CAN CUSTOMIZATION OF PRIVACY SETTINGS PROMOTE PERSUASIVENESS
OF PERSONALIZED RECOMMENDATION AGENTS?

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ABSTRACT

Online recommender systems have introduced widespread privacy concerns due to their extensive acquisition and processing of user data for providing personalized services to users. In order to minimize the privacy-personalization tradeoff, some systems allow users to express their needs (i.e., reactive personalization) rather than automatically pushing services to them (i.e., proactive personalization). The relative preference for reactive personalization is likely due to the greater human agency it affords than proactive personalization. But it constantly calls for user action, which can be detrimental to user experience. One potential solution to this problem may be the affordance of customization, which is known to ensure a positive user experience by providing a strong sense of control. Can customization of privacy settings alleviate privacy concerns arising from personalization?

This study delineates differences in privacy concerns raised by different personalization mechanisms (reactive vs. proactive) in a recommender system, and investigates the role played by customization of privacy settings—either through user action or as an interface cue—in influencing users’ privacy-related perceptions, their disclosure behaviors, and their evaluations of personalized recommendations. To test this, we conducted a 2 (Personalization: Reactive vs. Proactive) X 3 (Customization: Action vs. Cue vs. Absence) factorial online experiment (N = 299) with a movie recommender system. Findings provide more evidence for the personalization-privacy tradeoff phenomenon, and show that interface cues suggesting customization are quite effective in enhancing user experience, even in the presence of proactive personalization. In addition, users’ previous memory of privacy intrusion and disposition to value privacy were found to play a significant role in their experience interacting with different personalization mechanisms and customization modes.
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INTRODUCTION

Thanks to successful mining of big data and rapid development of machine learning technologies, online recommender systems have become quite common, offering individually tailored content recommendations to users, via such popular sites as Netflix and Amazon.com. The most distinctive feature of recommender systems is personalization—the provision of personally relevant suggestions and services based on individual users’ unique characteristics and needs (Xiao & Benbasat, 2007). Recommendations provided by these systems include suggestions for music (e.g., Pandora), movies (e.g., Netflix), and e-commerce purchases (e.g., Amazon.com), to name a few.

Users favor personalization because it reduces their cognitive load by automatically offering services that match one’s interests and needs (Chin, 2007). But, they also worry about their privacy because the system would need to acquire and process personal user information (e.g., online profile, purchase history) in order to provide good recommendations (Chellappa & Sin, 2005). They are concerned about the likelihood of privacy breaches, because such data tracking and collection are often unsolicited (Lin et al., 2012b) and shared with unknown parties (Bennett & Lanning, 2007a). The unpredictability of recommender systems’ data usage has raised widespread privacy concerns (Malhotra et al., 2004) even though users prefer personalized services, giving rise to a phenomenon known as “privacy-personalization tradeoff” (Awad & Krishnan, 2006; Chellappa & Sin, 2005).

In order to minimize the trade-off, some personalization systems offer users an opportunity to signal whether or not they would like a particular recommendation (e.g., Netflix lets users filter movie genre and rate the content they’ve watched for movie recommendations). This is commonly referred to as “reactive personalization” in that the system reacts to the user’s expressed need at the moment of service delivery. This type of
personalization is in contrast to the more common practice of “proactive personalization” in which the system delivers personalized service without explicit consent of the user (Bellavista, Kupper, & Helal, 2008). While proactive personalization may provide better service quality by automatically pushing relevant content to users, it can induce more privacy concerns than reactive personalization because it is perceived as being more intrusive (Berendt & Teltzrow, 2005; Unni & Harmon, 2007). The underlying factor that distinguishes these two mechanisms is the locus of agency—users of technology or technology itself. Reactive personalization gives users more human agency because it allows them to initiate requests, whereas proactive personalization is associated with more machine agency by automatically serving users. Therefore, the relative preference for reactive personalization over proactive personalization is likely due to the greater human agency afforded by the former. But, this too comes at a cost, namely constant calls for user action, which can be intrusive and detrimental to user experience.

One potential solution to this problem may be the affordance of customization, which is known to ensure a positive user experience by providing users with a strong sense of control (Marathe & Sundar, 2011). It has even been known to override privacy concerns (Culnan & Armstrong, 1999; Sundar & Marathe, 2010). Therefore, adding a customization feature (e.g., privacy setting) to personalized recommendation systems may serve to attenuate the preference for reactive over proactive personalization. That is, when a recommendation system whose privacy settings have been customized by the user offers proactive personalization, it is likely to be better received and raise less privacy concerns. This means, users may no longer prefer reactive over proactive personalization; indeed, it might be the opposite, given the intrusive calls for action required by the former.
This hypothesis lies at the core of this dissertation, which delineates differences in privacy concerns raised by different personalization mechanisms (reactive vs. proactive) in a recommender system, and investigates the role played by customization of privacy settings in influencing users’ privacy-related perceptions, their disclosure behaviors, and their evaluations of personalized recommendations.

The goal of this investigation is to advance our knowledge about online users’ decision-making, by providing explanations for the many paradoxical phenomena related to personalization and privacy, and shed light on persuasiveness of online recommendation agents. The study of interface aspects (e.g., privacy settings, personalization delivery mechanisms) has design implications for making recommendation systems more psychologically accessible and more protective of user privacy.

The study tested these possibilities via an online experiment, the procedures for which will be discussed in the Methods chapter. First, a literature review covering the central concepts under study will be presented, as part of the theoretical warrant for hypotheses to be tested.
Chapter 1

LITERATURE REVIEW

This section first introduces personalization and its effects on privacy concerns and persuasion outcomes in an online recommender system. It will then explicate customization, delve into its psychological effects, and discuss how it may alleviate privacy concerns caused by personalization and enhance persuasive appeal of personalized agents in a recommender system.

**Personalization in online recommender systems**

Personalization can be defined as system-initiated tailoring of content (e.g., products, services) that accommodates individuals’ characteristics and needs (Chellappa & Sin, 2005). It is the most prominent feature of recommender systems (Burke, 2002). Advances in data mining technologies have led to wide adoption of recommender systems by both online vendors and mobile applications (Adomavicius & Tuzhilin, 2005), ranging from e-commerce to social networking sites. Such systems are known for their capability in tracking, storing, and analyzing user data (e.g., purchase history, profile information) to understand user contexts and predict users’ preferences and needs (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012), so as to provide personalized suggestions and services (Brusilovsky, 2001; Xiao & Benbasat, 2007). Commonly collected user data for personalization in recommender systems includes demographic information recorded through users’ online registration, which can be combined to pinpoint one’s individual characteristics (e.g., gender, age, address, credit card number), as well as object-associated data that is gathered through users’ online behavior (e.g., browsing history, purchase history), indicating one’s preferences and behavioral patterns.
Employing personalization can establish a positive relationship between service providers and users (Riecken, 2000). Personalization is critical to recommender systems, because understanding user information and producing tailored services can serve the purpose of forecasting user demand, enhancing user engagement, and increase impulsive purchasing (Blattberg & Deighton, 1991; Peppers, Rogers, & Dorf, 1999). From users’ perspective, personalization is also of great importance, because it provides more convenient and relevant services (Chellappa & Sin, 2005), reduces users’ cognitive load in online decision making, and improves overall user experience (Knijnenburg et al., 2012). Because of these advantages, leading recommender systems such as Amazon.com and Netflix have been emphasizing the role of personalized recommendations.

**Personalization and privacy**

The key to successful personalization in recommender systems lies in extensively acquiring, storing, and analyzing user data, which is often achieved via machine learning and data mining techniques (Hirsh, Basu, & Davison, 2000). In particular, users’ clicking behaviors are collected via cookies to analyze their “travel patterns” online, and their purchase history is gathered by vendors to predict similar future needs. With such data, recommender systems build an individual profile for each user to infer a need pattern, and offer personalized content and services based on the pattern (Raghu, Kannan, Rao, & Whinston, 2001). Advanced technologies have made it possible to trace every single bit of users’ information and behaviors online, leading some scholars to argue that the idea of privacy becomes an illusion (Schneier, 2010).

Therefore, to obtain the exciting benefits promised by personalized recommendations, one has to trade in his/her own privacy to some extent (Culnan, 2000); this is known in the
literature as “privacy-personalization tradeoff” (Awad & Krishnan, 2006; Chellappa & Sin, 2005). For example, in order for highly accurate predictions to be generate, users will need to put up with constant and unsolicited tracking of their online activities (Lin et al., 2012a). Moreover, relevant commercial recommendations inevitably involve information sharing with third-parties without users’ consent (Bennett & Lanning, 2007b). These practices are contradictory to users’ intention to protect their private information, raising significant privacy concerns and diminishing users’ intention to share personal information (Kim, Chan, & Gupta, 2007; Xu, Luo, Carroll, & Rosson, 2011).

**Personalization delivery mechanisms: reactive vs. proactive**

In addressing these privacy concerns and engaging users with recommendation services, personalization in recommender systems is often delivered to users via two mechanisms—reactive (i.e., pull or covert) and proactive (i.e., push or overt). These two mechanisms illustrate the two different methods of recommendation acquisition and delivery (Bellavista et al., 2008), and plays a critical role in influencing users’ impressions about the service content and provider, and their privacy attitudes and behaviors. Past research has labeled these two mechanisms (i.e., reactive vs. proactive) in various ways, for example, pull vs. push (Unni & Harmon, 2007), overt vs. covert (Xu, Luo, Carroll, & Rosson, 2011), explicit vs. implicit (Koren, Bell, & Volinsky, 2009), to name a few. Although the labels vary when used in different contexts (e.g., marketing/advertising, machine learning), their underlying meanings remain the same.

The role users play, or the degree of human agency (in contrast with machine agency), denotes the main difference between the two mechanisms. For instance, in location-based services (e.g., GPS), reactive personalization is invoked by a one-time user request (human
agency), and the system provides personalized responses accordingly. Proactive personalization, on the other hand, automatically detects the user’s location and delivers personalized content pre-subscribed by the user (Lee, Kim & Sundar, 2015) (machine agency). However, there is often no absolute boundary between human agency and machine agency in an interaction between the user and the technology; the type of agency lies rather on a continuum (as illustrated in Figure 5 on p. 38), where human and machine agency can coexist. Proactive personalization represents machine agency solely, as the whole process from user data gathering to personalized service delivery is performed by the system or machine. But reactive personalization involves the user making a request before the system generates any personalized content even though the tailoring is performed by the system, leading to a hybrid of machine agency and human agency.

Reactive personalization, as its name indicates, reacts to users’ requests for information. Such requests include explicit information seeking (e.g., an inquiry on local restaurants), and direct data input from users that clearly expresses their preferences and tastes, such as product ratings and movie critiques (Chen & Pu, 2012; Gena, Brogi, Cena, & Vernero, 2011). Reactive-personalization-based recommender systems respond to these explicit requests by generating suggestions based on them. For example, in a reactive mechanism, when a user searches for a watch to purchase, the system will accordingly provide various watch options based on the search criteria the user enters (e.g., price range, brand, color) and his/her personal information saved on record (e.g., age, gender, income level), or the user’s past ratings on related items purchased before (e.g., other watches, brands, designs).
Proactive personalization, on the other hand, involves predicting users’ needs on the basis of system-analyzed user preferences and behavioral patterns, and automatically “pushing” personalized content to users. This approach does not demand user attention or interaction for generating requests (Bellavista et al., 2008), but relies heavily on covertly observing user behaviors and synthesizing user data (i.e., “implicit feedback”) online (Koren et al., 2009), in contrast to explicit user input (e.g., active search, product rating). Implicit feedback data includes browsing history, purchase history, mouse clicking behaviors, and search patterns that users leave behind unintentionally (Koren et al., 2009), which is often clustered automatically by data mining algorithms to identify user-item connections for future recommendations (Hauser, Urban, Liberali, & Braun, 2009). Proactive personalization is trendy today with the advances of context-aware computing in recent years—embedded sensors in everyday objects now enable user data to be tracked, recorded, and computed more seamlessly in an anytime-anywhere manner, without need for active user input of information (Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002). With these sensors, the system can get a multi-dimensional picture of users’ personal information—demographics, health status, mood, location, and past behaviors—and surrounding physical situations (e.g., existing objects, temperature, noise, humidity) to infer users’ real-time preferences and needs, so as to accurately generate recommendations (Adomavicius & Tuzhilin, 2011). In other words, although users do not explicitly express their demands, their tendencies can be automatically speculated based on system-stored data and their behavioral patterns.

Previous research has compared the differences between the two personalization mechanisms. Reactive personalization requires users to be agentic in initiating requests and willing to subjectively give out information, whereas user effort is not necessary for proactive
Therefore, the main difference lies in the presence of user initiative. Proactive personalization usually appeals to online vendors because it obviates the need to actively lobby users to opt in, pushes more content to users and thereby stimulates impulse buying (Unni & Harmon, 2007). To users, however, proactive personalization can be intrusive because system-initiated recommendations are often unexpected, which means that user data are tracked without consent. This could diminish the perceived value of recommendations, and even trigger negative reactions such as avoidance of system use (Edwards, Li, & Lee, 2002) and privacy concerns (Berendt & Teltzrow, 2005; Unni & Harmon, 2007) toward the recommender system. However, the convenience of use of proactive personalization may as well engender positive attitudes toward the system, especially for non-power users (i.e., none-experts in the use of technology) who prefer not to expend much cognitive effort in setting up the system (Sundar & Marathe, 2010). Also, reactive personalization has been found preferable in location-based advertising, because users feel that they are more in control over the level of information releasing with the reactive mechanism (Lee et al, 2015; Unni & Harmon, 2007). In all, reactive personalization is likely to empower users with a sense of control, whereas proactive personalization may provide users with more seamless convenience and recommendations of higher quality, but also trigger a sense of intrusiveness that leads to privacy concerns. Therefore, we hypothesize and propose:

\[ H1: \text{Reactive personalization will elicit more sense of control than proactive personalization.} \]

\[ H2: \text{Proactive personalization will lead to better perceived recommendation quality than reactive personalization.} \]
**H3: Proactive personalization will cause more privacy concerns than reactive personalization.**

Given the mixed findings and impressions about the influence of proactive and reactive personalization, it is unclear how personalization mechanism affects users’ general attitude toward the system that delivers personalized service, and whether their intention to use the system in the future is influenced. In a system with proactive personalization, would users be willing to disclose personal information in exchange for convenient services or hesitant to do so because of the potential higher privacy risks? We thus propose the following research question:

**RQ1: What is the relationship between personalization mechanism and a) attitude toward the system, b) behavioral intention to use the system in the future, and c) willingness to disclose to the system?**

Reactive personalization is based on users initiating requests for content, or providing consent to the system for delivering services. Such agentic action on the user end sounds similar to but is different from another concept, customization. Customization allows users to be their own source such that they are in full charge of their experience, but reactive personalization only treats users’ needs as a trigger to elicit personalized services. If reactive personalization indeed leads to more sense of control and less privacy concern as hypothesized, could customization at a global level, i.e., the level of the entire system or interface (especially customization of privacy settings), be the key to invoke a higher sense of user control and thereby reduce privacy concerns in proactive personalization systems? If the answer is yes, then it eschews the need for reactive personalization, thus sparing users the
need to constantly provide consent and preferences. With this in mind, the next section explicates the concept of customization and examines its psychological effects.

**Defining customization**

The Merriam-Webster dictionary defines “customize” as “to build, fit, or alter according to individual specifications” (Merriam-Webster online). Following this definition, customization denotes the action, function, or outcome of individual configuring, which can be seen almost everywhere today, both online and offline, such as decorating one’s room, changing one’s online profile picture, adjusting the privacy setting on an e-commerce website, using various phone cases, to name a few. Traditionally, the phenomenon of customization has been studied in various venues. For example, Vinsel, Brown, Altman, and Foss (1980) described how college students customized their dormitory room decorations, and Wells (2000) studied customization in office space. In information system and product management literature, customization has been conceptualized as a business strategy—as in “mass customization”—to provide customers individually designed products and services (Davis, 1989; Kaplan & Haenlein, 2006), which “reach(es) customers in the mass market economy but treat(s) them individually as in the pre-industrial economies” (p.2) (Da Silveira, Borenstein, & Fogliatto, 2001).

With the advancement of computing technologies, engineers treated software as a new form of product and service (Sun, Zhang, Guo, Sun, & Su, 2008), and the concept of customization was adopted to represent the ability for software and operating systems to be modified by programmers, users, or lower-level applications (Nidumolu & Knotts, 1998). Denys, Piessens, and Matthijs (2002) explained that the purpose of allowing clients to modify system features and policies is to let them better achieve their goals. And Bolin, Webber, Rha,
Wilson, and Miller (2005) listed several ways of customizing software interfaces with programming languages, including “changing defaults for form fields, filtering or rearranging web page content, and changing fonts, colors, or element sizes” (p. 163).

The notion of customization became even more popular as the Internet penetrated people’s lives, when audiences became “users,” and users progressed from passive receivers to active content creators. Users today can interact with technologies through interface-level features, and also have a say in content consumption based on personal preferences. In this context, customization is often defined as a user activity—“a user initiated and user controlled activity that lets them play an active role in influencing different factors in their interactions with the interfaces” (Marathe, 2010), which is motivated by the will to efficiently access information, accommodate individual differences, and express identity (Blom, 2000). Essentially, customization has two core characteristics: individual tailoring and user influence.

As emerging technologies keep expanding the range and scope of user interactions with them, another definition of customization describes it as a technological attribute that supports user tailoring—the ability of an interface to let users change certain aspects of it to increase personal relevance (Blom, 2000). Rather than attributing the individualized tailoring to users, this conceptualization credits the action possibility to technologies. Objective action possibilities generated by systems that support user interactions are called “affordances” (Gibson, 1977; Norman, 1988). Technological affordances refer to the capability of technological features of a system (e.g., website, mobile app) in enabling user interactions (Gaver, 1991), which are influential in altering users’ attitudes and behaviors (Sundar, 2008b, 2009). Along these lines, Sundar and colleagues conceptualize customization as an offshoot of source-interactivity affordance in modern media interfaces. Source interactivity is defined by
Sundar (2007) as the degree to which the interface allows users to be the source of communication, which manifests itself through users’ ability to customize. A two-week field study by Sundar, Oh, Bellur, Jia, and Kim (2012) empirically explored source interactivity by operationalizing it as two types of customization—changing interface appearance (cosmetic customization) and modifying utility tools on the interface (functional customization). They found that customizing appearance of the interface has a psychological appeal in generating users’ desire for expression, and some degree of functional customization can improve task efficiency. Along the same lines, previous research has repeatedly confirmed the positive effects of customization on user psychology (e.g., Kalyanaraman & Sundar, 2006; Sundar & Marathe, 2010).

In sum, technologies afford users an opportunity to customize. As a technological affordance, customization presents itself as a functionality or feature of systems (e.g., profile editing, privacy setting), which indicates the possibility for users to make modifications to reflect their tastes and needs, but the flexibility of changes is determined by the system (Andriessen, Hettinga, & Wulf, 2003).

When seen as a technological affordance, customization is often referred to as customizability (Denys, Piessens, & Matthijs, 2002; Jiao & Tseng, 2004). And this is a well-known feature of adaptable systems (Stuerzlinger, Chapuis, Phillips, & Roussel, 2006). To optimize efficiency and overall performance, such systems allow for some flexibility in functionality and policies for lower-level applications and mass users to adjust, so as to accommodate individual preferences and attain a better balance between the system’s goals and users’ needs. The computer-supported cooperative work (CSCW) community took a step further to conceptualize customization as inherent to group activities. For example, MacLean
et al. (1990) discovered a “tailoring culture” among users of a customizable technology called “Button,” such that users understood that making changes to buttons was an acceptable social behavior and expected by others, which largely encouraged collaboration and sharing among users. Similarly, Mackay (1990) found that customization practices triggered spontaneous sharing in social networks. Dourish (2003) conceptualized this broader view of customization as technology appropriation, meaning a “process by which people adopt and adapt technologies, fitting them into their working practices” (p. 465).

