacy and security (Sheng et al. 2008). Regardless of certain benefits from personalized recommendations, users may feel uneasy about their information possibly being disclosed to third parties without their consent (Ho 2006). Trust in the agent can help to overcome these concerns and a trusting relationship guides a user to think positively about the personalization agent fulfilling its obligations. Therefore, we anticipate that:

**H5:** Competence trust in the personalization agent will positively affect a user’s attitude towards the personalization agent.

**H6:** Integrity trust in the personalization agent will positively affect a user’s attitude towards the personalization agent.

According to the theory of reasoned action, an individual’s behavioral intention depends on his or her attitude about the behavior (Ajzen & Fishbein 1980). Therefore, online users who have a positive attitude toward the personalization agent will have an intention to use the personalized services in the future. Conversely, online users who have a negative attitude toward the personalization agent, because of malfunctioning services, will have an intention not to use the personalized services in the future. We anticipate the following:

**H7:** A user’s attitudes toward the personalization agent will positively affect a user’s intention to use the personalization agent.
As literature suggests that a user’s disposition of trust and institution-based trust (McKnight et al. 2002, 2004) may also affect his or her attitude towards the trusting target, we will include these variables as control variables in our data analysis. In the current research, we set up a personalized music website with the collaboration of a digital music content provider, EolAsia. We conducted an online study with 143 student participants to collect data to test the above hypotheses. The next section will present the methodology of the study.

3 METHODOLOGY

3.1 Participants

We cooperated with a large digital music retailer, EolAsia, in the Asia Pacific region, to conduct an online study. We posted advertisements in public areas of the university to recruit participants. Those who opted to participate could input a hyperlink into the web browser to start the process. Participants could start the online study at any time and location. In this study, our data analysis focused on 143 participants (90 females and 53 males, average age = 22), and all of them had experience in downloading digital music. The online study was made up of five rounds of music download, and participants could download at most one song per day. Overall, they contributed 3,693 song samplings. As a token of appreciation, each participant was given five free music tracks (i.e., one free track per session) and a chance to join a lucky draw for special gifts. They would download their free track from our music study website.

3.2 Provision of Personalized Recommendations

We self-developed a personalized music website. Participants could log on our website at anytime, from anywhere. Our personalized website generated six personalized recommendations for each user in each log on. To simulate the problem of irrelevant recommendations, some participants received the most recently-published music albums of the artists and some participants received six personalized recommendations from old music albums. To simulate the problem of biased recommendations, some participants received six personalized recommendations from the list of their six favorite artists, i.e., one recommendation per artist, and some received six personalized recommendations from the same artist and this artist was the sixth most preferred one chosen by participants, i.e., all six recommendations from the same artist. In this setting, some users received relevant recommendations and some received irrelevant recommendations, some users received unbiased recommendations and some received biased recommendations, which leads to variance in participants’ perceptions of personalized recommendations. In the data analysis, we examine how the differences in perceptions influence a user’s competence and integrity trust in the personalization agent.

3.3 Study Procedures

Participants were asked to fill in a questionnaire about their demographic information and digital music download habits, and to indicate their music preferences. They had to choose and rank their six most favorite artists from a selection list of ten. We used regular reports from the music billboard charts to decide which artists were included in the selection lists.

Then, all participants were requested to enter the study website to select and download a track they liked. The website provided more than 4,552 tracks from 100 popular artists provided by EolAsia and participants of a pilot test. Each track had a popular index. We allocated 20 different artists to each round based on the preferences of participants of the pilot test. At every logon session, after the participants logged on to the website, they chose the six different artists in their order of preferences.

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2 The popular indices were given by EolAsia. Our personalization algorithm took song popularity into consideration when generating the recommendations.
Then they found a main menu on the top and six personalized recommendations presented in the top or central area of the window (Figure 1).

![Figure 1. Homepage of the Personalized Music Website](image)

The [More Details] label of each track was a hyperlink. After clicking on the link, the participants could browse the details of the track, such as artist information and track duration (Figure 2). On the same page, two link options were provided with one labeled as “Listen”, and the other as “Add to Basket”. By clicking the “Listen” link, participants could listen to a 30-second preview track, then they could add any number of tracks to their shopping baskets. When participants clicked the “Basket” button on the top menu, items inside the basket were displayed. The participants then picked one of the tracks in their basket, and confirmed the final choice (Figure 3). The participants would receive their selected songs after they completed all the five rounds of song selections. Throughout the process, all click streams were recorded, and the participants completed a post-task questionnaire to report their experience.

