Examining the effects of malfunctioning personalized services on online users' distrust and behaviors

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ABSTRACT

Merchants adopt web personalization technologies to offer product recommendations in the hope of influencing online users' decision making in a shopping process. Although there is a large body of research on the favorable effects of web personalization on influencing online users' decision making, it is often assumed that web personalization functions well. Only scant research examines the adverse outcomes of web personalization on online users' perceptions and behavior when the personalized services malfunction. This research aims to fill this gap. Specifically, we examine malfunctioning personalized services that produce irrelevant and biased product recommendations in online shopping. Irrelevant recommendations are offerings not matched to online users' preferences, whereas biased recommendations are offerings generated for the merchant's interests. When online users encounter such malfunctioning personalized services, they may distrust the personalization agent, which influences their interactions with the agent. We drew on distrust theories to develop six hypotheses. To test the hypotheses, 245 participants were recruited for a field experiment in which they were tasked to download free music tracks from a personalized music download website. Our findings indicate that both irrelevant and biased recommendations lead to high distrust in a personalization agent's competence and integrity. Competence distrust, but not integrity distrust, in a personalization agent negatively influences online users' interactions with the agent.

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1. Introduction

The adoption of web personalization in electronic commerce is growing at a phenomenal rate. According to a survey by Unica [42], 73% of merchants considered using web personalization to facilitate communication with their customers. A report by KPMG reveals that investment in web personalization is a high priority in business [31]. Web personalization enables a merchant to identify each individual user, acquire information about users' preferences by having them provide information to the merchant either directly or through tracking devices on the websites, and provide special treatments in the form of individualized content and layout matched to their preferences [21,27–29]. The ultimate objective of a merchant adopting web personalization is to generate more business opportunities by providing online users with highly focused and relevant product recommendations [14,39,40]. This 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 transactions of online users [1]; and the individualized content is referred to as "personalized recommendations."

The proliferation of web personalization makes it a desirable area of study for information systems (IS) researchers. Prior work often suggests that web personalization favorably influences an online user's perceptions and behavior. For instance, one group of studies examines various personalization strategies and their effects on capturing the attention of online users and biasing their purchase decisions. Tam and Ho [39] conducted field experiments using a ring-tone download website to show that preference matching is an important factor affecting the acceptance of the offer for personalization agents. In another study, Tam and Ho [40] investigated the effects of content relevance and self relevance on users' cognitive processing and decision making when they use personalization agents. Ho et al. [16] looked at how the timing of web personalization influences a user's decision to take a recommendation. As the personalization agent works as a virtual sales agent, some IS researchers conceptualize it as a human being who develops an interpersonal relationship with an online user. Thus, they use the trust theories to explain how online users build (human) trust in the personalization agent.

Trust is particularly relevant to web personalization research because online users are involved in risks, such as privacy infringement or monetary losses [14,35]. Prior research has examined how the performance of a personalization agent influences online users' trust in the agent. Wang and Benbasat [45] found that perceived ease of use of a personalization

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agent[1] influences a user's trust in the agent, which in turn influences the perceived usefulness of the agent and a user's intention to use. Komiak and Benbasat [17] examined how the extent of preference matching influenced online users' cognitive trust and integrity trust in a personalization agent, and consequently, their decision to adopt the agent. Buczak et al. [5] looked at the personalization algorithm for generating a recommendation and conducted an experiment to demonstrate that users built trust in a personalization agent only when the agent adopted an algorithm that produced recommendations that were highly relevant to their preferences. In the context of mobile personalization, Ho and Bull [15] found that the personalization agent's capability to detect a mobile user's location influenced his or her competence trust and integrity trust in personalized mobile services.

However, the research design employed in prior studies might be biased toward findings that are favorable to the effectiveness of web personalization for two reasons. First, prior studies (e.g., [8,39,40,44,45]) investigated self-developed personalization agents for the specific purpose of experiments for data collection, in which participants worked on the same task. Thus, it was easy for their agents to understand the participants' preferences precisely. However, in practice, merchants have to make a significant investment in technologies, such as data mining and click stream analysis tools, to detect online users' preferences so accurately [1]. The issue is further complicated because a person's preferences are sometimes constructed spontaneously, especially in situations where he or she has little product knowledge or is not familiar with the online shopping environment [46]. Therefore, in practice, the prediction performance of recommendations made by primitive personalization methods that solely use registration profiles and past transaction records should be poor [28,30]. Consequently, personalization agents in commercial websites are unlikely to perform highly in servicing online customers.