Some previous research has used the term customization interchangeably with personalization, because both of these two concepts aim at having users access individually relevant content and experience. But what conceptually distinguishes them is the process of achieving such tailoring—customization is tailoring that is performed by users themselves, whereas personalization refers to user tailoring performed by the system or content provider (Sundar & Marathe, 2006). Sundar and Marathe (2010) discovered that power users tend to prefer customization over personalization, but non-power users prefer personalization. The authors explained that this might be because power users are more cautious about potential privacy risks and want to have control over their own content consumption, and non-power users tend to favor convenient services that do not require much cognitive effort.

In sum, given the trend in communication technologies that provide countless user-tailoring opportunities, customization is defined here as a technological affordance that provides users with the possibility to modify certain aspects of an online system to increase individual relevance based on their needs.
**Customization in the privacy context**

Rapid advancement of modern technologies dramatically elevates users’ online experience by providing personalized services, but also introduces unprecedented privacy threats, as high-quality, individualized services always rely on the access and use of user data (Li & Unger, 2012). To alleviate concerns and protect privacy, common practices employed by online service providers include presenting consent and privacy statements. But, lately, there has been an emphasis on providing choices to users so that they can make privacy decisions according to their needs and preferences. For example, the World Economic Forum (2013) has advocated a framework for consumers to customize their permissions on data use with various levels of granularity, rather than merely providing a consent offering yes-or-no at the very beginning of data collection.

Previous research has shown that reactive personalization can elicit less privacy concerns compared with proactive personalization because it gives users a higher sense of control while they interact with the system (Berendt & Teltzrow, 2005; Unni & Harmon, 2007). But as a mechanism to deliver personalization, it still tracks user data to a large extent to provide individually tailored services, thus it is likely to trigger privacy concerns and other negative reactions. If the agentic feeling of user requests in reactive personalization is indeed the key to eliminating privacy concerns and facilitating decision making, enhancing users’ sense of control by providing a customization feature will be of great importance to enhance positive perceptions about personalized systems and their services.

Privacy customization thus far has been widely advocated by online service providers in various venues. Most websites now give users certain levels of flexibility in customizing the extent to which they reveal personal data (Chavez, 2011; Richter, 2011). Netflix, for
instance, lets users customize their “taste profile” (Figure 1) to indicate viewing preferences and habits, including the genre types users like, frequency of watching different genres, and ratings of the movies they watched before. With such information, Netflix can create an individual profile for each user and recommend content that is better suited to their preferences.

![Taste Preferences](image)

**Figure 1. Netflix's taste preference setting**

Facebook has a privacy-setting interface within which users can customize how they want to share information with different types of audiences. To make the privacy settings more visible and easier to adjust, it also displays a privacy shortcuts tab that includes instructions on checking the user’s current privacy settings, and links to change the scope of audiences who can see the user’s shared content, contact the users, and instructions on blocking someone (Figure 2).

In addition, both Android and Apple mobile platforms include a system-level privacy setting interface for users to manually toggle on or off the access of personal data by different
applications, which again suggests the emphasis of customization in the privacy context across different platforms.

![Facebook's privacy shortcuts](image)

**Figure 2. Facebook's privacy shortcuts**

**Psychological effects of customization**

As an affordance, customization has generally shown positive effects on user psychology. For instance, Wells (2000) found that customization of office space led to employees’ increased job satisfaction and well-being; in a more technological environment, Coner (2003) showed that customers of a financial website with customization features got more value and were more willing to disclose personal information compared to a generic website; and a few studies revealed that customization in e-commerce websites could promote perceived financial value of products and services (Franke, Schreier, & Kaiser, 2010; Jiang, 2002) as well as encourage future website visits (Ansari & Mela, 2003). The existence of customization can also fulfill users’ needs for expressing unique identities (Lynn & Harris, 1997; Walsh & White, 2007).
The agency model of customization (Sundar, 2008) suggests that control is at heart of customization. Indeed, affording users the opportunity to customize something is in fact granting them the power to manage, manipulate, and decide, after all, to have control over things. Therefore, customization affords ontological control, which in turn leads to perceived control (Marathe, 2007), a very, if not the most, critical psychological outcome.

In the privacy context, customization is often conceptually equated with ontological control (Adjerid, Acquisti, & Loewenstein, 2014). And regulators have been urging service providers to pay attention to such control by increasing users’ choices in the system’s accessing to and using of personal data (FTC, 2012). As a result, developers and designers have been employing customization of privacy settings in response to this call. However, in contrast to the predominantly positive effects of general customization discussed above, findings from privacy research seem mixed. For example, some scholars argue that letting users to customize their privacy settings is the service provider’s strategy to pass responsibility to users and adding to their cognitive burden in decision making (Schwartz, 2005; Solove, 2013). An unwanted consequence is that overloaded users just give up their choices and follow the default opt-ins, which goes against the original intention to protect them. Another study found that, when given the freedom to make choices and exert control, users may feel an illusion of control such that they do not take full advantage of the power, but in contrary be more willing to share their personal information by ignoring the choices (Brandimarte, Acquisti, & Loewenstein, 2013). Does this mean that users need to exercise control in order to feel in control, or is it sufficient to provide them the option of exercising control? How should control be conceptualized in the privacy-setting domain, and what is the relationship between customization and control?
The role of control

Frequently conceptualized as an ontological construct, control has been defined as a power to direct the behavior of a live being or the function of something in a certain way (Merriam-Webster online). This power refers to people’s actual ability to manipulate external environment and objects (e.g., electronic shocks) (Staub, Tursky, & Schwartz, 1971). The proliferation of media technologies enriches this definition by extending the objects of control to computers, DVDs, video games, and other digital devices and content supported by computing technologies (Burgoon et al., 1999; Huhtamo, 1999; Preece, 1993). In education psychology, Shin, Schallert, and Savenye (1994) conceptualized control as an ability of learners to “navigate multiple pathways through the information” (p. 33). In marketing research, Ariely (2000) described consumers’ control as the ability to manage “the flow of their information system (control over what information will be presented, for how long it will be presented, and what information will follow)” (p. 233). Control in interpersonal communication has been equated with the ability to freely adjust the initiation, pace, and target of communication process (Kayany, Wotring, & Forrest, 1996). And human-computer interaction (HCI) scholars study control in terms of how users operate computers (Huhtamo, 1999), interact with interfaces and input devices (Nielson, 2000; Shneiderman, 1992), and use navigation tools (Heeter, 1989). These conceptualizations are all rooted in an ontological perspective, such that users can exert their willingness by actually behaving to change or choose things, which are “behavioral control” (Averill, 1973). The corresponding operationalizations are therefore straightforward—whether or not users are given such behavioral execution or choices to manipulate the medium, the content, and other relevant
elements (Ariely, 2000; Shin et al., 1994; Wise & Reeves, 2007). Applying this perspective in technologies, customization affords users the possibility of behavioral control.

In contrast to defining control as an actual behavior, the concept has also been employed as a psychological variable—often referred to as perceived control (Rothbaum, Weisz, & Snyder, 1982) or a sense of control (Rodin, 1986). Reeves and Nass (1996) pointed out that human perceptions are crucial to HCI research, and ontological features of media technologies can often trigger perceptual impressions. On the one hand, a sense of control can be a direct outcome of behavioral control, as a psychological satisfaction resulting from successfully changing things (Weisz & Stipek, 1982). Following this distinction, Skinner, Chapman, and Baltes (1988) defined perceived control as a primary control—an agentic feeling about the extent to which one can behave with free will and produce desired outcomes. And Langer and Saegert (1977) equated cognitive control with a sense of having predictability of potential threats, which is secondary control—individuals do not need to be able to administer anything, but just be acknowledged of what will happen. Consistent with the psychology literature, perceived control has been found to be able to affect human behaviors even more than behavioral control (Skinner, 1996).

**Control in the privacy context.** Conceptualization and operationalization of privacy are often associated with control (Culnan, 1993; Smith, Milberg, & Burke, 1996). For example, Miller (1971) states, “the basic attribute of an effective right of privacy is the individual’s ability to control the circulation of information relating to him” (p. 25). Stone, Gueutal, Gardner, and McClure (1983) define privacy as “the ability of the individual to control personal information about one’s self” (p. 460). Fried (1984) maintains, ”(p)rivacy is not simply an absence of information about us in the minds of others, rather it is the control
we have over information about ourselves" (p. 209). Elgesem (1996) suggests, "to have personal privacy is to have the ability to consent to the dissemination of personal information" (p. 51). Lessig (2002) also claims that privacy is a means of information control, which is similar to copyright: “(j)ust as the individual concerned about privacy wants to control who gets access to what and when, the copyright holder wants to control who gets access to what and when” (p. 250). And lastly, according to Margulis (2003), privacy is “control over or regulation of or, more narrowly, limitations on or exemption from scrutiny, surveillance, or unwanted access” (p. 244). The statements listed above signal the critical role of control in privacy-related research, but they mostly point to behavioral control such as the choice of opting out of system’s information access in an online service, which in fact points to the action execution of customization.

In terms of perceived control, prior research has shown that it is closely associated with attitudes toward privacy, such that privacy concerns will be induced when people feel that their personal information may be accessed or misused by others, which is often linked with lack of perceived control (Xu, Dinev, Smith, & Hart, 2011). As a result, system designers strive to implement various privacy customization features as coping strategies to override privacy concerns (Heitmann, Kim, Passant, Hayes, & Kim, 2010). Although the underlying assumption is that perceived control is the direct outcome of customization, which is crucial to privacy-related perceptions and decision making, a refined conceptualization of perceived control is missing (Margulis, 2003), thereby hindering an appropriate adoption of it in developing privacy theories and in exploring use and evaluations of an online recommender system. Among a few empirical examinations of perceived control in the privacy context, Xu et al. (2011) defined perceived privacy control as “an individual’s beliefs in his or her ability
to manage the release and dissemination of personal information” (p. 804), which reflects the aforementioned primary control; Laufer and Wolfe (1977) showed that perceived control is an intervening variable between behavioral control and other psychological outcomes; and Johnson (1974) argued that perceived control should be a precondition for privacy protection.

Research has also shown that psychological control is linked with privacy concerns in various online services. For example, a lack of perceived control over collection and usage of information has been found to lead to a greater sense of privacy invasion among online consumers (Culnan & Armstrong, 1999; Sheehan & Hoy, 2000); Milne and Boza (1999) showed that, when individuals feel that they can control the revealing and use of personal information, they tend to be less concerned about privacy; Acquisti and Gross (2006) discovered the same pattern among Facebook users, such that those who were not worried about privacy of their online posts also felt a greater sense of control over the information provided; and Xu and Teo (2004) proposed three privacy assurance mechanisms in a location-based service to elevate users’ perceived control, which were found effective in reducing privacy concerns. Among these cases, it is worth noting that perceived control only reflects users’ psychological impressions of the service/system, which is not necessarily tied to how extensively they can manage their private information. Past research has also suggested the existence of a “control paradox,” that is, even imbued with behavioral control over information publication, users may not make good use of it and still take the risk to disclose about themselves. And the more granular these control settings are, the more likely users are to give up their privacy to larger audiences (Brandimarte et al., 2013). It seems that the more actual control (i.e., customization) given, the less users need it. This might be due to the fact
that the presence of customization features enhances users’ perceived control, making them less vigilant about privacy invasions even without any real actions.

Due to its critical influence on both behavioral and perceived control, customization has been employed in vast online services to reduce privacy concerns and justify disclosure behaviors. It holds the potential of balancing privacy and benefits of disclosing information. A common deployment of customization in online systems is via certain types of user settings, such as profile editing, or privacy setting, and such deployment can often be achieved through two distinct notions of customization—either actual exercise of control (the actions that users undertake to tailor their settings), or mere provision of control (the knowledge that users can control their settings if they want to, not necessarily involving any actual behavior). These two notions of customization resonate with the two psychological routes—the action route and cue route—of processing a technological affordances proposed by the theory of interactive media effects (TIME) (Sundar, Jia, Waddle, & Huang, 2015), as discussed in the next section.

**Customization: the action route vs. the cue route**

**TIME model.** The theory of interactive media effects (TIME) suggests that a technological affordance can influence user psychology through two routes: 1) the action route—affordances trigger actions on the part of the user, for example, customizable privacy settings of an online service allow users to manually turn the permissions on and off; 2) the cue route—mere presence of affordances (e.g., a screen-shot of the privacy-setting interface) suggests the possibility of user action without their real behaviors, which triggers cognitive heuristics (or mental shortcuts) about the interface that shape user attitudes and behaviors (Sundar et al., 2015). Based on this model, it is reasonable to expect that customization may
affect user psychology and behaviors through both the cue and the action routes, but it remains unclear which is more effective, and the underlying psychological mechanisms that determine these two routes.

Little consensus has been reached about the difference in effectiveness between these two routes. Akbiyik (2012) found that people who learned about a technological program through a demonstration (involves face-to-face interaction) gained more knowledge than people who learned through a tutorial (presented as a video). This finding suggests the superiority of the action route over the cue route. But in another study, Zhang, Appelman, Choi, and Han (2013) did not find any significant difference between the effects of cue (i.e., presenting navigation buttons on the interface without user action) and action (i.e., users’ actual interaction with navigation tools) of interactivity on users’ perceptions about a virtual travel website. They also showed that participants exposed to either the cue or the action condition perceived greater interactivity of the interface than those in the control condition. Such findings show that both visual cues of interactivity and actual interactions are responsible for triggering interactivity-related heuristics.

In line with these findings and the preceding discussion, not only the action route of customization can affect users’ attitudes and behaviors via a sense of control, but also interface cues suggesting the possibility of customization, such as a privacy-setting panel, are likely to trigger the “control heuristic” (i.e., having control is good) by presenting users with options to manipulate their system settings. These customization indicators can convey the message of good service and content quality, and users’ role in shaping them, thereby influencing attitudes and behaviors. Based on this rationale, the following research question is posited:
RQ2: What is the relationship between mode of customization (action vs. cue vs. absent) and a) sense of control, b) content perception, c) system perception, d) privacy concerns, e) willingness to disclose personal information, and f) behavioral intention in an online recommender system.

Customization: the action route. Customization as an attribute of technology offers a great range of gatekeeping options to users, and the most distinctive characteristic of it is allowing users to change aspects of an interface to make it more personally relevant. By executing this action of self-tailoring, users obtain a strong sense of agency—or a feeling of being the source or authority—through freely making changes (Sundar, 2008b). Klug and Schell (2006) explain this sense of agency as perceived instant control, a perceived power to manage or direct. Marathe and Sundar (2011) empirically demonstrated that users gained significantly higher sense of control after customizing an online interface.

Marathe (2007) detected a positive correlation between people’s need for control and the degree of customization action they perform. And through a content analysis, Sundar, Marathe, and Kang (2009) further showed that major health websites allow users to perform a wide variety of customization actions to imbue them control, suggesting predictable outcomes of actions, letting users initiate interactions, and offering multiple choices to users. Therefore, ontologically, users exert actual control over their interaction with the system through customization, which leads to a psychological feeling of being in charge. Marathe and Sundar (2011) further classified customization into functional and cosmetic customization—referring to task-based modifiability and presentation-based modifiability respectively. They showed that in an information consumption management system, engaging in functional customization (i.e., widget set-up) can lead to a sense of control. In all, sense of control is a powerful
psychological effect of the action of customization because it allows people to be in charge and influential (Wind & Rangaswamy, 2001), indeed empowered (Weissman, 1988).

Along the same lines, according to the uses and gratifications theory (Rubin, 2002), especially its application in the modern technological environment, users seek and obtain gratifications from ontologically interacting with technological affordances such as customization. Sundar and Limperos (2013) have proposed various new gratifications particularly associated with new media technologies, such as agency-enhancement, filtering/tailoring, dynamic control, ownness, and so on. Many of these new gratifications emphasize user autonomy, or a sense of user control. Perceived control has already become a gratification granted by media technology use, and customization is a direct source of it. Therefore, the following hypothesis is proposed:

\textit{H4: Engaging in the action of customization will lead to a sense of control.}

Sense of control has become an important user-experience concept in today’s highly technological environment, as more and more media outlets allow users to be the source of their online interaction (Saffer, 2009). Perceived control can contribute to various positive psychological effects, such as better attitudes toward the interface and content (Kalyanaraman & Sundar, 2006), more involvement with the content (Kim & Sundar, 2011; Sundar, 2008b), and a higher level of autonomy and self-determination (Katz & Assor, 2007).

First, a sense of control is strongly related to individuals’ wellbeing and health. Control was found to be able to improve physical and mental health by allowing individuals to relax, to avoid pressure, to manage moods, and to deal with strong emotions (Westin, 1968). Self-determination theory also suggests that autonomy and competence—concepts closely related to control—facilitate integrated action, need fulfillment, and wellness (Sheldon, Ryan,
Deci, & Kasser, 2004; Vansteenkiste, Ryan, & Deci, 2006). However, a lack of control can result in a lack of confidence, doubts about self, and more severely, depression and anxiety (Johnson, 1974; Margulis, 2003).

Perceived control can also overcome fear about risks. As an important factor in determining risk perception and risk-taking behaviors, psychological control can encourage people to be more inclined to take risks, and less concerned about the severity of those risks (Harris, 1996; Klein & Kunda, 1994; Nordgren, Van Der Pligt, & Van Harreveld, 2007; Slovic, 1987; Weinstein, 1984). This tendency generated from sense of control can then serve to reduce privacy concerns, and encourage more information disclosure online (Brandimarte et al., 2013).

In addition, a vast body of empirical work has also shown that perceived control can lead to elevated attitude toward the system/interface that affords control (Moon & Kim, 2001), more trust toward the system (Shepherd & Zacharakis, 2001), more engagement with the system (Marathe, 2010), as well as more intention to use the system in the future (Hsu & Lu, 2004). Given these positive influences of sense of control identified in previous research, we continue to propose that it positively mediates the relationship between action of customization and other outcome variables:

\textit{H5: Sense of control positively mediates the relationship between action of customization and a) attitude toward the system; b) perceived recommendation quality; c) less privacy concerns; d) future use intention; and e) willingness to disclose personal information.}

Apart from the psychological benefits listed above, sense of control also imbues users a feeling of freedom or autonomy. Action of customization lets users decide how to manage content and to be in control over their interaction with the system, or to be self-determining.
(Deci & Ryan, 1985). As discussed previously, sense of control is a new gratification that can be gained from technology use. It is also a well-acknowledged predictor of motivation identified by psychology research (Garris, Ahlers, & Driskell, 2002; Cordova & Lepper, 1996). According to self-determination theory (Deci & Ryan, 1985), when users are offered freedom to engage in a behavior, they tend to be inherently motivated to do so. In other words, they are likely to spontaneously engage in activities (e.g., customizing the interface) that provide choices and allow users to be their own sources (Deci, Schwartz, Sheinman, & Ryan, 1981). Therefore, when customization triggers a sense of control, users’ intrinsic motivation to further engage in customization actions is enhanced. Users simply enjoy the feeling of controlling, so the motivation is not contingent upon rewards, or external control (Deci & Ryan, 2010). However, such intrinsic motivation cannot be simply equated to enjoyment. In fact, prior research including self-determination theory (Deci & Ryan, 1985) and flow theory (Csikszentmihalyi, 1990) has shown a set of variables pertaining to the subjective feeling when engaged in intrinsically motivated activities. These variables include (1) hedonic enjoyment and interest (Deci & Ryan, 1985), (2) sense of flow such that a high level of skill is met with a high level of challenge (Csikszentmihalyi, 1988), and (3) a feeling of self expressiveness (Waterman, 1990). In the current study, the latter two dimensions are especially important factors of intrinsic motivation, because the ability to customize not only provides an enjoyable experience, but also poses the challenge to make decisions on one’s own, and allows one to express oneself through the process of customization.