![Figure 2. An Example of the Interface Showing Details of Artist and Song](image)
A pre-test with 13 participants was administered to test the performance of the digital music download system. Normally, participants could complete the whole process in 10 minutes. All of them agreed that the navigation process and the selection task were smooth.

4 FINDINGS

4.1 Measurement Model Results

The statistical analysis technique applied is partial least squares (PLS), as implemented in SmartPLS version 2.0 (M3). Throughout the paper, individual items have been standardized unless noted otherwise. PLS and LISREL are two ways of modeling latent variables and their relations to each other within a set of manifest variables. Both are used for causal modeling. They simultaneously assess the reliability and validity of theoretical construct measures and estimate the relationships among these constructs (Chin 1998; Goodhue et al. 2007). LISREL requires stronger theory than PLS and is preferred for confirmatory testing of the fit of a theoretical model to observed data (Barclay et al. 1995). PLS is better suited for theory development; thus, we used PLS to analyze our data.

PLS judges the adequacy of a measurement model by three criteria: (1) individual item reliabilities, (2) the convergent validities of measures associated with individual constructs, and (3) discriminant validity between constructs (Hulland 1999).

To assess the reliabilities of individual items, we checked the composite reliabilities in Table 1. The individual item reliabilities were above 0.9; thus, the first criterion was met. To assess convergent validity, we checked all loadings and confirmed that all were greater than the recommended threshold of 0.70 (Nunnally 1978). Hence, the second criterion was fulfilled. To assess discriminant validity among the constructs, Fornell and Larcker (1981) suggest that researchers use average variance extracted (AVE) to measure the variance between a construct and its measures. A rule for assessing discriminant validity requires that the square root of AVE be larger than the correlations between constructs (Barclay et al. 1995). As shown in Table 2, the square roots of the AVE values are consistently greater than the off-diagonal correlations, suggesting at least adequate discriminant validity at the construct level.
### Table 1. Composite Reliability of the Constructs

<table>
<thead>
<tr>
<th>Construct</th>
<th>Cronbachs Alpha</th>
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<tbody>
<tr>
<td>1. Attitude towards the Personalization Agent</td>
<td>0.955</td>
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<tr>
<td>2. Intention to Use</td>
<td>0.967</td>
</tr>
<tr>
<td>3. Competence Trust</td>
<td>0.974</td>
</tr>
<tr>
<td>4. Integrity Trust</td>
<td>0.961</td>
</tr>
<tr>
<td>5. Perceived Biased</td>
<td>0.960</td>
</tr>
<tr>
<td>6. Perceived Preference Matched</td>
<td>0.936</td>
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</table>

### Table 2. Latent Variable Correlations

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Attitude towards the Personalization Agent</td>
<td><strong>0.957</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>2. Intention to Use</td>
<td>0.808**</td>
<td><strong>0.984</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Competence Trust</td>
<td>0.878**</td>
<td>0.814**</td>
<td><strong>0.964</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Integrity Trust</td>
<td>0.781**</td>
<td>0.739**</td>
<td>0.807**</td>
<td><strong>0.963</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Perceived Biased</td>
<td>-0.205</td>
<td>-0.204</td>
<td>-0.233</td>
<td>-0.338*</td>
<td></td>
<td><strong>0.962</strong></td>
</tr>
<tr>
<td>6. Perceived Preference Matched</td>
<td>0.809**</td>
<td>0.733**</td>
<td>0.858**</td>
<td>0.769**</td>
<td>-0.266**</td>
<td><strong>0.942</strong></td>
</tr>
</tbody>
</table>

Notes: * denotes significant correlations at the p < 0.05 level; ** denotes significant correlations at the p < 0.01 level.
The diagonal elements (in bold) represent the square root of AVE.

4.2 Structural Model Results

The predictors used in this study did a good job of explaining the variance in users’ competence trust in the personalization agent ($R^2 = 73.6\%$), users’ integrity trust in the personalization agent ($R^2 = 61.0\%$), users’ attitudes to using the personalization agent for song selection ($R^2 = 78.9\%$), and their intentions to use the agent ($R^2 = 65.3\%$). Figure 4 summarizes the findings.

H1 was supported ($t = 24.323$, $p < 0.01$, $\beta = 0.856$). Results showed that the perceived relevance$^3$ of personalized recommendations to a user’s preferences was a significant factor affecting users’ competence trust in the personalization agent. The positive coefficient showed that when users perceived recommendations to be preference-matched, they had a higher competence trust. Conversely, when users perceived recommendations to be irrelevant to their preferences, they had a lower competence trust.