Second, the objective function of personalization agents tested in prior research (e.g., [14,15,17]) is relatively simple – to maximize the benefits of online users in a shopping process – and the agent simply presents personalized recommendations that attempt to satisfy experimental participants as much as possible. However, in practice, a merchant has to strike a balance of benefits among multiple parties, including online users, product vendors, and the merchant itself. The merchant wants to attract and retain online users with personalized recommendations that fulfill their shopping requirements and help them complete their shopping process efficiently. Further, the merchant wants to assist product vendors to promote their products, which may be less popular but of a high profit margin, to online users. As the merchant's revenue hinges on both the sales to online users and commissions from product vendors, the merchant is unlikely to use only one criterion – maximizing the benefits of online users – for the generation of personalized recommendations, and has incentives to provide recommendations that are less preference-matched (but of a higher profit margin) to online users for benefiting product vendors as well as the merchant.

The objective of this research is to examine how the above two "problems" of web personalization influence online users' perceptions and behavior toward the personalization agent. We refer to these problems as irrelevant recommendations and biased recommendations. *Irrelevant recommendations* are incorrect recommendations that do not match online users' preferences caused by a merchant's lack of full understanding of the preferences. *Biased recommendations* are a merchant's product recommendations that are not generated based on the benefits of online users. We collectively refer to these problems as *malfunctioning personalized services*. Apart from online users' privacy concerns regarding the personalization agent's use of their information for purposes other than providing recommendations without seeking their prior consent (such as selling the information to marketers or using it for other promotional activities organized by the agent), this paper examines the following research questions.

1. How do irrelevance and bias of recommendations influence online users' distrust in a personalization agent?
2. How does online users' distrust in a personalization agent affect their interactions with the agent?

In this study, we conducted an online experiment for data collection. We collaborated with one of the largest digital content providers in Pacific Asia to set up a personalized music website. Unlike the experiments in prior research, this website purposely generated irrelevant or biased recommendations to online users. We invited 245 participants to sample and download digital music from our website multiple times. After each round of download, they completed a questionnaire to report their experience with the personalization agent.

The reminder of this paper is structured as follows. Section 2 reviews the literature on distrust and prior research on personalization agents. Section 3 outlines the theoretical framework of this study and develops the hypotheses. Section 4 outlines the methodology and Section 5 presents the research findings. The paper concludes with a discussion of the study's theoretical contributions and practical implications, as well as future research directions.

2. Theoretical background

2.1. Distrust: A psychological state

Trust has drawn much attention from IS researchers. Prior research (e.g., [11,38]) has examined why and how trust in a technology influences an online user's behavior toward the technology. It also investigates the multidimensionality of trust (competence, integrity, and benevolence) [22,23]. According to the literature on trust, trust and distrust are two distinct constructs [3,19,20] and not two opposite ends of the same construct. Specifically, while trust brings people a feeling of safety and security, distrust brings people a feeling of worry, suspicion and fear [24,41]. The two groups of feelings (i.e., safety and security; and worry, suspicion and fear) can co-exist—trust and distrust are two distinct constructs that can co-exist. Findings from prior neuroeconomics studies suggest that trust and distrust are not two opposite ends of the same concept—people secrete different types of hormones [48] and have different kinds of brain activities [9] depending on whether they are in a trusting or distrusting state (not a higher or lower amount of the same kind of hormones or brain activities). The current research takes the perspective that distrust is distinct from trust, and anticipates that the adverse effects of irrelevant recommendations and biased recommendations on an online user's shopping behavior are more than just a reduction of trust in the personalization agent. It uses distrust as a mediating mechanism to explain the adverse effects of malfunctioning personalized services that produce irrelevant and biased recommendations on an online user's interactions with the personalization agent.

There is scant IS research on the effect that distrust in a technology has on user behavior. One exception is McKnight et al., who developed a conceptual model of distrust [23,24] and instruments to measure the constructs in the model [25], and empirically tested the model in the context of Internet expert advice websites [26]. In particular, McKnight et al. synthesized prior research from various social science disciplines to form a conceptual model that links three aspects of distrust—disposition to distrust, institutional-based distrust, and interpersonal distrust. Disposition to distrust captures a person's general tendency, or traits, to distrust other people in general, which includes his or her distrusting stance and suspicion of humanity [23,26]. Institutional-based distrust consists of two components. The first component, (negative) structural assurance, explains the distrust of a person in an institution, such as companies and websites [23,24]. The second component, (negative) situational normality, captures a person's distrust in a situation that takes place in the institution, such as conducting business transactions with a company or on a website [23]. Interpersonal distrust captures a person's

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