Prior research has also shown that freedom of choice can elevate perceived value of actions, which further increases intrinsic motivation to engage in such actions (Iyengar & DeVoe, 2003). The Technology Acceptance Model (TAM) also proposed a positive
relationship between internal control and intrinsic motivation (Venkatesh, 2000). Hence, the following hypothesis is posited:

**H6: Sense of control will positively influence intrinsic motivation.**

Venkatesh (1999) identified intrinsic motivation as a predictor of improved user perceptions of a technological system and enhanced behavioral intention to use the system in the future, which is in line with TAM. The Theory of Reasoned Action (TRA) (Fishbein, 1979) and other empirical studies applying TAM and TRA have also revealed a link between intrinsic motivation and positive affect as well as intention to engage, which positively influence users’ attitudes toward the system and content, and evoke their willingness to interact with the system further (e.g., Moon & Kim, 2001). Such inherent motivation is likely to ease users’ concerns about privacy and encourage them to disclose more about themselves, in order to further engage with the system. Therefore, given the rationale above, the intrinsic motivation induced by sense of control is likely to mediate the subsequent effects. We hypothesize that:

**H7: More intrinsic motivation created by sense of control will lead to a) better attitude toward the system; b) better perceived recommendation quality; c) less privacy concern; d) more future use intention; and e) more willingness to disclose personal information.**

Based on the hypotheses above, the following theoretical model is proposed for the action route of customization.
Figure 3. Theoretical model for the action route of customization

**Customization: the cue route.** As stated by TIME, in addition to affecting users via actions that they undertake, technological affordances can also impact user psychology and behavior by simply displaying interface cues. This is known as the cue route. Psychology literature has pointed out that human beings tend to be “cognitive misers” by relying on limited available mental resources when they make judgments (Fiske & Taylor, 2013). They strive to save time and effort through different ways in interacting with the outside world. Booming media technologies make this tendency especially salient, because users often fall short of cognitive capacity while multitasking online. Indeed, in a fast-paced online environment, it is hard to keep a clear mind and carefully consider the worthiness of each and every behavior, every single time. Instead, users often act heuristically online. Limited-time rewards, complex choices, and inert human nature all prevent users from analytically going through the benefits and risks of each situation. In other words, individuals tend to sacrifice thoroughness for efficiency. Rather than deliberate analyses, human beings use heuristics—“judgmental shortcuts that generally get us where we need to go—and quickly” (Gilovich &
Savitsky, 2002) to make judgments and behave accordingly (Sundar, 2008a). Tversky and Kahneman (1973, 1974) have empirically demonstrated that individuals are likely to behave efficiently, not analytically, with the help of heuristics.

According to the MAIN model (Sundar, 2008a), the sheer presentation of technological affordances in the form of interface cues (e.g., clickable buttons suggesting adjustable settings) online can trigger cognitive heuristics that users employ to evaluate the interface and the content. For example, star-ratings and comments showing other users’ reviews of products in an e-commerce website can trigger the “bandwagon heuristic” (i.e., if everybody thinks it is good, then it must be good for me as well), whereas expert endorsement or a brand name can trigger the “authority heuristic” (i.e., if this information is from a trusted authority, then it must be credible) (Sundar, Xu, & Oeldorf-Hirsch, 2009). In a study on users’ privacy perceptions and disclosure behaviors in a mobile restaurant recommendation service, researchers found that the presence of a security warning banner triggered the security heuristic (i.e., online is not safe, thus risky); while an instant gratification cue, a free prize draw upon registration, triggered a persuasive intent heuristic (i.e., if the service provider tries to persuade me to do something, then it is suspicious and risky), which both led to negative evaluations of the recommendation service (Zhang, Wu, Kang, Go, & Sundar, 2014). Thus, technological affordances are likely to affect user psychology and behaviors via heuristics.

Interface cues often manifest themselves in two ways—one simply as indicators of potential action possibilities, such as buttons or fields on the interface, and the other as signals demonstrating outcomes based upon specific actions, such as progress bars and star ratings. In triggering heuristics, presence of the former type suggests ontological possibilities but doesn’t have to involve real actions, whereas the latter form displays outcomes of real actions by the
user (e.g., progress bar) or other users (e.g., star ratings). According to MAIN Model, both forms of cues convey messages about the interface and trigger heuristics about the quality of the interface and its content.

As action indicators, customization cues often include user-controlled choices on the interface, such as account settings. The action route of customization (i.e., making actual choices) can engender a sense of control, which in turn enhances intrinsic motivation and influences users’ perceptions and behaviors. But, according to the cue effect argued by Sundar (2008), indicators of technological affordances can also convey their potential without real user actions. So customization cues, such as editing buttons (e.g., radio buttons), transmit the message that certain aspects of the interface/system are modifiable, that users can make choices freely. Such a message can then elicit the thought, “I am the source, thus I have power to control,” which promotes a high level of confidence in interacting with the system that positively influences users’ judgments.

On the other hand, as an outcome signal, customization cues hold the potential of delivering transparency and certainty; examples include progress bars and color indicators suggesting password strength. This form of cues does not exist independently from actions, but displays as an “add-on” to actual behaviors and presents action consequences to users. In other words, it can be interpreted as an “action+cue” scenario. For instance, presenting a progress bar on a privacy-setting interface to users informs them where they are in the middle of customization, or the level of information disclosure based on their settings, which reduces uncertainty by improving transparency. Another example is the commonly used star-rating mechanism, often signifying the quality of certain products or contents based on massive user reviews, which is an outcome signal based on action by several users, not just one individual.
Contingent outcomes suggested by such cues can help users find their actions more meaningful. This is along the same line with the predictability factor of customization proposed by Sundar et al. (2009), who posit that via customization, users can comfortably predict what information they will consume. This type of transparency/predictability has also been equated with controllability by Klug and Schell (2006) in video games, such that customization elements allow users to be aware of how outcomes are achieved, what outcomes are awaiting, thereby feeling more in control. Therefore, no matter displayed as an action possibility without action (i.e., cue only) or as a result indicator together with customization action (i.e., action + cue), a customization cue is likely to trigger the control heuristic, leading to the conclusion that “if the website offers me control, then it is good and safe.” And if the control heuristic is triggered, it is likely to further influence user perceptions and behaviors as sense of control does (H5). So we hypothesize that:

\[ \text{H8: The presence of customization cue will trigger the control heuristic.} \]

\[ \text{H9: Control heuristic triggered by customization cue will, in turn, lead to a) better attitude toward the system; b) better perceived recommendation quality; c) less privacy concern; d) more future use intention; and e) more willingness to disclose personal information.} \]

But the presence of customization cue can be a double-edged sword. By merely observing various customization choices (i.e., customization cue as action possibility indicator) on an interface, users could get overwhelmed by too much freedom without real action to offload the burden. Even if actions are afforded, an outcome signal (i.e., customization action + customization cue as action result indicator) may still add to users’ cognitive burden because now they feel obliged to make the right choices, otherwise the
customization cue will warn them about a bad outcome. Through three experiments, Iyengar and Lepper (2000) challenged the conventional pursuit of unlimited choices by showing that people could get overloaded by too much freedom to choose, and tend to have optimal satisfaction with their selections when only limited choices were provided. Along the same lines, Schwartz (2004) also listed a number of cases where consumers find too much choice to be a burden in handling daily activities, such as choosing medical care, utilities, beauty services, to name a few. Following such findings, customization cues indicating various choice possibilities are likely to trigger the choice-overload heuristic, “Too many choices means too many decisions.” Therefore, depending on specific contextual factors and users’ individual differences, the presence of customization cue may also trigger the choice-overload heuristic, the influences of which on user perceptions and behaviors are likely to be reversed in comparison with the control heuristic. Therefore, we propose the following hypotheses:

**H10:** The presence of customization cue will trigger the choice-overload heuristic.

**H11:** Choice-overload heuristic triggered by customization cue will, in turn, lead to a) worse attitude toward the system; b) worse perceived recommendation quality; c) more privacy concern; d) less future use intention; and e) less willingness to disclose personal information.

The following theoretical model illustrates the hypotheses proposed for the cue route of customization.
In sum, there are two routes by which users can experience customization on an interface—the action route and the cue route. And for the cue route, customization cues may either be presented as visual elements without affording any user action (i.e., cue-only condition, such as a screen shot), or work as a contingent outcome signal based on user actions (i.e., action+cue condition).

Customization is sometimes contrasted with personalization, based on the locus of agency (human vs. system), as discussed in the next section.

**Personalization vs. customization**

**Locus of agency.** Privacy concern about personalization comes from users’ unexpectedness of data tracking and uncertainty about data use, both of which imply lack of perceived control. Prior empirical evidence suggests that customization can imbue in users a sense of control, as discussed previously, which is a core factor in affecting user psychology related to privacy (Klug & Schell, 2006; Marathe & Sundar, 2011) and persuasion effects.
Recommender systems typically come with the personalization function by default, hence adding customization functions as a separate layer in such systems holds great potential in influencing the persuasiveness of personalization and affecting users’ perceptions and behaviors regarding privacy.

The two concepts, customization and personalization, have in the past been used interchangeably as an approach to achieve individualized content tailoring by media sources. As the prevalence of user-generated content online and booming interactive technologies gradually transform passive media audiences to active technology users, individuals now gain more initiative in their interactions with technologies. In this context, personalization refers to system-initiated tailoring, whereas customization refers to user-initiated tailoring. Sundar and Marathe (2010) compared customization and personalization as two values of the same variable, and concluded that under a low-privacy situation, customization (user-tailoring) is preferred over personalization (system-tailoring) by power users.

Customization lets users be the source of creation and changes, which according to the agency model of customization (Sundar, 2008b), is the most distinctive characteristic and psychological benefit of customization. This self-as-source feeling is also referred to as human agency (i.e., sourceness), the crux of which is psychological control. On the other hand, the entity that executes personalization is the system/technologies, and that’s where agency is located in personalization. Therefore, one underlying factor that distinguishes customization and personalization is the locus of agency—users of technology or technology itself. Sundar (2007) distinguished them in terms of human agency and machine agency. According to the agency model of customization, one of the core psychological reflections of human agency is sense of control (Sundar, 2008b), whereas machine agency leaves users with
a lack of control, since technology is the source of activities. Along this line, agency can be indirectly measured by sense of control— the more human agency, the more sense of control; the more machine agency, the less sense of control among users.

However, there is often no absolute boundary between human agency and machine agency in an interaction between the user and the technology, but rather they are like two poles of a single spectrum (Figure 5). These two types of agency can coexist. For example, although personalization is mainly achieved by the system, the agency distribution between human and machine varies based on the personalization delivery system. Proactive personalization induces machine agency solely as the whole process from user data gathering to personalized service delivery is performed by the system or machine. But reactive personalization involves the user making a request before the system generates any personalized content even though the tailoring is initiated by the system, leading to a hybrid of machine agency and human agency. Customization, on the other hand, possesses mostly human agency, as it is initiated and executed entirely on the user’s end. Customization, personalization, and their relative positions on the agency spectrum are illustrated in Figure 5. In addition to locus of agency, to more clearly draw a line between customization and personalization, the system’s mastery of the user’s contextual information also explains the distinction between the two: the affordance of customization does not need to acquire any data of user context but only to provide action possibilities, whereas the basis for personalization is knowledge of users’ contextual information (true for both reactive and proactive personalization) so as to generate individualized content for users.
Figure 5. Customization, personalization, and their positions on the agency continuum

Based on the agency argument for customization and personalization, treating them as affordances at two separate layers may evoke a combinatory effect on agency (reflected as sense of control). If a user first performs/observes customization on one interface before receiving personalized (reactive or proactive) content, s/he is likely to feel a higher level of control compared to those passively accepting personalized services without exerting self agency. Likewise, users who interact with a reactive personalization interface may experience more sense of control than those who interact with a proactive personalization interface, as they feel that they are the source of initiating personalized recommendations. Thus, the combination of customization and reactive personalization can either have a synergy effect to boost users’ sense of control and evaluations of the system, or lead to a boomerang effect such that there is a threshold for optimal agency, beyond which too much human agency may mean burdensome calls for action. In contrast, combining customization and proactive personalization is likely be complementary in affecting users’ sense of control. Customization is examined in the form of either interface cue or user action in this study, but there is little evidence suggesting the difference between these two modes, so it remains unclear how different modes of customization can influence sense of control, which adds more uncertainty to its interaction with personalization mechanism. In terms of other dependent variables, since
we hypothesize that proactive personalization will improve users’ perceived recommendation quality by the recommender system (H2), but will engender more privacy concerns (H3) compared to reactive personalization, we wonder whether the addition of customization function will influence perceived recommendation quality and attenuate the concerns about privacy. Therefore, the following research question is proposed:

\[ RQ3: \text{How does the interaction effect between customization mode (action vs. cue vs. absent) and personalization mechanism (reactive vs. proactive) influence a) sense of control; b) perceived recommendation quality; and c) privacy concerns?} \]

Figure 6. Interaction effect of customization and personalization on sense of control

**Disclosure behaviors: Detecting a privacy paradox.**

With the pervasiveness of recommender systems, better and more relevant services are always tied to the utilization of large amounts of personal data. Therefore, online users are constantly facing the trade-off between benefits from personalized services and privacy risks caused by information misuse. However, online users’ privacy concerns do not seem to translate to privacy-enhancing behaviors such as less disclosure on the Internet. Scholars call this incongruity between intentions of protecting information privacy and actual information disclosure behaviors as “privacy paradox” (Awad & Krishnan, 2006), implying the mismatch between users’ attitudes and actual behaviors pertaining to privacy.
Over the past decade, empirical studies also have verified the existence of this paradox. In a two-phase longitudinal study, Norberg et al. (2007) first asked participants’ disclosure intentions toward various personal information in a survey, then after twelve weeks, collected their real disclosure behaviors in a mock-up marketing scenario. Findings suggested that participants’ intention to disclose was significantly lower than their actual disclosure, which demonstrated the privacy paradox. Both Barnes (2006) and Acquisti and Gross (2006) found a similar pattern among Facebook users, such that individuals who claimed to be concerned about privacy still revealed a great amount of information about themselves in the network. Likewise, in an online shopping environment, Spiekermann, Grossklags, and Berendt (2001) showed that consumers did not live up to their stated privacy concerns, but voluntarily disclosed their addresses and other types of personal information during an interaction with a shopping-agent robot. This paradoxic phenomenon is especially salient in recommender systems due to the temptation of personalized recommendations (Xu et al., 2011).

Scholars have made many attempts to explain the discrepancy between general privacy dispositions and actual disclosure behaviors. One group of researchers argues that the privacy paradox results from individual differences. For example, Joinson, Reips, Buchanan and Schofield (2010) found that although users’ privacy concerns were negatively associated with information disclosure, high trust toward the content provider could substantially compensate for such negative influence. But in another study, Utz and Krämer (2009) discovered that dispositional trust did not account for the privacy paradox in social networking sites; instead, other individual differences—narcissism and impression management motives—explained
users’ relatively less restrictive privacy settings and willingness to reveal information about themselves. The concern for privacy was overshadowed by the desire to “show off.”

Another identified explanation is an “endowment effect”—people tend to feel more comfortable in paying to gain something than giving away things they possess (Kahneman, Knetsch, & Thaler, 1990). According to this effect, online users would be more willing to accept rewards as an exchange of information disclosure rather than sacrifice their privacy for other benefits. Although these two exchanges are essentially identical, the ways they are framed indicate different emphases—the former is to gain, whereas the latter to lose. This claim has found empirical evidence in previous studies (Acquisti, John, & Loewenstein, 2009; Tsai, Egelman, Cranor, & Acquisti, 2011). Therefore, framing messages to convey that users are gaining benefits by revealing personal information can lead to more voluntary disclosure.

One factor leading to information disclosure regardless of the intention of protecting privacy is the sequence of disclosure inquiries that vary in intrusiveness. Acquisti, John, and Loewenstein (2012) found that people are more likely to divulge if disclosure requests are presented in a decreasing order of intrusiveness, such that more sensitive behavioral questions (e.g., “Have you masturbated at work or in a public restroom?”) were asked first followed by less sensitive ones (e.g., “In the last year, have you eaten meat, poultry, or fish?”). Such order was found to be able to alter people’s judgments on perceived intrusiveness of the requests, even though the content of the requests remained identical. Therefore, exposing questions in a decreasing order of intrusiveness shields the privacy risks from users, which can cause them to behave in ways that are contrary of their intentions.

There have been some strategies developed to remedy the situation by reducing privacy concerns to encourage information disclosure. Common practices include providing...
explanations for information use and showcasing other users’ disclosure behavior. For example, Wang and Benbasat (2007) suggested that acknowledging users about how and why their information is used can improve their trust toward online recommenders, which eventually leads to more disclosure. Kobsa and Teltzrow (2005) showed that directly presenting the benefits of information disclosure were effective in promoting this behavior. In another study, Acquisti et al. (2012) found that users were likely to reveal information about themselves if the system showed that others did so as well. Therefore, with such explanation mechanisms, users seem to overcome their privacy concerns and divulge personal details about themselves. Built on previous findings, we wonder whether personal traits can predict online users’ various disclosure behaviors and whether the action of revealing (through customization of privacy setting) will, in turn, affect their evaluation of an online service. These findings can inform us about the paradoxical phenomenon in a personalized recommender system. Therefore, we pose the following research question (illustrated in Figure 7):

**RQ4:** In the action condition of customization, a) how do individual differences (e.g., disposition to value privacy, perceived value of personalization) predict disclosure behaviors? b) how do disclosure behaviors in customizing privacy setting influence subsequent evaluations (e.g., attitude toward the system, perceived recommendation quality, privacy concern, and future use intention) of the recommender system?

![Figure 7. Role of disclosure behaviors](image-url)
In sum, the study proposes to test the effects of two different personalization mechanisms (reactive and proactive personalization) and three customization modes (absent vs. action vs. cue) on a set of attitudinal, behavioral intention, and behavioral outcomes.
Chapter 2

METHOD

Study Design

A 2 (Personalization: Reactive vs. Proactive) by 3 (Customization: Absent vs. Action vs. Cue) factorial, between-subjects online experiment was conducted to test the hypotheses and research questions of the current study. Pre- and post-experiment method was employed to account for various pre-existing individual differences.

Stimulus

In this study, a fictitious Bollywood movie recommendation website, “Bollybox,” was created as the stimulus recommender service. Bollybox aimed to provide personalized Bollywood movie recommendations to users based on their individual preferences and settings and consisted of three pages: an “About” page to introduce the movie recommendation service, a privacy page with customization function, and a personalized recommendation page. To operationalize the two independent variables (i.e., customization and personalization), three versions of the privacy page reflecting the customization conditions (absent vs. action vs. cue) and two versions of the recommendation page representing the personalization conditions (reactive vs. proactive) were constructed. Except for the independent variables under investigation, content and visual design of different versions of the same interface remained consistent. All of the interfaces had a header with a designed “Bollybox” logo and a menu bar with options labeled “About”, “Recommendations”, and “Privacy”.

Each participant was first exposed to the “About” page, followed by the customization and personalization page. The “About” page briefly introduced Bollybox’s services and what
to expect while navigating through the website. It also reminded participants to pay close attention to the content and fully interact with the website. The customization interface was essentially a privacy-setting page featuring user choices regarding disclosure of three types of personal information (e.g., genre preference, time of watching, social sharing) pertaining to Bollywood movie viewing that the system ostensibly accesses and uses. It was titled “Privacy,” and displayed privacy-setting options for the aforementioned three types of user data. The personalization interface was the system’s main functionality page with personalized Bollywood movie recommendations. It presented five Bollywood movies that ranged in genres and their descriptions and reviews upon clicking. Detailed explanations of the independent variable manipulation are presented next.