H2 was supported ($t = 14.344$, $p < 0.01$, $\beta = 0.730$). Results showed that the perceived relevance of personalized recommendations to a user’s preferences was a significant factor positively affecting users’ integrity trust in the personalization agent. Conversely, when users perceived recommendations to be irrelevant to their preferences, they had a lower integrity trust.

H3 suggested that the extent to which users perceived personalized recommendations to be biased towards an online merchant’s benefit had no effect on competence trust. Our data analysis empirically demonstrated this insignificant relationship, supporting H3 ($t = 0.123$, $p > 0.1$, $\beta = -0.006$). As an insignificant effect might be due to a small sample size, one may wonder whether the relationship was

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$^3$ We used “perceived relevance” rather than “perceived irrelevance” in the questionnaire, because we would like to ask the participants in a natural way. This approach is always adopted in prior personalization research (e.g., Tam and Ho 2005, 2006).
definitively insignificant or the insignificance was caused by a small sample. To eliminate this concern, we looked at the effect size. According to Goodhue et al. (2006), in PLS analysis, sample sizes of 90 or above gave sufficient power to test a hypothesis. As our sample size was 143, we concluded that our sample size was large enough to create sufficient power. The insignificant result of H3 was not due to a small sample size.

Figure 4. Research Findings

H4 was supported ($t = 2.338, p < 0.05, \beta = -0.144$). Perceived biases towards online merchants’ benefit exerted a significant effect on users’ integrity trust towards the personalization agent. Participants who believed that the personalization agent would give them recommendations that an online merchant planned to promote had low integrity trust.

We then examined the effects of competence trust and integrity trust on a user’s attitude towards the personalization agent. H5 looked at competence trust. We found that when users have a higher competence trust in the agent, they are more like to have a positive attitude towards the agent. H5 was supported ($t = 8.524, p < 0.01, \beta = 0.702$). H6 looked at integrity trust. We found that when users have a higher competence trust in the agent, they are more like to have a positive attitude towards the agent. H6 was supported ($t = 2.532, p < 0.05, \beta = 0.226$).

As predicted, users who have a more positive attitude towards the personalization agent have a more positive intention to use the personalization agent in their future visits to the website, supporting H7 ($t = 21.858, p < 0.01, \beta = 0.808$).

5 DISCUSSION

Table 3 summarizes our findings. While prior research (e.g., Tam & Ho 2005, 2006) has shown that web personalization is effective in influencing online users’ decision making in a shopping process, our understanding of the impacts on a user’s attitude and intention when the user encounters poor
quality personalized services is far from conclusive. This research aims to bridge the gap between the potential growth of web personalization and the lack of understanding of the effects of malfunctioning personalized services. No prior IS research, of which the investigators are aware, examines this issue. This research used a self-developed personalized music website to conduct an online study with Internet music downloaders. Our results show that malfunctioning personalized services lead to a decrease in competence trust and integrity trust. Our findings can provide to firms evidence of the consequences of bad personalized services. This can help them judge whether to invest in web personalization if limited resources mean they cannot offer the best services.

Table 3. A Summary of Findings

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Results</th>
</tr>
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<tbody>
<tr>
<td>H1: Irrelevant personalized recommendations will negatively affect a user’s competence trust in the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H2: Irrelevant personalized recommendations will negatively affect a user’s integrity trust in the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H3: Biased personalized recommendations will not affect a user’s competence trust in the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H4: Biased personalized recommendations will negatively affect a user’s integrity trust in the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H5: Competence trust in the personalization agent will positively affect a user’s attitude towards the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H6: Integrity trust in the personalization agent will positively affect a user’s attitude towards the personalization agent.</td>
<td>Supported</td>
</tr>
<tr>
<td>H7: A user’s attitudes toward the personalization agent will positively affect a user’s intention to use the personalization agent.</td>
<td>Supported</td>
</tr>
</tbody>
</table>

The current research has two implications. First, it is a first step to examining “malfunctioning” aspects of web personalization. The current research looks at two types of malfunctions, irrelevant recommendations and biased recommendations. These problems of web personalization are on-going. Giving irrelevant recommendations to online users is a technological problem. As an online merchant cannot afford costly data mining technologies to identify the exact needs of a user, the personalization agent is incapable of providing highly relevant recommendations to online users. Even if the online merchant invests a lot in web personalization and the relevance of personalized recommendations increases, as online users’ expectations of, and demand for, high-quality services increases, there will always be a gap between system performance and the online user’s expectations and wants. Personalized recommendations can never be perfectly relevant. On the other hand, giving biased recommendations to online users is a business problem. The online merchant collaborates with their product vendors and chooses to present recommendations that their product vendors prefer, rather than products the user wants. This may increase the online merchant’s sales commissions. As our findings empirically show that biased recommendations reduce a user’s integrity trust in the personalization agent, the online merchant should be aware of this consequence and look for a way to strike a balance between online users’ interests and product vendors’ interests.