**Independent Variables**

**Customization.** Manipulation of customization had three levels: absent, action, and cue. In the customization-absent condition (Figure 23, p. 139), participants were presented with a privacy interface showing a list of user data that could be accessed and used by the website. There was no button or any other indicator suggesting that the setting was modifiable. In the customization-action condition (Figure 24, p. 140), the privacy-setting interface displayed radio buttons next to the information requested and allowed participants to actually “allow” or “deny” the disclosure of each specific type of information. The setting statuses resulting from the customization action condition were captured. In the customization-cue condition (Figure 25, p. 140), participants were exposed to the same privacy-settings captured from the action condition in order to yoke the two conditions and avoid content confounds, but the actual customization options were disabled, which left them with a sample user setting of the interface.
Personalization. Personalization was the main functionality of the stimulus website, Bollybox. In the current study, it was represented by personalized recommendations of Bollywood movies. Since the interfaces are mocked-up, we did not really track participants’ data. The personalization service was designed as a Bollywood movie recommendation service in order to avoid participants’ familiarity with popular western movies and potential detection of inaccurate recommendations. In the personalization interface (Figure 26 & 27, p. 141), five Bollywood movies ranging in audience ratings and genres were presented as personalized recommendations, which were identical for participants in both reactive and proactive conditions to achieve content equivalence across conditions (i.e., avoid content confounds) and thereby enhance internal validity. In the reactive personalization condition, participants were first told to imagine that they were in the mood for watching a Bollywood movie and to request one by entering keywords in a search box. After initiating a movie search, participants would then see the five prepared movie recommendations and their information in the personalization interface. Participants were repeatedly reminded that the system generated recommendations based on both their requests and their preferences. In the proactive personalization condition (Figure 27, p. 141), right after participants were directed to the personalization interface, recommendations of the five Bollywood movies prepared ahead of time would automatically display to reflect proactivity without asking for participants’ requests. Participants were told that the movies were personalized for them, but not informed about how their information was collected.

Participants (data collection)

Three hundred and twenty-six participants were recruited from Amazon Mechanical Turk (AMT) (http://www.mturk.com), a well-known crowd-sourcing service for online
studies. The sample pool was restricted to include only participants who had a North American IP address, a Human Intelligence Task (HIT) (e.g., questionnaire) approval rate of 90% or higher, and access to the Internet. Participants were compensated $1 each for completing the study. In the end, we retained valid data from 299 participants as the final sample. The criteria for elimination included: successful completion of all parts of the study, spending at least three minutes browsing and interacting with the stimulus website, and entering movie-related search terms (e.g., genre, actor) in the reactive personalization condition. Numbers of participants in the six conditions—proactive personalization + absence of customization, reactive personalization + absence of customization, proactive personalization + customization action, reactive personalization + customization action, proactive personalization + customization cue, reactive personalization + customization cue—are 45, 50, 53, 52, 51, and 48 respectively. The final sample consisted of 166 males (55.5%) and 133 females (44.5%), with the average age being 33.13 (SD = 10.49, range = 18-67). Most of the participants were Caucasian (74.3%), with the rest being Asian (7.2%), African American (6.3%), Hispanic (3.9%), Native American (1.8%), Pacific Islander (.6%), and others (.6%). The participants also had a wide range of educational backgrounds, including less than high school (.7%), high school of equivalent (21.7%), associate degree or equivalent (15.4%), current college student (11.7%), bachelor’s degree (42.5%), master’s degree (7.4%), and doctoral degree (.7%).

**Procedure**

Participants were randomly assigned to one of the six experimental conditions and completed the entire procedure on their own computers. The cover story of the study was framed as user evaluation of a newly launched Bollywood movie recommendation service,
Bollybox. Upon accepting the task on AMT, participants were presented with a brief introduction about the purpose (i.e., user evaluation), procedure, and requirements of the study. Then, they clicked on a link to the consent form on Qualtrics, followed by the pretest questionnaire to start the study.

**Pretest questionnaire.** Participants’ individual characteristics, including disposition to value privacy, technology expertise (i.e., power usage), previous privacy invasion experience, perceived value of online personalization, need for control, interest in Bollywood and foreign movies, TV/movie watching habits, Netflix use, and demographic information (age, gender, education, ethnicity), were measured as control variables and moderating variables in the pretest questionnaire. Upon completing the pretest questionnaire, participants were directed to their assigned conditions. Their condition ID (i.e., 1-6) and uniquely assigned response ID (randomly generated) were both recorded from the beginning to the end of the study procedure. The amount of time they spent on the stimulus website was also recorded as a control variable.

**Interface interaction.** As mentioned above, participants went through three interfaces in total to interact with the stimulus website. They first were exposed to the “About” page with a brief introduction about the newly launched Bollywood movie recommendation service, Bollybox and what to expect while browsing the website. Then participants interacted with the customization interface—privacy setting page—based on their randomly assigned condition (1 out of 3, Figure 23-25, p. 139-140). They were instructed to either carefully go through all the information on the page (in the absent and cue conditions) or fully interact with the interface and make decisions honestly (in the action condition) as if they were customizing their own accounts.
Afterwards, participants were randomly directed to one of the two personalization interfaces. Those in the proactive personalization condition were presented with automatic personalized recommendations on five Bollywood movies (Figure 27, p. 141) generated by Bollybox, while participants in the reactive personalization condition were given a scenario to imagine their need for Bollywood movie recommendations and instruction on how to initiate a recommendation request, as a task to complete (Figure 26, p. 141). The request procedure was executed on participants’ own to simulate a spontaneous initiative. Participants in both conditions were instructed to carefully go over all the content on the interface and complete a browsing task to ensure enough attention and engagement. The time spent on all the interfaces was recorded. On average, participants spent 117.69 seconds browsing the stimulus website ($SD = 77.67$).

**Posttest questionnaire.** After interacting with the stimulus website, participants completed a posttest questionnaire containing all the dependent variables, such as sense of control, intrinsic motivation, perceived recommendation quality, future use intention, and privacy concern about the system. After they completed this questionnaire, each participant was thanked and offered a unique confirmation code for redeeming payment on AMT. The entire study lasted about 35 minutes on average.

**Measurements**

Based on extensive prior literature, previously validated scales are adapted to measure the main dependent and control variables in this study whenever possible. Specific items are rephrased to fit the Bollywood movie recommendation service context when necessary. Unless otherwise noted, the following measurements are all based on 7-point Likert-type
scales with “1” indicating the lowest level and “7” indicating the highest, unless otherwise noted. Detailed measurement scales are presented in Appendix D (p. 143-154).

**Manipulation check.** One manipulation check item for *personalization* asked participants which type of personalization to which they were exposed (i.e., “The recommendations provided by Bollybox were based on my request.”). For *customization*, the manipulation check involved one item tapping into the possibility of ontological customization (absent vs. cue/action)—“Bollybox is designed to allow users to manage the settings of privacy permissions”; one asking about actual behavior (absent/cue vs. action)—“I was able to manually change the settings of privacy permissions on Bollybox,” which emphasized whether the participants themselves were able to manually control the settings, or simply acknowledged the possibility. Participants were asked to indicate their agreement with these items on a 7-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (“strongly agree”).

**Dependent variables**

**Sense of control.** Sense of control has been measured in several different ways in previous work. The current measure was developed based on Ariely (2000), Venkatesh and Davis (2000), Witmer and Singer (1998), and Xu (2007), consisting of 15 items about one’s belief in being able to modify the privacy settings of the system (e.g., “I feel I have control over what personal information is used by Bollybox”), being able to initiate changes (e.g., “I feel I am able to initiate actions to modify my privacy settings on Bollybox”), and feeling free to make choices (e.g., “I feel I can make choices freely during interaction with Bollybox”) ($M = 4.88$, $SD = 1.21$, Cronbach’s $\alpha = .96$). This also serves as the measure for the control heuristic in the cue route of customization. Since heuristics are mental shortcuts triggered in
the moment, the nature of which makes it difficult to capture. Therefore, following Kahneman and Tversky (1972, 1973), self-reported judgments about control, an outcome evoked by the actual control heuristic was used as an approximation to measure the heuristic itself.

**Intrinsic motivation.** Measures were adapted from the Intrinsic Motivation Inventory established by Deci and Ryan (1985), tapping into participants’ spontaneous interest and engagement in interacting with the stimulus website. The eight items included, for example, “I got personally involved with the interface interaction”, “I wanted to keep browsing Bollybox’s movie recommendations once I started”, and “I liked what I was asked to do in this study” ($M = 4.66, SD = 1.29$, Cronbach’s $\alpha = .91$).

**Choice-overload heuristic.** To gauge the extent to which participants were overwhelmed by the privacy-setting choices, three statements asking participants to indicate their agreement were revised from Bollen, Knijnenburg, Willemsen, and Graus (2010) and Iyengar and Lepper (2000), including “I found it difficult to decide what information to disclose,” “I felt frustrated when making choices on the privacy setting,” and “The privacy setting task was overwhelming” ($M = 2.80, SD = 1.52$, Cronbach’s $\alpha = .89$).

**Attitude toward the system (i.e., Bollybox).** General attitude toward the system was measured by asking participants to evaluate how well a list of 10 adjectives described the Bollybox service; the Likert scale was anchored with “describes very poorly = 1” and “describes very well = 7”. The adjectives included “Attractive”, “Exciting”, “High quality”, “Appealing”, “Useful”, “Positive”, “Good”, “Pleasant”, “Likeable”, and “Interesting”, obtained from Kalyanaraman and Sundar (2006) ($M = 5.03, SD = 1.14$, Cronbach’s $\alpha = .97$).

**Attitude toward the content.** Pertaining to the movie content provided by the recommender system, perceived recommendation quality was evaluated via asking
participants to indicate their agreement with 3 items (i.e., “Bollybox’s recommendations can provide me with the kind of Bollywood movies that I might like”; “Bollybox’s recommendations can provide me with personalized Bollywood movies tailored to my activity context”; and “Bollybox’s recommendations can provide me with more relevant movies tailored to my preferences or personal interests”).) adopted from Zeithaml, Parasuraman, and Malhotra (2000), as attitude toward the content from a persuasion perspective.

**Behavioral intention.** There were two types of behavioral intention measured in this study. One was the intention to use Bollybox in the future, captured by 4 items (i.e., “I intend to use Bollybox in the future when it is available”, “I believe my interest toward Bollybox will increase in the future”, “I intend to use Bollybox as much as possible when it is available”, and “I recommend that other use Bollybox when it is available”) from Zarmpou, Saprikis, Markos, and Vlachopoulou (2012) ($M = 3.80$, $SD = 1.73$, Cronbach’s $\alpha = .96$). Another form of behavioral intention tapped into participants’ willingness to disclose their personal information to the system for personalized recommendations, measure of which consisted of two questions—“How interested would you be in having your personal information used in the system?” (anchored between “Not at all interested =1” and “Extremely interested =7”) and “How likely would you be to provide your personal information in exchange for using Netflix recommendation?” (anchored with “Extremely unlikely =1” and “Extremely likely =7”), adapted from Culnan and Armstrong (1999) ($M = 3.28$, $SD = 1.85$, Cronbach’s $\alpha = .89$).

**Privacy concern.** Measures for privacy concern about information leak in the system were adapted from Dinev and Hart (2006). Participants responded to 4 items about how concerned they were about personal information that might be improperly used or leaked—“I would be concerned that the information I submit to Bollybox could be misused”, “I would be
concerned that others could find private information about me from Bollybox”, “I would be concerned about providing information to Bollybox because of what others might do with it”, and “I would be concerned about providing information to Bollybox because it could be used in ways I could not predict” ($M = 3.84$, $SD = 1.51$, Cronbach’s $\alpha = .95$).

**Information disclosure.** *Information disclosure* was measured by real behaviors rather than self-reported perceptual items. As described in the stimulus section, the privacy setting customization interface displayed various types of information that could be accessed by the Bollybox system and provided modification choices for participants to make adjustments. The extent to which they set the privacy permission items as accessible by the system was evaluated as the real disclosure behavior. In other words, the number of items each participant allowed the Bollybox to access and use was used as the measure of their disclosure behavior. For this measure, the “deny” option for each item was coded as 0, and the “allow” option was coded as 1. By adding up the numerical values for all the information items on the privacy setting page, the sum was used as the disclosure measure. This measure only applied to the customization-action condition. In total, there were 13 pieces of movie genre data ($M = 9.25$, $SD = 3.99$), 3 pieces of watching time data ($M = 2.12$, $SD = 1.21$), and 3 pieces of social networking sites data ($M = .27$, $SD = .68$). Therefore, there were four disclosure behavior variables: genre disclosure with value that could range from 0 to 13, watching time disclosure with value that could range from 0 to 3, social networking disclosure from 0 to 3, and overall disclosure with potential value from 0 to 19.

**Control variables**

*Power usage* was measured by 12 items adopted from Marathe, Sundar, Bijvank, van Vugt, and Veldhuis (2007) pertaining to participants’ expertise in technology use (e.g., “Using
any technological device comes easy to me”; “I make good use of most of the features available in any technological device”) \((M = 5.44, SD = .86, \text{Cronbach’s } \alpha = .85)\).

**Disposition to value privacy** was measured via 3 items (i.e., “Compared to others, I am more sensitive about the way my personal information is handled”; “Keeping my information private is the most important thing to me”; “Compared to others, I tend to be more concerned about the threats to my information privacy”) from Xu et al. (2011) \((M = 4.97, SD = 1.38, \text{Cronbach’s } \alpha = .90)\).

**Previous privacy invasion experience** was asked via 3 questions evaluating the frequency of privacy misconduct participants experienced, such as “How often have you personally been a victim of what you felt was an improper invasion of privacy?”, “How often have you disagreed with an online service about their use of your personal information?”, and “How often have you experienced incidents where your personal information was used by an online service without your authorization?”, employed from Smith et al. (1996) \((M = 3.01, SD = 1.41, \text{Cronbach’s } \alpha = .85)\).

**Perceived value of online personalization** was evaluated by 6 items (e.g., “I value websites that are personalized for my usage experience preferences”; “I value websites that acquire my personal preferences and personalize the services and products themselves”) that asked participants to indicate their preference for personalized services online, derived from Chellappa and Sin (2005) \((M = 4.32, SD = 1.25, \text{Cronbach’s } \alpha = .84)\).

**Need for control** as an individual trait was measured by 20 items (e.g., “I enjoy making my own decisions”; “I enjoy having control over my own destiny”) from Burger and Cooper (1979) that pointed to a desirability of autonomy, manipulation, and freedom \((M = 4.99, SD = .79, \text{Cronbach’s } \alpha = .87)\).
**TV/movie watching.** To account for participants’ TV/movie watching behavior, we measured the number of hours they spent on watching movies on average per week \((M = 9.17, SD = 8.58)\), the frequency they watch foreign movies in general \((M = 2.92, SD = 1.38)\) and Bollywood movies in particular \((M = 1.98, SD = 1.21)\), and their level of interest in foreign movies \((M = 2.90, SD = 1.15)\) and Bollywood movies \((M = 2.12, SD = 1.08)\). We also asked whether participants were Netflix users, since Bollybox was a similar movie recommendation service, and found that 67.6% were Netflix users.

**Demographics.** Participants’ demographic information (i.e., age, gender, ethnicity, and education level) were also measured for control purposes.

**Data analysis**

**Descriptive statistics.** The data was examined for normality and outliers before proposed analyses. Table 1 displays the descriptive statistics for mediating, dependent, control, and moderating variables. The descriptive statistics indicated normally distributed data based on the rule of thumb proposed by Garson (2012) \((\text{skewness} < |2|; \text{Kurtosis} < |2|)\), except for one variable, disclosure behavior for different watching times.

Table 1. Descriptive statistics for measured variables across conditions

<table>
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<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>Skew.</th>
<th>Kurt.</th>
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<tbody>
<tr>
<td><strong>Control variables / Moderators</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Disposition to value privacy</td>
<td>4.97</td>
<td>1.38</td>
<td>1.00</td>
<td>7.00</td>
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<td>1.00</td>
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<td>.85</td>
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<td>7.00</td>
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<td>-.52</td>
<td>.85</td>
</tr>
</tbody>
</table>
Prior to specific analyses, zero-order correlations were conducted to test the interrelations among the measured variables. According to results shown in Table 2, the correlations were consistent with hypothesized relationships.

### Need for control

| Need for control | 4.99 | .79 | 2.95 | 7.00 | .25 | - .27 | .87 |

### Mediating / Dependent variables

<table>
<thead>
<tr>
<th>Sense of control</th>
<th>4.88</th>
<th>1.21</th>
<th>1.00</th>
<th>7.00</th>
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### Disclosure behaviors

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Table 2. Zero-order correlations of all variables

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57
General linear model. The proposed main effects and interaction effects (refer to Figure 8) were explored using a multivariate General Linear Model (GLM) with two manipulated independent variables—1) mode of customization (absent vs. cue vs. action; nominal level); 2) personalization mechanism (reactive vs. proactive; nominal level). Demographic measures, power usage, perceived value of personalization, need for control, and TV/movie watching were included as covariates. Disposition to value privacy and previous privacy invasion experience were both continuous moderators. Multivariate (MANCOVA) effects were first checked for the overall main effects of the IVs and their interaction effects on all the DVs considered together, before proceeding to univariate (ANCOVA and regression) effects, in order to reduce Type I error from testing multiple dependent variables separately. A MANCOVA revealed significant multivariate effects for the two IVs, personalization mechanism, Wilks’ $\Lambda = .90$, $F (8, 271) = 3.92$, $p < .001$, and customization mode, Wilks’ $\Lambda = .76$, $F (16, 542) = 4.96$, $p < .001$; and for the two moderators, disposition to value privacy, Wilks’ $\Lambda = .90$, $F (8, 271) = 3.90$, $p < .001$, and previous privacy invasion experience, Wilks’ $\Lambda = .88$, $F (8, 271) = 4.45$, $p < .001$. Other effects were non-significant. Then, comparisons with ANCOVA were checked to interpret specific differences for each IV-DV relationship and interaction effects.

Structural equation modeling. To test the proposed theoretical models (Figure 3 and Figure 4), a structural equation modeling (SEM) approach was adopted. There were several reasons for employing SEM. On top of the main effects and interaction effects detected with GLM analysis, SEM could further test whether the collected data conformed to the proposed conceptual model as a whole. SEM could also examine the hypothesized mediation effects by
employing the bootstrapping technique. In addition, SEM allowed us to account for measurement errors while establishing a statistical model.

Figure 8. Summary of main effects of personalization and customization

Note: Control variables are included as covariates
Chapter 3

RESULTS

The results are organized following the sequence of proposed hypotheses and research questions. First, the effects of personalization mechanisms are reported (H1 – H3, RQ1). Next, we delve into the effects of customization mode (RQ2, H4 – H11), including all the relationships proposed within the action and the cue routes. Then, the interaction effects between the two independent variables, personalization mechanism and customization mode, are analyzed (RQ3), followed by an investigation of actual disclosure in the customization action condition. Next, a systematic analysis of the theoretical models of the dual routes of customization is achieved through SEM. Last, the moderating effects of disposition to value privacy and previous privacy invasion experience are explored.

Manipulation check

**Customization Mode.** To test whether the manipulation of customization mode was effective, two items were created to capture: 1) whether actual customization actions were involved in the privacy setting interface (to compare action vs. cue/absence); 2) whether customization options were afforded as an attribute of the interface (to compare action/cue vs. absence). One-way ANOVA showed that, for item 1, participants in the customization-action condition perceived themselves to be able to manually perform actions to change the privacy settings ($M = 6.02, SE = .13$), which was significantly higher than those in the cue condition ($M = 4.40, SE = .25$) and the absence condition ($M = 3.53, SE = .17$), $F (2, 296) = 46.68, p < .001, \eta^2 = .24$. There was no significant difference between the latter two conditions. For item 2, participants in both the action condition ($M = 5.90, SE = .12$) and the cue condition ($M = 5.77, SE = .16$) perceived Bollybox to be designed with customizable privacy settings,
significantly more than the absence condition \((M = 3.97, SE = .15), F (2, 296) = 57.32, p < .001, \eta^2 = .28\). There was no significant difference between the action and the cue conditions on this measure, in line with our expectations.

**Personalization mechanism.** One item evaluating the manipulation of personalization mechanism asked participants whether Bollybox’s movie recommendations were based on their initiated request. One-tailed \(t\)-test result showed that participants in the reactive personalization condition \((M = 5.14, SE = .15)\) had significantly more agreement on this statement than those in the proactive personalization condition \((M = 4.62, SE = .15), t (294) = -2.52, p = .006\).

Therefore, our manipulations of the two independent variables were both successful.

**Effects of personalization mechanism**

**Sense of control.** H1 hypothesized that reactive personalization, operationalized by letting participants initiate personalized movie recommendations, would lead to more sense of control, compared to proactive personalization (i.e., the system automatically pushed recommendations based on users’ preferences). However, results showed that participants’ perceived sense of control did not differ significantly between these two conditions, \(F (1, 281) = .02, p = .88, \eta^2 = .00\). Thus, **H1 was not supported**.

**Perceived recommendation quality.** H2 predicted that proactive personalization would lead to better perceived recommendation quality compared to reactive personalization, because the former accurately predicts users’ needs and automatically fulfills them, without adding extra cognitive burden to users. Consistent with this hypothesis, the results showed that participants in the proactive personalization condition indeed perceived the Bollywood movie recommendations—although identical in content with those in the other condition—to
be more relevant and likeable ($M = 5.46, SE = .10$) than their counterparts in the reactive personalization condition ($M = 5.16, SE = .10$), $F (1, 281) = 4.52, p = .03$, $\eta^2 = .02$. In other words, when movie recommendations were automatically pushed to participants without asking them to initiate a recommendation request, participants felt that the movies were of higher quality. Thus, **H2 was supported**.

**Privacy concerns.** H3 hypothesized that proactive personalization would cause more privacy concern, because suggesting movies without explicitly asking for permission and request might make users feel wary. The data supported this hypothesis, by showing that participants in the proactive personalization condition felt a greater degree of privacy concern ($M = 4.11, SE = .11$) than those in the reactive personalization condition did ($M = 3.58, SE = .11$), $F (1, 281) = 10.80, p < .01$, $\eta^2 = .04$. Therefore, **H3 was supported**.

To respond to RQ1, we also tested the main effects of personalization mechanism on attitude toward Bollybox ($F (1, 281) = .01, p = .92$, $\eta^2 < .001$), behavioral intention to use Bollybox in the future ($F (1, 281) = 1.15, p = .29$, $\eta^2 = .004$), and willingness to disclose personal information to Bollybox for movie recommendations ($F (1, 281) = .34, p = .56$, $\eta^2 = .001$). But the results did not reveal any significant effect.

**Effects of customization mode**

RQ2 and H4 to H11 explored the effects of two modes of customization (action vs. cue) and a control (i.e., absence) condition on participants’ perceived a) sense of control; b) perceived recommendation quality; c) attitude toward Bollybox; d) privacy concerns; e) willingness to disclose; and f) behavioral intention to use Bollybox in the future. In addition, a few mediating relationships among the variables suggested by the two routes (i.e., action vs. cue) of customization were also examined.
Main effects of customization mode. In responding to RQ2 about comparing the three conditions of customization on the measured dependent variables, several univariate analyses were conducted. The test for sense of control yielded a significant main effect for customization, $F(2, 280) = 27.99, p < .01, \eta^2 = .17$. Participants who manually customized the privacy setting of Bollybox indeed reported a higher sense of control ($M = 5.28, SE = .11$) than those who only saw the customization cue ($M = 5.10, SE = .11$) and participants who were informed about the non-customizable privacy access page ($M = 4.21, SE = .11$).

According to Tukey HSD’s post-hoc test, the differences between the action and absence conditions and between the cue and absence conditions were both significant at $p < .001$, but there was no significant difference between the action and cue conditions on sense of control. Similar tests were conducted for other dependent variables, with the corresponding statistics listed in Table 3. In particular, there was a marginally significant main effect for customization mode on attitude toward Bollybox ($F(2, 280) = 2.68, p = .07, \eta^2 = .02$), a significant main effect on privacy concerns ($F(2, 280) = 3.06, p = .05, \eta^2 = .02$) and intention to use Bollybox in the future ($F(2, 280) = 3.82, p = .02, \eta^2 = .03$). The tests did not reveal significant main effect for customization mode on perceived recommendation quality ($F(2, 280) = 1.43, p = .24, \eta^2 = .01$) and willingness to disclose personal information to Bollybox ($F(2, 280) = 1.64, p = .20, \eta^2 = .01$).

Table 3. Effects of customization mode

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Note: Means with no subscript in common differ at $p < .05$.

To further probe the direct effect of customization in the form of action and cue respectively, we next test the hypotheses proposed based on the two customization routes.

**Sense of control: the action route.** H4 hypothesized that engaging in the action of customization would lead to a sense of control. This meant that participants in the customization-action condition should score significantly higher on the measure of sense of control compared to those in the absence condition. A univariate analysis for sense of control revealed a significant main effect for customization mode, $F(2, 280) = 27.99, p < .03, \eta^2 = .17$. And as shown in Table 3, participants who customized Bollybox’s privacy setting page in action felt a greater degree of sense of control ($M = 5.28, SE = .11$) than those only informed the privacy access without being afforded the action possibility ($M = 4.21, SE = .10$). The difference between the two conditions was significant according to Tukey HSD’s post-hoc test, $p < .001$. Thus, **H4 was supported**.

**Heuristics: the cue route.** According to the cue route of customization in TIME, the mere presence of customization interface cue—showing customizable privacy setting options but without actual user action (i.e., without affording actual actions in the current study)—can...
lead to similar effects compared to the action route, but by triggering heuristics. H8 predicted that the presence of such a cue would trigger the control heuristic (“If the website offers me control, then it is good and safe”, measured with same items as sense of control). In other words, without engaging in customizing the privacy options, participants would still feel the power of control by only seeing the existence of such options. The aforementioned univariate analysis result supported this hypothesis by showing that participants in the cue condition ($M = 5.10, SE = .11$) indeed processed the control heuristic, because their average sense of control was significantly higher than in the absence condition ($M = 4.21, SE = .10$), $p < .001$. In addition, the degree of triggered heuristic was not found significantly different between participants in the cue and the action ($M = 5.28, SE = .11$) conditions, which further suggested that the presence of the customization affordance itself, no matter whether real action was involved or not, had the potential of influencing user psychology through heuristics (refer to Table 3). Therefore, **H8 was supported**.

However, presenting users with ample choices but not letting them actually exert such control via real actions, may backfire by triggering a choice-overload heuristic (“Too many choices means too many decisions”) than those who were not aware of this option (i.e., the absence condition). Whether the control heuristic or the choice-overload heuristic was triggered largely depended on what existing thoughts and contexts were accessible at the moment of seeing the customization cue. Therefore, H10 hypothesized that the presence of customization cue in the form of privacy setting options would trigger the choice-overload heuristic. A univariate test found that a significant overall main effect for customization mode on choice-overload heuristic, $F (2, 280) = 17.77, p < .01, \eta^2 = .11$. However, contrary to expectation, participants in the cue condition reported a significantly lower degree of triggered
choice-overload heuristic ($M = 2.71, SE = .14$) than those in the absence condition ($M = 3.47, SE = .14$), $p < .001$. In other words, the existence of customization options without real action afforded made participants feel less overwhelmed than a condition without such a cue. So, **H10 was disconfirmed.** But the cue condition did indeed trigger significantly higher feelings of choice-overload than the action condition ($M = 2.28, SE = .14$), $p < .05$.

**Interaction effects of personalization mechanism and customization mode**

The same GLM analysis was conducted to explore the interaction effect between customization mode (action vs. cue vs. absence) and personalization mechanism (proactive vs. reactive) on sense of control, perceived recommendation quality, and privacy concerns in responding to RQ3. Although several main effects were detected with the two predicting variables individually, no significant interactions were observed. For sense of control, statistics for the interaction was $F(2, 277) = .27, p = .77, \eta^2 = .002$ (Figure 9); for perceived recommendation quality, $F(2, 277) = .46, p = .63, \eta^2 = .003$ (Figure 10); for privacy concerns, $F(2, 277) = 1.01, p = .36, \eta^2 = .007$ (Figure 11).

![Figure 9. Interaction between customization and personalization on sense of control](image-url)
As shown in Figure 9, the existence of customization options—whether real actions were involved or not—was the only factor that affected sense of control, whereas the difference between proactive and reactive personalization did not make participants feel a significant change in their perceived control and autonomy.

![Graph showing interaction between customization and personalization on perceived recommendation quality]

Figure 10. Interaction between customization and personalization on perceived recommendation quality

Figure 10 shows that, in general, the presence of customization possibility increased participants’ perceived recommendation quality of the suggested movies. And the existence of customization function was slightly more effective in boosting perceived recommendation quality for participants who interacted with reactive personalization than proactive personalization. However, the interaction was not significant.
Figure 11 suggests that the ability to manually customize one’s own privacy setting in Bollybox (red line in Figure 11) alleviated privacy concerns caused by proactive personalization, as the slope of the red line is lesser compared to the blue line (the absence condition), which is consistent with our expectation that the addition of customization could serve to reduce privacy concerns in recommender systems with proactive service. However, although the interaction patterns were interesting, none of the above analyses were statistically significant, so we should not over-interpret these results.

**Privacy disclosure behavior**

In the customization-action condition, participants were able to manually customize the privacy-setting interface by allowing or denying Bollybox’s access to 19 pieces of movie-watching-related personal information based on their preferences. Such behavior was valuable since it represented online users’ real disclosure, which has been found challenging to track and understand. In responding to RQ4, we recorded participants’ disclosure actions and coded them into four variables: genre disclosure, watching time disclosure, social networking disclosure, and overall disclosure.
First, to understand individual differences’ influences on the four disclosure behaviors, hierarchical regressions were conducted. Participants’ demographic information (i.e., age, gender, education) were entered as the first block to be accounted. Individual difference variables, including interest in Bollywood movies, previous privacy invasion experience, disposition to value privacy, perceived value of online personalization, need for control, and power usage, were entered as the second block as predictors for disclosure behaviors. Four types of disclosure variables were entered one at each time into the third block as the outcome variables. There were four hierarchical regressions tested.

**Genre disclosure.** The first demographics block did not explain a significant portion of the variance ($R^2 = .01$, $F (3, 101) = .42, p = .74$). The second block provided a significant incremental increase in variance explained, $R^2$ change = .23, incremental $F (6, 95) = 4.71, p < .001$, adjusted $R^2$ change = .18. As shown in Table 4, none of the demographic variables significantly predicted genre disclosure. In the second model, disposition to value privacy was a marginally significant negative predictor ($\beta = -.20, t (95) = -1.91, p = .06$); perceived value of personalization was a significant positive predictor ($\beta = .23, t (95) = 2.14, p = .04$). In other words, the more a user tended to value personal privacy, the less likely s/he was to disclose what movie genres s/he was interested in watching. But the more one saw the convenience and value of online personalized services, the more likely s/he was to tell the recommender service what s/he preferred watching.

Table 4. Regression statistics with genre disclosure as the dependent variable

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.061</td>
<td>.109</td>
</tr>
<tr>
<td>Gender</td>
<td>.072</td>
<td>-.021</td>
</tr>
</tbody>
</table>
Watching time disclosure. The first demographics block did not explain a significant portion of the variance ($R^2 = .01$, $F (3, 101) = .22, p = .88$). The second block provided a significant incremental increase in variance explained, $R^2$ change = .23, incremental $F (6, 95) = 4.74, p < .001$, adjusted $R^2$ change = .19. As shown in Table 5, none of the demographic variables significantly predicted watching time disclosure. In the second model, interest in Bollywood movies was a marginally significant positive predictor ($\beta = .18, t (95) = 1.88, p = .06$); perceived value of personalization was a significant positive predictor ($\beta = .29, t (95) = 2.67, p = .01$). This indicated that the more the user was into Bollywood movies and preferred personalized services online, the more likely s/he would give out information about movie watching behavior in different time periods to Bollybox for better recommendation quality.
Table 5. Regression statistics with watching time disclosure as the dependent variable

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.062</td>
<td>.113</td>
</tr>
<tr>
<td>Gender</td>
<td>.023</td>
<td>-.061</td>
</tr>
<tr>
<td>Education</td>
<td>.050</td>
<td>.007</td>
</tr>
<tr>
<td>Bollywood interest</td>
<td>.179***</td>
<td></td>
</tr>
<tr>
<td>Previous privacy invasion experience</td>
<td>-.139</td>
<td></td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td>-.143</td>
<td></td>
</tr>
<tr>
<td>Perceived value of personalization</td>
<td>.289***</td>
<td></td>
</tr>
<tr>
<td>Need for control</td>
<td></td>
<td>.071</td>
</tr>
<tr>
<td>Power usage</td>
<td></td>
<td>-.020</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.007</td>
<td>.235</td>
</tr>
<tr>
<td>$R^2$ change</td>
<td>.007</td>
<td>.229***</td>
</tr>
</tbody>
</table>

+ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

**Social networking disclosure.** The first demographics block did not explain a significant portion of the variance ($R^2 = .05$, $F (3, 101) = 1.91$, $p = .13$, adjusted $R^2 = .03$). The second block provided a significant incremental increase in variance explained, $R^2$ change = .21, incremental $F (6, 95) = 4.51$, $p < .001$, adjusted $R^2$ change = .22. As shown in Table 6, education level in the first block was a significant predictor for social networking disclosure ($\beta = .13$, $t (95) = 2.01$, $p < .05$). In the second model, interest in Bollywood movies was a
significant predictor \( \beta = .20, t (95) = 2.18, p = .03 \), as were disposition to value privacy \( \beta = .28, t (95) = 2.70, p = .01 \) and perceived value of personalization \( \beta = .34, t (95) = 3.15, p = .002 \). The findings suggested that participants with higher level of education were more likely to allow Bollybox to share their social networking account information with friends. Also, interest in Bollywood movies, tendency to protect personal privacy, and preference for personalization all predicted more behavior allowing Bollybox to share one’s movie watching record with friends. A stronger need for control, however, suggested more cautious sharing behaviors.

Table 6. Regression statistics with social networking disclosure as the dependent variable

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
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<td>-.074</td>
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<tr>
<td>Gender</td>
<td>-.015</td>
<td>.006</td>
</tr>
<tr>
<td>Education</td>
<td>.196</td>
<td>.127*</td>
</tr>
<tr>
<td>Bollywood interest</td>
<td></td>
<td>.203*</td>
</tr>
<tr>
<td>Previous privacy invasion experience</td>
<td></td>
<td>.014</td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td></td>
<td>.275**</td>
</tr>
<tr>
<td>Perceived value of personalization</td>
<td></td>
<td>.336**</td>
</tr>
<tr>
<td>Need for control</td>
<td></td>
<td>-.240*</td>
</tr>
<tr>
<td>Power usage</td>
<td></td>
<td>.004</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.054</td>
<td>.263</td>
</tr>
<tr>
<td>( R^2 ) change</td>
<td>.054</td>
<td>.210***</td>
</tr>
</tbody>
</table>

\(+ p < .10; \ast p < .05; \ast\ast p < .01; \ast\ast\ast p\)
Overall disclosure. The first demographics block did not explain a significant portion of the variance ($R^2 = .01$, $F (3, 101) = .44$, $p = .72$, adjusted $R^2 = -.02$). The second block provided a significant incremental increase in variance explained, $R^2$ change = .28, incremental $F (6, 95) = 6.30$, $p < .001$, adjusted $R^2$ change = .24. As shown in Table 7, none of the demographic variables significantly predicted overall disclosure. In the second model, interest in Bollywood movies was a significant predictor ($\beta = .20$, $t (95) = 2.16$, $p = .03$), as was perceived value of personalization ($\beta = .31$, $t (95) = 2.94$, $p = .004$). Therefore, in general, participants’ interest in Bollywood movies and their liking of personalized services predicted their disclosure behavior in the Bollybox recommender system.

Table 7. Regression statistics with overall disclosure as the dependent variable

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.052</td>
<td>.106</td>
</tr>
<tr>
<td>Gender</td>
<td>.062</td>
<td>-.031</td>
</tr>
<tr>
<td>Education</td>
<td>.084</td>
<td>.041</td>
</tr>
<tr>
<td>Bollywood interest</td>
<td>.197*</td>
<td></td>
</tr>
<tr>
<td>Previous privacy invasion experience</td>
<td>-.156</td>
<td></td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td>-.157</td>
<td></td>
</tr>
<tr>
<td>Perceived value of personalization</td>
<td>.307**</td>
<td></td>
</tr>
<tr>
<td>Need for control</td>
<td>.061</td>
<td></td>
</tr>
<tr>
<td>Power usage</td>
<td>.009</td>
<td></td>
</tr>
</tbody>
</table>
Since the disclosure action in the customization interface came before participants evaluated their psychological reactions in the post-test questionnaire, we also considered it as a predictor to the psychological outcomes. Next we analyzed the degree to which disclosure predicts perceived recommendation quality, attitude toward Bollybox, privacy concerns, and behavioral intention to use Bollybox in the future. Similar to regression analyses above, participants’ demographics and individual differences were entered as the first and second blocks respectively. Here, we focused on the predictive ability of the disclosure behaviors, which were entered as the third block.

**Perceived recommendation quality.** After accounting for demographics and individual differences, the third block in Table 8 added a significant incremental increase in variance explained, \( R^2 \) change = .08, incremental \( F (3, 92) = 4.63, p < .001 \), adjusted \( R^2 \) change = .07. Table 8 shows that genre disclosure was a significant positive predictor to perceived recommendation quality (\( \beta = .24, t (92) = 2.49, p = .01 \)); and social networking disclosure was a significant negative predictor (\( \beta = -.21, t (92) = -2.33, p = .02 \)). This suggested that the more the participant revealed their preferences for movie genres, the more likely they perceived the recommendations provided by Bollybox to be of high quality. In contrast, the more conservative they were about sharing their movie watching through social networks, the better quality they perceived.
Table 8. Regression statistics: disclosure behaviors predicting perceived recommendation quality

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
<th>Regression 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.228*</td>
<td>.179*</td>
<td>.130</td>
</tr>
<tr>
<td>Gender</td>
<td>.101</td>
<td>.056</td>
<td>.067</td>
</tr>
<tr>
<td>Education</td>
<td>-.060</td>
<td>-.130</td>
<td>-.110</td>
</tr>
<tr>
<td>Bollywood interest</td>
<td></td>
<td>.166</td>
<td>.158*</td>
</tr>
<tr>
<td>Previous privacy experience</td>
<td></td>
<td>-.063</td>
<td>-.014</td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td></td>
<td>.101</td>
<td>.215*</td>
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<tr>
<td>Perceived value of personalization</td>
<td></td>
<td>.360***</td>
<td>.354**</td>
</tr>
<tr>
<td>Need for control</td>
<td></td>
<td>.259**</td>
<td>.182*</td>
</tr>
<tr>
<td>Power usage</td>
<td></td>
<td>.011</td>
<td>.010</td>
</tr>
</tbody>
</table>

- Genre disclosure

| Watching time disclosure   |              | .072         |
| Social networking disclosure|            | -.207*       |

\[ R^2 \] 

| R^2 change                | .080*        | .317***      | .079**       |

\[ + p < .10; * p < .05; ** p < .01; *** p < .001. \]

**Attitude toward Bollybox.** The third block in Table 9 added a marginally significant incremental increase in variance explained, \( R^2 \) change = .04, incremental \( F(3, 92) = 2.46, p \)
Table 9 shows that, genre disclosure was a significant positive predictor to attitude toward Bollybox (\( \beta = .23, t(92) = 2.37, p = .02 \)). This meant that the more the participant revealed their preferences for movie genres, the better attitude they had toward Bollybox in general.