Second, the current research looks at the effects on trust of these two malfunctioning features of personalization. A decline of trust captures a loss of users’ confidence, but it cannot capture users’ fear of, worry about, and doubt about the malfunctioning agent. Social psychology literature conceptualizes these negative emotions to be “distrust”. An interesting area for further study will be how malfunctioning services lead to distrust. In addition, researchers have found other types of malfunctions (Stewart 2003; Darke & Ritchie 2007): for instance, a personalization agent may be incapable of keeping customers’ personal data confidential (Ho 2006, Sheng et al. 2008). Future work can explore other types of system malfunctions and their effects of trust and distrust.
6 CONCLUSION

In summary, the current work has investigated the effects of malfunctioning features of web personalization on online users’ trust. In particular, we look at irrelevant recommendations and biased recommendations. We used trust theories to establish our theoretical framework and examined how these malfunctions influence users’ attitude and behavior towards the personalization agent. In general, irrelevant recommendations lead to a low level of competence and integrity trust, and biased recommendations lead to a low level of integrity trust.

This study represents a first step toward understanding how malfunctioning personalized services affect users’ trust in and their attitudes towards personalized content, and ultimately their behavioral intention to use the agent again. It sheds light on the personalization literature by exploring the negative sides of personalization.

Acknowledgement
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REFERENCES


APPENDIX 1  QUESTIONNAIRE ITEMS

Disposition to trust (1 = Strongly Disagree; 9 = Strongly Agree)
1. I usually trust people until they give me a reason not to trust them.
2. I generally give people the benefit of the doubt when I first meet them.
3. My typical approach is to trust new acquaintances until they prove I should not trust them.

Institution-based trust (1 = Strongly Disagree; 9 = Strongly Agree)
1. Generally I feel good about how things go when I use a website function to give me recommendations to assist in my product selection process.
2. Generally I am comfortable selecting a product with the use of a website recommendation function.
3. Generally I feel at ease using a website recommendation function to help me select a product.

Attitude (1 = Strongly Disagree; 9 = Strongly Agree)

What are your general feelings about the Digital Music Personalization Agent?
1. Bad……. Good
2. Foolish……. Wise
3. Unimportant……. Important

Perceived Biases (1 = Strongly Disagree; 9 = Strongly Agree)
1. I feel that when the Digital Music Personalization Agent generates song recommendations, it biases towards music merchants' artist promotion interests, rather than towards my song preferences.
2. I feel that the Digital Music Personalization Agent inclines more to merchants' interest, than to my interests.
3. I feel that the Digital Music Personalization Agent takes more care of music merchants' artist promotion interests, than to my song preferences.

Perceived Relevance to One’s Preferences (1 = Strongly Disagree; 9 = Strongly Agree)
1. I feel that the Digital Music Personalization Agent provides song recommendations that I like.
2. I feel that the Digital Music Personalization Agent considers my artist preferences when generating song recommendations.
3. I feel that the song recommendations match my artist preferences.

Competence Trust (1 = Strongly Disagree; 9 = Strongly Agree)
1. The Digital Music Personalization Agent is competent and effective in providing suggestions on preference-matched songs.
2. The Digital Music Personalization Agent performs its role of giving song recommendations very well.
3. The Digital Music Personalization Agent is a capable and proficient recommender for songs.
4. The Digital Music Personalization Agent is knowledgeable about songs that match my preferences.

Integrity Trust (1 = Strongly Disagree; 9 = Strongly Agree)
1. The Digital Music Personalization Agent is truthful in its dealings with me.
2. I would characterize the Digital Music Personalization Agent as honest.
3. The Digital Music Personalization Agent is sincere and genuine.

Intention to Use (1 = Strongly Disagree; 9 = Strongly Agree)
1. If the music website provides the Digital Music Personalization Agent, I predict I would continue using it.
2. If the music website provides the Digital Music Personalization Agent, I plan to continue using it.