Table 9. Regression statistics: disclosure behaviors predicting system attitude

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
<th>Regression 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
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<td>.180*</td>
<td>.166*</td>
</tr>
<tr>
<td>Gender</td>
<td>.122</td>
<td>.053</td>
<td>.055</td>
</tr>
<tr>
<td>Education</td>
<td>-.114</td>
<td>-.163*</td>
<td>-.180*</td>
</tr>
<tr>
<td>Bollywood interest</td>
<td></td>
<td>.301**</td>
<td>.254*</td>
</tr>
<tr>
<td>Previous privacy experience</td>
<td>-.133</td>
<td>-.105</td>
<td></td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td>.127</td>
<td>.142</td>
<td></td>
</tr>
<tr>
<td>Perceived value of personalization</td>
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<td>.197*</td>
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</tr>
<tr>
<td>Need for control</td>
<td>.060</td>
<td>.063</td>
<td></td>
</tr>
<tr>
<td>Power usage</td>
<td>.127</td>
<td>.122</td>
<td></td>
</tr>
<tr>
<td>Genre disclosure</td>
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<td></td>
<td>.230*</td>
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<tr>
<td>Watching time disclosure</td>
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<tr>
<td>Social networking disclosure</td>
<td>.091</td>
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</tr>
<tr>
<td>(R^2)</td>
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<td>.404</td>
<td>.448</td>
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<tr>
<td>(R^2) change</td>
<td>.092**</td>
<td>.312***</td>
<td>.044*</td>
</tr>
</tbody>
</table>

+ \( p < .10 \); * \( p < .05 \); ** \( p < .01 \); *** \( p < .001 \).
**Privacy concerns.** The third block provided a significant incremental increase in variance explained, $R^2$ change = .06, incremental $F(3, 92) = 2.28, p = .01$, adjusted $R^2$ change = .04. Table 10 displays that genre disclosure was a significant negative predictor to privacy concerns, $\beta = -.26, t (92) = -2.29, p = .02$. In other words, the more the participant revealed their preferences for movie genres, the less privacy concerns (e.g., “I would be concerned that the information I submit to Bolylbox could be misused.”) they held for using Bollybox.

Table 10. Regression statistics: disclosure behaviors predicting privacy concerns

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
<th>Regression 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.023</td>
<td>-.005</td>
<td>.024</td>
</tr>
<tr>
<td>Gender</td>
<td>-.030</td>
<td>.057</td>
<td>.057</td>
</tr>
<tr>
<td>Education</td>
<td>.130</td>
<td>.128</td>
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<td>Bollywood interest</td>
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<td>-.087</td>
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<td>Previous privacy experience</td>
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<tr>
<td>Disposition to value privacy</td>
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<tr>
<td>Perceived value of personalization</td>
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</tr>
<tr>
<td>Need for control</td>
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<td>-.072</td>
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</tr>
<tr>
<td>Power usage</td>
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<td>-.067</td>
<td></td>
</tr>
<tr>
<td>Genre disclosure</td>
<td></td>
<td></td>
<td>-.261*</td>
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<tr>
<td>Watching time disclosure</td>
<td></td>
<td></td>
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<tr>
<td>Social networking disclosure</td>
<td></td>
<td></td>
<td>.148</td>
</tr>
</tbody>
</table>
Future use intention. The third block here added a significant incremental increase in variance explained, $R^2$ change = .03, incremental $F(3, 92) = 2.47, p = .07$, adjusted $R^2$ change = .02. Table 11 reveals that genre disclosure was a marginally significant positive predictor to behavioral intention to use Bollybox in the future ($\beta = -.26$, $t(92) = 1.87, p = .07$). Therefore, the more the participant disclosed their preferences for movie genres, the more likely they tended to use Bollybox in the future.

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Regression 1</th>
<th>Regression 2</th>
<th>Regression 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.140</td>
<td>.128</td>
<td>.104</td>
</tr>
<tr>
<td>Gender</td>
<td>.055</td>
<td>-.024</td>
<td>-.016</td>
</tr>
<tr>
<td>Education</td>
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<td>-.035</td>
<td>-.043</td>
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<tr>
<td>Bollywood interest</td>
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<td>.661***</td>
<td>.616***</td>
</tr>
<tr>
<td>Previous privacy experience</td>
<td>-.112</td>
<td>-.077</td>
<td></td>
</tr>
<tr>
<td>Disposition to value privacy</td>
<td>.224***</td>
<td>.257**</td>
<td></td>
</tr>
<tr>
<td>Perceived value of personalization</td>
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<td>.123</td>
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<tr>
<td>Need for control</td>
<td>.034</td>
<td>.021</td>
<td></td>
</tr>
<tr>
<td>Power usage</td>
<td>-.157*</td>
<td>-.158*</td>
<td></td>
</tr>
<tr>
<td>Disclosure</td>
<td></td>
<td></td>
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<tr>
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</tr>
<tr>
<td>Genre disclosure</td>
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</tr>
<tr>
<td>Watching time disclosure</td>
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</tr>
<tr>
<td>Social networking disclosure</td>
<td>.032</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| R²                          | .026 | .556 | .590 |
| R² change                   | .026 | .531*** | .033⁺ |

⁺ p < .10; * p < .05; ** p < .01; *** p < .001.

**Customization: the action route**

To test H5 through H7, we investigated the action route of customization by testing a structural equation model (SEM). To do so, we selected data in the customization-action condition only, which consisted of a sample size of 105. Figure 3 illustrates the proposed theoretical model (but with the variables in the model being latent rather than observed). The number of sample moments was 1128, and the number of parameters was 98, which yielded the degrees of freedom to be 1030. This suggested that the model was over identified, thus ready to be analyzed.

**Item parceling.** Due to the large number of items and model complexity, we considered item parceling. Referring to Little, Cunningham, Shahar, and Widaman (2002), there were two specific reasons for using this approach in the current study: 1) our interest was only in investigating the relationships between main constructs (i.e., customization action, sense of control, intrinsic motivation, Bollybox evaluations) rather than the measurement portion, thus involving all the individual items might introduce unnecessary complexity; 2) using all the individual items to estimate would require a huge sample size to stabilize estimation, typically five times of number of parameters. This would result in an ideal sample
size of $5 \times 98 = 490$ in the current case, but we only had 105 in the customization-action condition, which would be insufficient. Therefore, item parceling was performed. According to the model (Figure 3), constructs with many items that might require item parceling included sense of control (15 items), intrinsic motivation (8 items), and attitude toward Bollybox (10 items). For other constructs, the measurement items remained unchanged, as they had relatively less number of them (2-4 items).

Before parceling items, the first step was to ensure measurement unidimensionality for the scales of the three aforementioned constructs. First of all, the scales we used were all previously established measures, whose unidimensionality could be assumed based on their prior usage. Secondly, the item reliability tests revealed that the Cronbach’s $\alpha$s for all three scales were very good—sense of control ($\alpha = .96$), intrinsic motivation ($\alpha = .91$), attitude toward Bollybox ($\alpha = .97$). Thirdly, exploratory factor analysis results showed that, for each construct, all items strongly loaded on one factor, thus it seemed appropriate to aggregate these items. The next step was to form parcels. We followed Matsunaga’s (2008) recommendation to have three parcels per factor, which not only kept the number of parcels small to improve model fit, but also used multiple parcels to prevent estimation bias compared to the all-item-parcel approach. In addition, this strategy allows the measurement portion to be just identified. In terms of parcel-building method, we adopted Rogers and Schmitt’s (2004) factorial algorithm, which is guided by items’ factor loadings—“each parcel sequentially takes up the items with the highest to the lowest factor loadings, alternating the direction of item-picking turns through the parcels” (p. 286). This resulted in the following parcels for the three construct scales: sense of control (items 2, 8, 4, 7, 3; items 15, 13, 6, 9, 11; items 5, 1, 14, 10, 12), intrinsic motivation (items 8, 2, 1; items 7, 4, 3; items 6, 5), attitude (items 4, 3, 5;
items 8, 6, 1; items 7, 9, 10, 2) (refer to Appendix D, p. 150-152). The item numbers refer to the sequential position of the items in the scales we used. And we used these parcels to replace the items in the SEM analysis described below.

**Overall model fit.** Using the item parcels, the structural portion of the action-based model of customization (Figure 3) yielded a good fit after removing non-significant paths and adding a covariance between willingness to disclose and future use intention suggested by modification indices (MI): \( \chi^2 = 315.499, df = 182, p = .000, RMSEA = .061, 90\% CI: .049 - .072, CFI = .972 \). The final model of the action route with standardized path coefficients is shown in Figure 12. Based on this result, H6 was supported, such that sense of control positively influenced intrinsic motivation. The overall good-fitting model suggests that our theoretical prediction of the action route of customization mode indeed worked as expected, that is action of customization can influence people’s attitudes and behavioral intention through sense of control and intrinsic motivation.
Indirect effects. We then tested the hypothesized indirect effects of customization action via sense of control and intrinsic motivation in this model. The proposed theoretical model (Figure 3) predicted 5 potential one-step indirect paths through which the amount of sense of control mediates the effects of customization action on outcome variables (H5), and 5 two-step indirect paths through which the amount of sense of control and intrinsic motivation sequentially mediate the relationships (H7). The final action model we obtained (Figure 12) left one potential indirect path through which sense of control mediates the effect of customization action on privacy concern (H5c), and four two-step indirect relationships that sense of control and intrinsic motivation mediate the effects of customization action on the remaining four dependent variables (H7a, H7b, H7d, H7e), to be tested. To do this, bootstrapping procedures using 2000 bootstrap samples and 95% bias-corrected confidence intervals were employed.
intervals were employed. Results revealed that all five indirect effects were significant: 1) H5c: customization action $\rightarrow$ sense of control $\rightarrow$ privacy concern ($\beta = -0.19, p = 0.001$); 2) H7a: customization action $\rightarrow$ sense of control $\rightarrow$ intrinsic motivation $\rightarrow$ attitude toward the service ($\beta = 0.30, p = 0.001$); 3) H7b: customization action $\rightarrow$ sense of control $\rightarrow$ intrinsic motivation $\rightarrow$ perceived recommendation quality ($\beta = 0.25, p = 0.001$); 4) H7e: customization action $\rightarrow$ sense of control $\rightarrow$ intrinsic motivation $\rightarrow$ willingness to disclose ($\beta = 0.20, p = 0.001$); 5) H7d: customization action $\rightarrow$ sense of control $\rightarrow$ intrinsic motivation $\rightarrow$ future use intention ($\beta = 0.20, p = 0.001$). Therefore, H5c, H7a, H7b, H7d, and H7e were supported, and H5a, H5b, H5d, H5e, and H7c were rejected.

**Customization: the cue route**

For the cue route of customization (Figure 4), we also employed an SEM approach to test H8 through H11, and used the same parcels for items measuring control heuristic (i.e., sense of control) and attitude toward the service as explained in the action model. The cue model of customization also yielded a good fit after dropping non-significant paths and adding covariances between attitude toward service and perceived recommendation quality, attitude and future use intention, and between willingness to disclose and future use intention suggested by modification indices: $\chi^2 = 347.404, df = 198, p = 0.000, RMSEA = 0.063, 90\% CI: 0.052 - 0.073, CFI = 0.964$. The final model of the cue route with standardized path coefficients is shown in Figure 13. The overall good-fitting model supported the existence of the cue route of customization mode in addition to but independent from the action route. Therefore, customization indeed can influence people’s attitudes and behavioral intention through both the action and the cue routes.
Indirect effects. The proposed theoretical model of the cue route (Figure 4) predicted 10 potential one-step indirect paths through which either the control heuristic (H9) or the choice-overload heuristic (H11) mediates the effects of customization cue on outcome variables. However, as shown in Figure 4, for each dependent variable, there were two mediators (i.e., control heuristic and choice-overload heuristic) present in this model, which made it impossible to tell which particular path would result in a potential significant indirect effect of customization cue on the dependent variables, or whether the two mediators would cancel out each other’s significant effect to lead to an overall insignificant indirect effect. The key is that both heuristics were hypothesized to be operating at the same time in this model. To resolve this issue, we adopted the phantom model approach (Macho & Ledermann, 2011;
Kim & Sundar, 2013, 2015), which allowed us to test the indirect effects with both mediators in a single analysis and also tell us which path (or both, or neither) would result in significant indirect effects from customization cue to the dependent variables.

Figure 14. Illustration of phantom model analysis

The logic of the phantom model approach lies in the notion that imaginary “phantom variables” are added as latent variables corresponding to the main theoretical model under study. The phantom variables’ error variances are all equal to zero, and the path coefficients are constrained to match those in the main model. For example, the original customization condition \( \rightarrow \) control heuristic (i.e., sense of control) \( \rightarrow \) attitude toward system path is replicated as the customization condition \( \rightarrow \) CS (“C” stands for customization, “S” stands for sense of control) \( \rightarrow \) CSA (“A” stands for attitude) (i.e., A1 \( \rightarrow \) B1) path in the phantom model, and the original customization condition \( \rightarrow \) choice overload heuristic \( \rightarrow \) willingness to
disclose path is replicated as the customization $\rightarrow$ CC (first “C” stands for customization, second “C” stands for choice overload heuristic) $\rightarrow$ CCW (“W” stands for willingness to disclose) (i.e., A2 $\rightarrow$ C5) path in the phantom model. All the path coefficients (e.g., A1, B1, C1) here are unstandardized, and the ones in the phantom model are identical with their counterparts in the original model. Based on this logic, we performed the following steps for the phantom model approach:

1. Twelve phantom variables were created and added to the main model, corresponding to the ten indirect paths in the original model. The phantom variables were named based on the variables the original path passes through. The latent phantom variables did not have any error variance.

2. Path coefficients in the phantom model were constrained to be identical with their counterparts in the original model. Therefore, as shown in Figure 14, A1, A2, B1 through B5, and C1 through C5, all corresponded with the respective coefficients in the original model.

3. To test the indirect effects, 5000 bootstrap samples at 95% bias-corrected confidence interval were used for the estimates. Results from this analysis on the ten indirect effects are shown in Figure 15.
Based on the results, seven out of ten hypothesized indirect paths were significant (paths 1, 2, 3, 4, 5, 9, 10), and two were marginally significant (paths 7, 8). Therefore, H9 was supported, such that the presence of customization cue influenced user attitudes and
behavioral intent by triggering the control heuristic; **H11d and H11e were supported**, such that the presence of customization cue induced less choice-overload heuristic, which was associated with greater intention to use the Bollybox service in the future and willingness to disclose personal information to it. **H11a through H11c were rejected**, such that the choice-overload heuristic reduced by the presence of customization cue did not subsequently lead to significant changes in attitude toward Bollybox, perceived recommendation quality, and privacy concerns (paths 6, 7, and 8).

**Distinguishing sense of control and control heuristic**

As mentioned previously, the measure for control heuristic was adopted from the same validated scale for sense of control, consisting of 15 items about one’s belief in being able to modify the privacy settings of the system, to initiate changes, and feeling free to make choices ($M = 4.88$, $SD = 1.21$, Cronbach’s $\alpha = .96$) (Ariely (2000), Venkatesh and Davis (2000), Witmer and Singer (1998), and Xu (2007)). Since heuristics are mental shortcuts triggered in the moment, it is difficult to capture them directly without being obtrusive to study procedures. Therefore, following Kahneman and Tversky (1972, 1973), self-reported judgments about control, an outcome evoked by the actual control heuristic, was used as an approximation to measure the heuristic itself. And the findings of this study indeed revealed that the mere presence of customization cue, in comparison to the absence condition, triggered such a control heuristic captured by measure of sense of control. However, this still begs the question: how are control heuristic and sense of control empirically distinct? Can we be confident that it was indeed an application of the heuristic, rather than a change in attitude as a function of the customization cue? According to self-determination theory (Deci & Ryan, 1985), when users are offered freedom to engage in a behavior, they tend to be inherently
motivated to do so. This suggests that the sense of control imbued via the action route of customization influences outcome perceptions through intrinsic motivation. Therefore, when customization action leads to a sense of control, users’ intrinsic motivation to further engage in customization actions is enhanced. Prior research has also shown that freedom of choice can elevate perceived value of actions, which further increases intrinsic motivation to engage in such actions (Iyengar & DeVoe, 2003). The Technology Acceptance Model (TAM) also proposed a positive relationship between internal control and intrinsic motivation (Venkatesh, 2000). Therefore, the action route should take effect on the outcome variables through sense of control and intrinsic motivation sequentially. In contrast, the mere presence of customization can also be suggestive about the user control it is offering, without engaging users to operate on it. According to TIME (Sundar et al., 2015), the psychological consequence of such visual cues of technological affordances is mental shortcuts, or heuristics, formed by previous knowledge and experience and triggered by an accessible visual cue. The heuristics thereafter influence other psychological and behavioral outcomes, without necessarily involving intrinsic motivation.

Figure 12 already showed the sense of control→intrinsic motivation mechanism of the action route, such that four out of five dependent variables—attitude toward the service, perceived recommendation quality, willingness to disclose personal information, and future intention to use the service—were influenced significantly by the customization action through both mediating variables (sense of control and intrinsic motivation). Figure 16 shows the model without intrinsic motivation: the difference in Chi-square is \(315.449 - 263.554 = 51.895\), \(\Delta df = (182 - 144) = 38\). According to the Chi-square distribution, the model fit of Figure 16 (without intrinsic motivation) is marginally significantly poorer than the action
route model with both sense of control and intrinsic motivation as subsequent mediators, $p < .01$, which suggests that intrinsic motivation is an important mediator of the action route.

Figure 16. SEM for the action route of customization without intrinsic motivation

Chi-square = 263.554, DF = 144, $p = .000$
RMSEA = .065, 90% CI: .052 -.077, CFI = .973

To empirically verify the distinction between control heuristic and sense of control, we first ran the cue route model with the control heuristic only as the mediator (Figure 17). Results showed a good-fitting model: $\chi^2 = 247.504, df = 144, p = .000, RMSEA = .061, 90% CI: .048 -.074, CFI = .973$. Then we added intrinsic motivation (Figure 18), and the difference in model fit is: $\Delta \chi^2 = (348.101 - 247.504) = 100.597, \Delta df = (180 - 144) = 36$, which suggests that adding intrinsic motivation caused the cue route to be significantly poorer, $p < .001$. Therefore, as theory predicted, intrinsic motivation is a critical mediator for the action route and the control measures capturing sense of control. But for the cue route, intrinsic motivation is not a critical mediator and therefore the control measures are capturing a perception of control heuristic rather than a feeling of sense of control among users..This
comparison empirically distinguishes control heuristic in the cue route from the sense of control in the action route, although the same measures were used in this study.

Chi-square = 247.504, DF = 144, p = .000  
RMSEA = .061, 90% CI: .048 - .074, CFI = .973

Figure 17. SEM for the cue route of customization with control heuristic only
Moderating role of previous privacy intrusion experience

In addition to the main effects of personalization mechanism and customization mode, we also detected some interesting moderation effects of participants’ previous privacy experience, which captured the frequency of privacy misconduct participants had experienced before. It is worth noting that previous privacy intrusion experience was measured as a continuous variable on a 7-point Likert scale, and all the statistics reported here were based on tests with the continuous variable. But for the ease of illustration, we performed a median split on previous intrusion experience and made it a two-level ordinal variable in the figures, with the two levels being less previous intrusion (blue lines in Figure 19 & 20) and more intrusion (red lines).
Figure 19 shows a significant interaction between personalization mechanism and previous privacy intrusion experience on participants’ privacy concerns about Bollybox, $F(1, 281) = 4.50, p < .05$. More specifically, for users with relatively less negative privacy experience, there was not much difference between proactive and reactive personalization in triggering users’ concerns about privacy. For those with more intrusion experience before, proactive personalization, or the system automatically pushing tailored recommendations to users, caused more concerns, compared to reactive personalization. This shows that negative prior experience might make people more wary about the system’s access and use of their data for proactively personalizing content for them.

![Graph showing interaction between personalization and previous privacy experience on privacy concern](image)

Figure 19. Interaction between personalization and previous privacy experience on privacy concern

Previous privacy intrusion experience also moderated the effects of customization mode on participants’ sense of control, $F(2, 279) = 3.07, p < .05$. As shown in Figure 20, this interaction especially manifests for the action and cue conditions of customization. In particular, although the presence of a customization feature (i.e., privacy setting) led to more sense of control compared to absence of it universally, those with less negative privacy experience felt assured even by just acknowledging that such a feature existed (cue condition),
whereas those with worse prior experience would appreciate manually being able to adjust the privacy settings themselves (action condition).

![Figure 20. Interaction between customization and previous privacy experience on sense of control](image)

**Moderating role of disposition to value privacy**

Another interaction effect ($F(2, 279) = 4.69, p = .01$) was found between customization mode and participants’ disposition to value privacy, with the latter tapping into one’s tendency to care about information privacy. It was also measured as a continuous variable, but illustrated in Figure 21 as a dichotomous one through a median split. The red line represents those who are more sensitive about their information privacy, and the blue line represents those who tend to be less concerned about privacy. Figure 21 shows that, for those who were less cautious about privacy, the presence of a customization feature, no matter in the form of an interface cue or real action, did not influence participants’ intention to use
Bollybox in the future much. However, the customization feature strongly influenced behavioral intentions of those who were more sensitive about information privacy. In particular, the indication of an existing customization feature (cue) evoked users’ interest in using the service in the future compared to absence of the feature; being able to manually customize privacy settings (action) led to even stronger intentions.

![Figure 21. Interaction between customization and disposition to value privacy on future use intention toward Bollybox](image)

**Summary of findings**

The above section presents findings on how the two manipulated variables, personalization mechanism (proactive vs. reactive) and customization mode (action vs. cue vs. absence), in a movie recommender online service influenced users’ perceptions, behavioral intention, and actual disclosure behavior. Main findings are summarized below.

**Effects of personalization mechanism.** Personalization mechanism, in the form of proactively pushing tailored movie recommendations to users, enhanced perceived
recommendation quality from the service, but also triggered more privacy concern, compared to reactive personalization, which allows users to express their needs in the tailoring process. This somewhat contradictory finding shows that users on the one hand favor high quality brought by system-controlled personalization, but on the other also fear the potential privacy infringement that accompanies it. Counter to expectation, we did not find any significant difference between these two types of personalization mechanisms on sense of control and other outcomes.

**Effects of customization mode.** Customization was manipulated in three modes—absence of it, actual action, and interface cue. We found that, compared to the absence condition, both actual interaction with the customization feature and merely seeing interface cues suggesting the customization possibility, led to greater sense of control, however the difference between the action and cue conditions was not significant. This effect pattern was consistent for other dependent variables as well, such that the presence of customization cue had the same effects as actual interaction with customization feature and the differences between cue and action were non-significant. Specifically, the presence of customization action or cue reduced privacy concerns and increased participants’ intention to use the movie recommendation service in the future.

**Customization: the action route.** Based on the TIME model, we tested the action route and cue route as two separate path models. Results showed that the action of customization influenced outcome variables via exerting sense of control and promoting intrinsic motivation. Specifically, the act of performing customization actions imbued in users a stronger sense of control, which in turn alleviated privacy concerns. This sense of control also engendered greater intrinsic motivation, leading to more favorable attitudes and
behavioral intentions, such as better attitude toward the service, higher perceived recommendation quality, more willingness to disclose personal information, and higher intention to use the service in the future.

**Customization: the cue route.** The predictions based on the cue route of TIME also resulted in a good-fitting model. Our findings suggested that the presence of customization cue without involving actual action could still influence user attitudes and behavioral intentions by triggering certain heuristics. In particular, seeing the indication of customization possibility gave users confidence in having everything under their control if they so desired, thereby resulting in more favorable attitude toward the movie recommendation service, higher perceived recommendation quality, more willingness to share personal information, and reducing privacy concern. However, contrary to our hypothesis, the presence of customization cue negatively evoke the choice-overload heuristic, meaning that seeing the customization cue without actual interaction did not burden users’ cognitive capacity, but somehow made them less stressed about the choices, which in turn improved perceived recommendation quality, but reduced intention to reveal personal information and use the service in the future.

**Moderating role of previous privacy intrusion and disposition to value privacy.**

Previous privacy intrusion was found to moderate the effect of personalization mechanism on the level of privacy concern. Although proactive personalization evoked more privacy concern than reactive personalization, this difference was significantly more pronounced for those who had more negative past experience about privacy. For those who had less privacy intrusion experience, level of privacy concern triggered by personalization was much lower and the difference between proactive and reactive personalization was not significant. Previous privacy intrusion also moderated the effect of customization on sense of control. For those
with more negative memory about privacy, being able to actually interact with the customization feature (i.e., the action condition) resulted in greatest sense of control, but for those who didn’t have much privacy intrusion experience, even the presence of customization cue would generate a strong sense of control, comparable with the action condition.

Disposition to value privacy also moderated the effect of customization mode on behavioral intention to use Bollybox in the future. With less disposition to value privacy, the presence of a customization function, no matter in the form of actual action or interface cue, did not influence the interest in using the movie recommendation service in the future. But for those who generally cared about information privacy, the presence of a customization cue elevated participants’ behavioral intention compared to the absence condition; and this intention was heightened when they were able to actually customize privacy settings.

**Privacy disclosure behavior.** The personal information disclosure behavior in the privacy setting page (only available in the customization action condition) predicted several dependent variables measured after the interaction. In particular, revealing genre preference negatively predicted privacy concern about using Bollybox, but positively predicted perceived quality of movie recommendations, attitude toward Bollybox, and behavioral intention to use the service in the future. Disclosing about social media accounts led to lower perceived recommendation quality. We also identified several individual difference factors that predicted privacy disclosure behaviors. For instance, disposition to value privacy negatively predicted disclosure on movie genre preference, but positively predicted one’s revealing on social media account information. Perceived value of personalization performed as a positive predictor of disclosure on movie genre preference, content watched during different time periods, social media account information, and also overall disclosure. Interest in Bollywood
movies in general was another positive predictor of disclosure of movie watching at different times, social media information, and overall personal information. In addition, need for control negatively predicted disclosure on social media accounts.
Chapter 4

**DISCUSSION**

The purpose of the current study is to investigate the psychological effects of personalization mechanism and customization mode in an online movie recommendation service through an online controlled experiment. Personalization mechanism was manipulated in the form of either proactively pushing tailored content to users without consent (i.e., proactive personalization) or allowing user input in the process of personalizing content (i.e., reactive personalization). Customization mode had three conditions--one was absence of privacy setting that simply showed a list of information without implying any user interaction possibility, which was used as the control (baseline) condition; the second one allowed participants to manually modify privacy permissions that the recommendation service requested; and the third condition showed an interface cue suggesting the possibility to modify privacy settings without involving actual actions. Participants’ sense of control, intrinsic motivation, attitude toward the movie recommendation service, perceived quality of movie recommendation, privacy concern in using the website, intention to use the service in the future, and willingness to disclose personal information to the website were measured after participants interacted with the stimulus. Participants’ actual disclosure behavior (available in the customization-action condition only) was also recorded for analysis. Our findings suggested that different types of personalization and customization mode respectively shaped users’ feelings, attitudes, and behavioral intentions significantly both toward the website and the content displayed via the website. As predicted, proactive personalization significantly elevated participants’ perceived quality of movie recommendation from the service but also heightened their privacy concern, compared to reactive personalization. And the presence of customization in the form of privacy settings—either in the form of action or
simply as a cue on the interface—evoked a stronger sense of control and reduced privacy concern. The interaction effect was not significant, which meant that the presence of customization did not effectively resolve the issues arising from personalization. However, we demonstrated that in the case of customization, interface cues were as powerful in influencing user perceptions as actual action, by establishing two good-fitting models pertaining to the action and cue routes of customization, thus providing support to the theory of interactive media effects (TIME).

This chapter interprets these findings and discusses the theoretical and practical implications of them in light of limitations of the current study, and provides directions for future research.

**Interpretation of findings**

**Effects of personalization mechanism: privacy-personalization tradeoff.** We hypothesized that, in contrast to reactive personalization, proactive personalization would lead to less sense of control, higher perceived recommendation quality, and more privacy concern. The latter two hypotheses were supported, whereas the first one was rejected. When users were offered automatic movie recommendations based on their interests and preferences without prior acknowledgement, they indeed realized the smartness of the system and evaluated the quality of the movie recommendations significantly higher compared to the reactive personalization condition that asked for their input. But this high-quality service came with a price, such that the tailored content relied on the online service’s tracking and analyzing of user data, which did not ask for permission and could be construed as an invasion of one’s privacy. Participants were clearly wary of this approach, as evidenced by the significantly higher scores on privacy concern in the proactive personalization condition.
Reactive personalization, on the other hand, took a more overt approach by seeking users’ needs first, which allowed users to exert some degree of agency and be prepared for the personalized service later. This effectively alleviated participants’ privacy concern, but was not pronounced enough to imbue a significantly higher sense of control.

These data patterns confirm the privacy-personalization tradeoff identified in the literature (Awad & Krishnan, 2006; Chellappa & Sin, 2005), such that the benefits promised by personalization come at the price of compromising privacy, and participants in the proactive personalization condition apparently realized that while assessing recommendation quality and privacy concern in comparison with those in the reactive personalization condition. While most systems see proactive personalization as the gold standard to boost user experience and impulsive buying, some try to take a softer approach by employing the reactive personalization mechanism, aiming to imbue in users a higher sense of control and alleviate their privacy concerns. However, sense of control was not significantly enhanced by reactive personalization, according to our findings, even though privacy concern was indeed effectively reduced. In addition, the service quality delivered was also perceived as lower by participants in the reactive personalization, which would not be an ideal situation for service providers. Such findings suggest that proactively offering personalized services can lead to positive impression of the content delivered by the medium, but the accompanying privacy concern should not be neglected and needs to be addressed. However, reactive personalization may not be an ideal solution as it undermined users’ satisfaction with the content, which is a core value for online services.

**Effects of customization: can customization reduce privacy concern?** It is notable that although reactive personalization and customization both allow users to exert a certain
degree of human agency by expressing their own will through actions, the essence is different. Reactive personalization functions through the system creating individualized content, even though the user is the one to initiate this process, therefore the majority of locus of agency is still the system, or the machine. But customization is under total control of the user—the user decides whether or not to take actions, what content can be tailored and how, and the system only responds to the user’s arrangement passively. The locus of agency for customization is entirely human. Aforementioned findings suggest that reactive personalization did not provoke enough sense of control, which may have been suppressed by the dominant machine agency communicated by personalization. From a business perspective, reactive personalization is not an ideal solution either, as it would not be cost-effective to sacrifice users’ satisfaction with their service. Since privacy concerns always come from a lack of certainty, security, or a sense of control, we hypothesized that adding a separate layer of control, such as customization of privacy settings, instead of asking users to initiate requests as they receive personalized recommendations, might solve the problem in an elegant way.

Customization can be operationalized in many different forms, from user settings to interface decoration, the goal of which is to provide a sense of autonomy, making users feel in control. In the current privacy context, we adopted the form of privacy settings in particular to help reduce users’ concerns about privacy, as a potential way to attenuate the personalization-privacy tradeoff in a recommender system. We had users exposed to customization first, in order to make them feel more empowered while confronting the potential risks of personalization later on. The objective of our proposed privacy-setting page was to build a level of control in users, for them to feel competent while interacting with personalized services and not to be frustrated when they encounter privacy risks. As expected, the
provision of customization in privacy settings did indeed enhance participants’ sense of control, such that both the action of customizing privacy permissions and merely seeing the possibility to do so increased participants’ feeling of being in control, compared to the absence of any customization. But there was no significant difference between the effects of customization-action and customization-cue on sense of control. Along the same lines, the presence of customization (either action or cue) significantly reduced participants’ privacy concerns, and subsequent analysis suggested that sense of control indeed played a mediating role in eliminating privacy concern from customization. In addition, similar effect patterns of customization action and cue were found on participants’ attitude toward the stimulus website and the intention to use the recommendation service in the future. Therefore, as a general strategy, providing users opportunities to customize privacy settings can serve to enhance user agency and minimize privacy concerns, resulting in a number of positive psychological outcomes.

However, none of the interaction effects between personalization and customization on psychological outcomes were significant. The pattern of means in the interaction effects we tested (Figures n10 & n11) appears to support employing customization as an effective solution to enhance perceived recommendation quality and reduce privacy concern, even if not quite statistically. Perhaps the customization options for privacy settings ought to be more elaborate, or perhaps the privacy intrusion represented by proactive personalization ought to be more apparent to users. While future research can attempt these improvements, designers can benefit from the trend represented in our interaction graphs (Figures n10 and n11) and attempt to assuage privacy concerns emerging from personalization by offering robust tools.
for customizing privacy settings. This would allow systems to offer the benefits of proactive personalization while minimizing its risks to privacy.

**Delivering an Effective Customization Mode.** Another intriguing finding of the current study is that merely presenting interface cues of customization without having users actually take actions to customize privacy settings could lead to similar outcomes, such as heightened sense of control, better attitude toward the movie recommendation service, less privacy concern, and more intention to use the service in the future. Specifically, by merely seeing the existence of privacy settings, users would feel almost as comfortable as when they make actual selections on the same interface. Users clearly appreciate the ability to modify changes in using an online system and receiving services rather than none, but don’t have to put such potential into practice. This finding suggests that the technological affordance, customization, in the form of privacy setting in an online movie recommendation system, influences users’ perceptual outcomes through two distinct psychological paths. To further verify this dual-route argument and detect the underlying mechanisms of the two potential paths, we proposed two theoretical models (Figures n3 and n4) and employed SEM to test them statistically. Data revealed that customization indeed influenced participants’ feelings and evaluations of the recommendation service through both letting them modify privacy settings manually and displaying this function without allowing actual action. In other words, both the action route and the cue route of customization were supported.

Based on the action-route model (Figure 12), making changes to the privacy settings imbued a strong sense of control or self-agency among users, and this appears to have alleviated their privacy concerns. This can be explained by the fact that privacy concern is often associated with a lack of security or certainty, which is associated with a sense of
control. The enhanced sense of control also increased the magnitude of intrinsic motivation, such that those who engaged in customizing the privacy settings reported being more intrinsically motivated to use the Bollybox service than those who did not. And this increased intrinsic motivation led to a series of positive reactions and behavioral intentions with regard to the movie recommendation service, namely better attitude toward the service, higher perceived quality of movie recommendations, more willingness to disclose personal information to the website, and more intention to use the service in the future. Consistent with previous literature on intrinsic motivation (Venkatesh, 1999), greater level of intrinsic motivation resulted in more favorable attitudes toward the movie recommendation system and the content, as well as more behavioral intention toward using it.

Data on the cue route of customization (Figure 13) demonstrated that seeing interface cues of customization without engaging in setting privacy permissions can also lead to similar outcomes. Customization cue took effect through triggering cognitive heuristics, or mental shortcuts accessible in participants’ mind, which exerted comparable influence on participants’ perceptions. The two identified heuristics were control heuristic and choice-overload heuristic. Control heuristic is a belief that if a system offers user control, then it must be safe and good, which works similarly as sense of control and was measured with the same set of items. The presence of the privacy-setting cue was clearly effective in triggering this heuristic, because participants reported significantly higher level of perceiving the control heuristic in the cue condition. Given a more assured experience through heightened certainty and safety, privacy concern was alleviated, and perceptions toward the online service were rendered more positive. The other heuristic, choice-overload heuristic, however, did not work as expected. We hypothesized that merely seeing customization cues in the form of privacy settings but not
able to make changes might add to users’ cognitive load in making decisions about the service, thereby frustrating them and leading to negative outcomes. However, data showed that the presence of the customization cue without real action in fact did not overwhelm users, but on the contrary even reduced this burden. One possible explanation is that when participants saw the customization cue as privacy settings, the feeling that the website was trying to protect them surpassed the cognitive load brought by multiple choices. The negative association between choice-overload heuristic and perceived recommendation quality might be because that cognitive overload could negatively influence one’s judgment about the source that created the burden. Interestingly, the associations between choice-overload heuristic and willingness to disclose, and with intention to use the service in the future were both positive. However, it is worth noting that these two associations were negative without controlling for the control heuristic’s effects in the same model. This suggests that the counter intuitive positive relationships between choice-overload heuristic and the two behavioral intention variables in the context of control could be a case of suppression effects, such that the presence of the control heuristic in the same model is taking away the negative effect of choice-overload, and the variance leftover on the behavioral intentions was positively affected by choice-overload because it served to motivate users to take action when they could not feel that they had control over the cue’s operation.

The findings discussed above verified the dual-route argument of the theory of interactive media effects (TIME) (Sundar et al., 2015), which suggests the powerful role of interface cues, especially in terms of triggering cognitive heuristics (mental shortcuts) that can influence user perceptions and judgments. Clearly, the sense of control (i.e., control heuristic) signaled by customization cues on the interface translates into positive perceptions of the
system and positive attitudes toward the recommendations made by the system. This finding has important design implications, such that well-deployed interface-level elements can be powerful in influencing users’ decision making, which may not require sophisticated implementation of actionable settings. This further suggests the importance of good interface cues, as they seem to have the same capacity in influencing user psychology compared with actual interaction on the interface.

**Role of previous negative privacy experience and disposition to value privacy.** Although we identified various results for personalization mechanism and customization mode, their effectiveness was moderated by individuals’ previous experience with privacy intrusions. As Figure 19 (p. 93) shows, users without much negative privacy experience may not have appreciated the nuances underlying the difference between proactive and reactive personalization, thus their privacy concerns did not differ much. However, those with more experience with privacy intrusions tended to be more vigilant about potential data breaches, thus proactive personalization seemed more suspicious to them. Along the same lines, although we found that customization cue had similar effects with actual customization actions in general, it seems that this strategy might only have worked for those with less negative privacy memories (Figure 20, p. 94). Individuals who had been victims of privacy infringement did not derive as much sense of control from customization cues, unless they actually acted on the customization options offered by the interface. It is not difficult to understand that previous negative experience may make users more vigilant and suspicious when their personal data are accessed and used. Both the Elaboration Likelihood Model (ELM) and the Heuristic-Systematic Processing Model (HSM) suggest that individuals process information either superficially or deeply (Petty & Cacioppo, 1986; Chaiken, 1980).
When forming impressions and judgments of a message, individuals can go through two mental routes: either superficial thinking without in-depth analysis, or effortful, analytical thinking. Additionally, ELM holds that the information processing route to persuasion is determined by motivation and ability (Petty & Cacioppo, 1979). Motivation refers to whether information is personally relevant and consequential, while ability is related to the possibility that people have the mental and physical resources to think (Petty & Cacioppo, 1986). ELM suggests that if either motivation or ability is low, people tend to rely on heuristic cues in making evaluations. Applying this argument in our findings, people who had more negative privacy experience may have found the privacy information more personally relevant, thus felt motivated to process the information with more mental effort, which led them to find the customization cue less reliable than actual actions. In comparison, those who had less privacy intrusion experience may have processed the customization cue peripherally, thereby perceiving the cue and action as similarly influential.

This again suggests that privacy permission interfaces and any services involving use of personal data need to be designed and implemented strategically for triggering appropriate perceptions of user control so that they can mitigate privacy concerns arising from prior negative experiences.

The effects of customization mode on future intention to use the online recommendation service was also moderated by participants’ disposition to value privacy (Figure 21, p. 95). The identified pattern that participants in the action and cue conditions had more intention to use the Bollybox service in the future, compared to those who were unaware of the customization possibility (i.e., the customization absence condition), was only true for those who tend to value information privacy. And for this group of privacy-conscious
individuals, employing actual action of customization significantly drove the intention to use Bollybox in the future. However, for those who generally pay less attention to privacy protection, the addition of customization, no matter in what mode, did not make a big difference. This suggests that the effectiveness of customization, either in an action mode or a cue mode, has to be discussed under the premise that users understand the severity of privacy issues. Without sufficient awareness of potential privacy risks, no matter how elegantly customization is designed and deployed, the technological affordance will likely be ineffective in persuading users to trust the service.

**Theoretical implications**

The investigation of the influences of customization and personalization on online users’ privacy-related perceptions and behaviors in recommender systems, and the effect of customization of privacy settings on the persuasiveness of personalized agents, advances our knowledge about the psychology of online users’ decision-making process in a personalized recommendation context, and offers explanations for the paradoxical phenomenon of privacy-personalization tradeoff. Previous privacy literature has many times demonstrated this phenomenon and argued how the ever more advanced personalization technologies can cause widespread privacy concerns. This study took a different approach—instead of simply revealing and revalidating what privacy-related outcomes can come out of a personalized recommender system, it attempted to explore the fine distinction on locus of agency between two types of personalization delivery mechanisms, proactive and reactive personalization. These two types had mostly been discussed in technical research in terms of building algorithms to mine user data and push tailored content to them. The current study is among the first that sheds light on a nuanced understanding of the psychology surrounding different
personalization delivery mechanisms by demonstrating that while the “smartness” brought by proactive personalization technologies can lead to higher perceived quality of content recommendations, users do worry about the privacy risks accompanying the benefits. Although the difference in manipulation—the presence of a users-initiated request—was subtle, significant findings on perceived recommendation quality and privacy concern between these two mechanisms verified the psychological driver that leads to a safety-assured personalization experience—human agency.

Since reactive personalization reduced privacy concern through compromising service satisfaction, we then took a step further to explore the effectiveness of employing customization in the form of privacy setting as a potential solution. While previous literature focused on distinguishing the two, the current study investigated the combinatory effects of employing both in a system to boost user experience. Customization indeed was found to evoke a strong sense of control as expected, but the effect was not pronounced enough to moderate the influence of personalization. Nevertheless, sense of control is indeed a key factor to explain users’ privacy-related perceptions and a psychological driver of intrinsic motivation, which is closely linked to favorable attitudes toward the service.

The most significant theoretical insight of this study is the demonstration of the dual-route model of a technological affordance. According to TIME (Sundar et al., 2015), not only interacting with a technological affordance can result in certain psychological outcomes, mere presence of interface cues also can have powerful effects via triggering cognitive heuristics. However, studies have rarely directly compared the effectiveness of the two routes, thus little empirical evidence exists. To this end, the current study examined customization in three distinct modes—absence, action, and cue, and provided strong support for TIME by showing
that the effects of interface cues were comparable to actual actions on elevating attitudes toward the recommendation system, reducing privacy concerns, and increasing intention to use the system in the future. This unique contribution enriches our understanding of customization and has implications for both research and design of interfaces aimed at delivering individualized user experiences.

**Practical implications**

The current study holds several practical implications to guide better design of personalized recommendation services and interactive interfaces in general.

First of all, the current study once again demonstrates the privacy-personalization tradeoff, which is especially pronounced in a proactive fashion. Our findings suggest that, for personalization to achieve its optimal effect in boosting user satisfaction with the service but not eliciting serious privacy concern, an efficient way is to add certain forms of user control to imbue human agency, while keeping the convenient and “smart” aspect of tailoring content for individualized tastes. Our attempt in employing customization of privacy settings in a personalized movie recommendation system provides a new approach to guide designers away from merely focusing on adding new features to boost personalization appeal. But although we found that the patterns of the interactions between customization and personalization were in the right direction, the effectiveness in balancing the privacy-personalization tradeoff was very small. System designers need to think of creative ways of embedding customizable features to enhance user control.

Secondly, our findings suggest that well-deployed interface-level elements can be powerful in influencing users’ decision making, which may not require sophisticated implementation of actionable settings. This further suggests the importance of good interface
cues, as they seem to have the same capacity in influencing user psychology compared with actual interaction on the interface. Embedding interactive functions in an interface often requires lots of commitment in time and algorithm creation; if interface cues are only what users demand and psychologically powerful, why not go for the smarter option? However, designers should use caution in deploying of interface cues, because sometimes an interface cue can trigger multiple heuristics simultaneously depending on what is accessible in users’ mind. If a negative heuristic is triggered, it is likely to suppress the favorable attitudes resulting from a positive heuristic, downgrading the value of the interface cue.

Our data also imply the need to segment users on the basis of their knowledge and previous experience about privacy, and provide sufficient instruction and education when necessary. As shown in the findings, although in general various effects of customization and personalization were identified, when previous experience and disposition to value privacy were taken into consideration, it was clear that the effects were mostly driven by those who had had negative privacy experience before and who cared about protecting privacy in general. No matter how customization and personalization were delivered, they would not have a notable effect on those who lack experience or awareness. Therefore, it is important to raise awareness of privacy and educate users, which sets the foundation for a successful interface design.

After all, the discussion of agency effects in the context of online privacy also has its unique implications. The privacy setting in online services is special in that it serves as the main gatekeeper for users. In other words, users exert their autonomy by creating gates for sharing information and setting restrictions for their online exposure through this setting. In this sense, privacy is all about which of these user-created gates one wants to let open, to
whom, and in which context or app. Given the various factors affecting users’ decision making, privacy settings in one app are not directly transferrable to other contexts, but rather users feel the need to take an active role to assess these gates in a context-specific manner, which makes human agency even more critical in an online environment dominated by machine agency.

**Limitations**

Findings of the current study need to be interpreted in light of several important limitations.

The biggest limitation is that the stimulus used was not a fully functioning recommendation service, but only an interactive mock-up website created for the purpose of operationalizing variables manipulated in the context. We designed the stimulus content around a specific topic, Bollywood movie recommendations, which limited the ecological validity of the study and therefore the generalizability to other content. But since the mock-up website was established to carefully vary the levels of the independent variables while keeping the rest of content identical, it provided strong internal validity. We also provided a well-designed context of Bollywood movie recommendations to convince participants that this was an existing service. Given the nature of a mock-up system, several drawbacks were unavoidable. For example, to ensure content equality, participants in all conditions saw recommendations of the same five movies. Even though we attempted to select Bollywood movies that were foreign to most American viewers to prevent familiarity, and mixed genres to avoid the impression of incorrect recommendations, the movies were not really personalized after all. This may have to some degree influenced participants’ perceptions of
the online service and the content transmitted, and even affected their decision-making process.

Customization was operationalized as privacy permission setting of the movie recommender service. This was very specific to the privacy context in a movie recommendation service, thus limiting its ability in generalizing our findings to other forms of customization, or to another type of online recommender service. Future research should investigate more diverse system and content types with the same theoretical framework.

The use of Amazon Mechanical Turk to recruit participants also gave rise to limitations. Based on our measure of power usage, the sample was significantly skewed toward the power-user end, which meant that our respondents were not typical users. Also, most Turkers are already very familiar with the procedure of online studies, and the purpose of their completion is to get paid within the shortest time, thus they might have not paid enough attention to all the descriptions and instructions throughout the study, thus reducing the validity of some of our study assumptions.

Another methodological limitation was using the same self-report measures for capturing both sense of control in the action route of customization and the control heuristic in the cue route. The reason for doing so was that heuristics are mental shortcuts triggered in the moment, the nature of which makes it difficult to capture. Therefore, following Kahneman and Tversky (1972, 1973), self-reported judgments about control, an outcome evoked by the actual control heuristic, was used as an approximation to measure the heuristic in the post-test questionnaire. However, given the timely nature of heuristics, such delayed measurement, far removed from the actual moment when control heuristic was triggered, bears the risk of
inaccurate memory. Future research should try to resolve this limitation by establishing more innovative measures of heuristics that are assessed at the time of cue exposure.

**Conclusion**

Personalization technologies have become prevalent today as service providers’ effort in pursuing a smart online environment that boosts user experience, which are fundamentally redefining the way we communicate with online systems and receive content. Especially thanks to the rapid development of data mining techniques, we are now stepping into a virtual world that has everything tailored based on our past behaviors and preferences. To this end, system developers are attempting to make this process even more automatic by promoting the idea of proactive personalization, such that pushing individualized content to users without asking for requests or consent. In this context, findings of the current study provide empirical evidence for the personalization-privacy tradeoff phenomenon in an online movie recommender system. Users on the one hand appreciate the convenience brought by personalization technologies and perceive higher quality of their recommendations, yet on the other hand worry about the privacy risks accompanying the benefits. To balance this tradeoff, this study proposed and examined employing customization of privacy settings to imbue users with a sense of control. The findings revealed that although adding customization appeared to motivate a preference for proactive over reactive personalization as we had expected, the interaction failed to achieve statistical significance. But our data do suggest that customization has a strong psychological appeal. In fact, simply displaying customization cues without involving real actions on the part of the user was almost as powerful in positively influencing users’ sense of control, perceived recommendation quality, and judgments about privacy. System designers need to consider privacy-related user experience in a holistic sense and
realize that customization and personalization carry deep symbolic meanings to users that not only affect their disclosure behaviors but also their attitudes toward the system. Researchers should continue exploring these meanings by empirically evaluating how technological affordances influence user psychology and behaviors through different routes. This will advance our understanding of the trade-off between human agency and machine agency that inevitably occurs whenever users interact “smart” machines.
REFERENCES


Utz, S., & Krämer, N. (2009). The privacy paradox on social network sites revisited: The role of individual characteristics and group norms. *Cyberpsychology, 3*(2).


Appendix A: Stimulus Website Links

Introduction page (Figure 22):  
https://my.up.ist.psu.edu/buz114/Intro1.php

Customization (IV1)  
Customization-Absent condition (no action, no cue) (Figure 23):  
https://my.up.ist.psu.edu/buz114/Cus1.php

Customization-Action condition (action, no cue) (Figure 24):  
https://my.up.ist.psu.edu/buz114/Cus2.php

Customization-Cue condition (screenshot, final ones were based on participants’ choices in the above condition) (Figure 25):  
https://my.up.ist.psu.edu/buz114/Cus3.php

Personalization (IV2)  
Proactive (Figure 27):  
https://my.up.ist.psu.edu/buz114/Per1.php

Reactive (Figure 26):  
https://my.up.ist.psu.edu/buz114/Per2.php
Appendix B: Stimulus Interfaces (Screenshots)

Figure 22. Stimulus: introduction page

Figure 23. Customization-absent condition (no action, no cue)
**Figure 24.** Customization-action condition (with radio buttons for action)

**Figure 25.** Customization-cue condition (screenshot of a random participant's customization outcome in the action condition)
Figure 26. Reactive personalization condition (with a search bar)

Figure 27. Proactive personalization condition
Appendix C: Study Instruction

We are conducting a study about users' opinions of a movie recommendation service that aims to recommend Bollywood movies to users based on their personal preferences. The service is still in its prototype phase, so your participation is very important to us.

We will show you the service's websites and let you interact with them, and then we will ask for your opinions about it based on your interaction experience in a questionnaire. The whole study will take about 15 to 20 minutes to complete and consists of five steps:

Step 1. Answer a few questions about yourself.
Step 2. Observe the service's privacy interface.
Step 3. Learn about the service and interact with its movie recommendation interface.
Step 4. Fill out a questionnaire to receive a CONFIRMATION CODE.
Step 5. Submit the CONFIRMATION CODE at the bottom of this M-Turk page to receive payment.

Please read and follow the instructions of each step carefully. Click the link below to start the study (If the link doesn't work, try copy and paste it into a new window). At the end of the study, you will receive a code to paste into the box below to receive credit for participating.
Appendix D: Measures for Pre and Post Questionnaires

Pre-Questionnaire

Disposition to value privacy

Please indicate your agreement with the following statements.

1. Compared to others, I am more sensitive about the way my personal information is handled.
2. To me, the most important thing is to keep my information private.
3. Compared to others, I tend to be more concerned about threats to my information privacy.

Strongly disagree (1) – Strongly agree (7)

Power usage

Please indicate your attitude toward the following statements about technology (e.g., Internet, smartphone, e-commerce, GPS, and etc.) use.

1. I think most of the technological gadgets are complicated to use.
2. I make good use of most of the features available in any technological device.
3. I have to have the latest available upgrades of the technological devices that I use.
4. Use of information technology has almost replaced my use of paper.
5. I love exploring all the features that any technological gadget has to offer.
6. I often find myself using many technological devices simultaneously.
7. I prefer to ask friends how to use any new technological gadget instead of trying to figure it out myself.
8. Using any technological device comes easy to me.
9. I feel like information technology is a part of my daily life.

10. Using information technology gives me greater control over my work environment.

11. Using information technology makes it easier to do my work.

12. I would feel lost without information technology.

Strongly disagree (1) – Strongly agree (7)

**Previous privacy invasion experience**

Please indicate how often you have experienced the following incidents.

1. How often have you disagreed with an online service about their use of your personal information?

2. How often have you experienced incidents where your personal information was used by an online service without your authorization?

3. How often have you personally been a victim of what you felt was an improper invasion of privacy online?

Never (1) – Extremely often (7)

**Perceived value of personalization**

Please indicate your agreement with the following statements.

1. I value webpages that are personalized for the device (e.g. computer, smartphone, tablet, etc.), browser (e.g. Google Chrome, Internet explorer) and operating system (e.g. Windows, Mac OS) that I use.

2. I value websites that are personalized for my usage experience preferences
3. I value websites that acquire my personal preferences and personalize the services and products themselves.

4. I value goods and services that are personalized based on information that is collected automatically (such as IP address, pages viewed, access time) but cannot identify me as an individual.

5. I value goods and services that are personalized on information that I have voluntarily given out (such as age range, salary range, Zip Code) but cannot identify me as an individual.

6. I value goods and services that are personalized on information I have voluntarily given out and can identify me as an individual (such as name, shipping address, credit card information).

Strongly disagree (1) – Strongly agree (7)

Need for control

Please indicate your agreement with the following statements.

1. I prefer a job where I have a lot of control over what I do and when I do it.

2. I enjoy political participation because I want to have as much of a say in running government as possible.

3. I try to avoid situations where someone else tells me what to do.

4. I would prefer to be a leader rather than a follower.

5. I enjoy being able to influence the actions of others.

6. I am careful to check everything on an automobile before I leave for a long trip.

7. Others usually know what is best for me.
8. I enjoy making my own decisions.

9. I enjoy having control over my own destiny.

10. I would rather someone else took over the leadership role when I’m involved in a group project.

11. I consider myself to be generally more capable of handling situations than others are.

12. I’d rather run my own business and make my own mistakes than listen to someone else’s orders.

13. I like to get a good idea of what a job is all about before I begin.

14. When I see a problem I prefer to do something about it rather than sit by and let it continue.

15. When it comes to orders, I would rather give them than receive them.

16. I wish I could push many of life’s daily decisions off on someone else.

17. When driving, I try to avoid putting myself in a situation where I could be hurt by someone else’s mistake.

18. I prefer to avoid situations where someone else has to tell me what it is I should be doing.

19. There are many situations in which I would prefer only one choice rather than having to make a decision.

20. I like to wait and see if someone else is going to solve a problem so that I don’t have to be bothered by it.

Strongly disagree (1) – Strongly agree (7)
Movie watching

On average, how many hours do you spend on watching movies (e.g., online, on TV, in a cinema) in a given week? Please enter in the number format.

Hour(s) per week: __________

Please indicate how often you do the following things:

1. How often do you watch foreign (non-American) movies?
2. How often do you watch Bollywood movies?

Never (1) – Extremely often (7)

Please indicate your level of interest in:

1. Foreign (non-American) movies
2. Bollywood movies

Not interested at all (1) – Extremely interested (7)

Do you use Netflix?

○ Yes

○ No

(If “Yes” is selected)

How long have you been using Netflix? Please enter in the number format (e.g., 2 years and 6 months).

Year(s) __________
Month(s) __________

How often do you use Netflix services (e.g., streaming video online, renting DVDs)?

Never (1) – Extremely often (7)

Demographic information

1. What is your age? (select from a drop-down menu)

2. What is your gender?
   - Male
   - Female
   - Other

3. What is the highest level of education you have received?
   - Less than high school
   - High school of equivalent
   - Associate degree or equivalent
   - Current college student
   - Bachelor’s degree or equivalent
   - Master’s degree or equivalent
   - Ph.D. or doctoral degree or equivalent

4. How would you best describe your racial / ethnic group? Please check all that apply.
5. How would you describe your current sexual orientation?
   - Bisexual
   - Homosexual
   - Heterosexual
   - Questioning
   - Prefer not to answer
   - Others

Post-Questionnaire

Manipulation check

Please indicate your agreement with the following statements based on your interaction with the Bollybox.

1. Customization
1) Bollybox is designed to allow users to manage the settings of privacy permissions.

2) I was able to manually change the settings of privacy permissions on Bollybox.

2. Personalization

1) The movie recommendations provided by Bollybox were based on my search.

2) I can dictate which movie recommendations I want to receive.

Strongly disagree (1) – Strongly agree (7)

Sense of control

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. I feel I have control over how personal information is used by Bollybox.

2. I feel I can control my personal information provided to Bollybox.

3. I feel I have control over what personal information is used by Bollybox.

4. I feel I can control my interaction with Bollybox.

5. I feel I can influence how the movie recommendation works on Bollybox.

6. I feel I am able to initiate actions to modify my privacy settings on Bollybox.

7. I feel I am able to adapt the movie recommendation in a way I want.

8. I feel I am in charge of my experience with Bollybox.

9. I feel I am able to adapt Bollybox’s movie recommendations to my personal taste.

10. I feel like I can pretty much be myself on Bollybox.

11. I feel I can make choices freely during interaction with Bollybox.

12. The movie recommendation is rigid and inflexible to interact with. R
13. I feel like I am free to decide for myself how to do things on Bollybox.

14. I generally feel free to express my ideas and opinions on Bollybox.

15. I experience a lot of freedom on Bollybox.

Strongly disagree (1) – Strongly agree (7)

_Intrinsic motivation._

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. I kept browsing Bollybox’s movie recommendations only because I was asked to. R

2. I wanted to keep browsing Bollybox’s movie recommendations once I started.

3. Interacting with Bollybox’s interfaces did not hold my attention at all. R

4. I got personally involved with Bollybox’s movie recommendations.

5. I enjoyed participating in this study.

6. I felt good about the overall experience in this study.

7. I liked what I was asked to do in this study.

8. The activity I was asked to do with Bollybox was fun.

Strongly disagree (1) – Strongly agree (7)

_Choice-overload heuristic._

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. I found it difficult to decide what information to disclose in the privacy-setting interface.
2. I felt frustrated when making choices on the privacy setting.
3. The privacy-setting task was overwhelming.

Strongly disagree (1) – Strongly agree (7)

**Attitude toward the system.**

Please indicate how well each of the following adjectives describes Bollybox.

1. Attractive
2. Exciting
3. High quality
4. Appealing
5. Useful
6. Positive
7. Good
8. Pleasant
9. Likable
10. Interesting

Describes very poorly (1) - Describes very well (7)

**Attitude toward the content (recommendation quality)**

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. Bollybox’s recommendations can provide users with the kind of Bollywood movies that I might like.
2. Bollybox’s recommendations can provide users with personalized Bollywood movie recommendations tailored to my activity context.

3. Bollybox’s recommendations can provide users with more relevant recommendations tailored to my preferences or personal interests.

Strongly disagree (1) – Strongly agree (7)

Behavioral intention I: Intention to use the recommender system in the future

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. I intend to use the Bollybox in the future when it is available.
2. I believe my interest toward Bollybox will increase in the future.
3. I intend to use Bollybox as much as possible when it is available.
4. I recommend that others use Bollybox when it is available.

Strongly disagree (1) – Strongly agree (7)

Behavioral intention II: Willingness to disclose

1. How interested would you be in having your personal information (e.g., viewing history, genre preferences, social media account information) used in Bollybox?

Not interested at all (1) – Extremely interested (7)

2. How likely would you be to provide your personal information (e.g., viewing history, genre preferences, social media account information) in exchange for using Bollybox?

Extremely unlikely (1) – Extremely likely (7)
Privacy concern.

Please indicate your agreement with the following statements based on your interaction with Bollybox.

1. I would be concerned that the information I submit to Bollybox could be misused.

2. I would be concerned that others could find private information about me from Bollybox.

3. I would be concerned about providing information to Bollybox because of what others might do with it.

4. I would be concerned about providing information to Bollybox because it could be used in ways I could not predict.

Strongly disagree (1) – Strongly agree (7)
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SELECTED PUBLICATIONS

