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Being at the Cutting Edge of Online Shopping: Role of Recommendations and Discounts on Privacy Perceptions

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BEING AT THE CUTTING EDGE OF ONLINE SHOPPING:
ROLE OF RECOMMENDATIONS AND DISCOUNTS ON PRIVACY PERCEPTIONS

Abstract

Despite the explosion of selling online, customers continue to have privacy concerns about online purchases. To alleviate such concerns, shopping sites seek to employ interventions to encourage users to buy more online. Two common interventions used to promote online sales are: (1) recommendations that help customers choose the right product either based on historic purchase correlations or recommendations suggested by the retailer; and (2) discounts that increase the value of products. Building on privacy calculus, we theorize about how and why *key, representative combinations of recommendations and discounts* influence the effects of inhibitors and enablers on online purchase intention. Our research design incorporated recommendations coming from different sources for the recommendation (retailer and other customers' preferences) product relatedness (related products with historic purchases correlated to the focal product and unrelated products with no historic purchase correlation to the focal product) and two types of discounts (regular and bundle). Participants completed a browsing task in a controlled online shopping environment and completed a survey (n = 496). We found mixed results of moderating effects of recommendations and product relatedness on the effect of inhibitors and enablers on purchase intention. Although recommendations did not enhance the effects of inhibitors, they did enhance the effects of enablers on online purchase intention. We also found that product relatedness did not enhance the effect of privacy enablers on online purchase intentions. The results also showed that discounts enhance the effects of enablers, and that discounts can counteract the moderating effect of recommendations on the relationship between inhibitors and purchase intention under certain circumstances. We discuss theoretical and practical implications.

Keywords: recommendation systems; recommendation agents; discounts; privacy calculus; privacy paradox

1. INTRODUCTION

Recommendation systems are known to be a means to enhance customer satisfaction and to increase revenues. However, the associated analytics and algorithms lead customers to feel as if they are under surveillance and thereby amplify privacy concerns. A recent study found that approximately a third of all respondents are willing to switch companies or providers over data and data sharing policies (Redman & Waitman, 2020). Thus, it is essential for firms to understand how retailer interventions in online shopping environments may interact with customer privacy concerns to influence online purchase intentions.

Researchers have studied customer's privacy-related behaviors in online settings and investigated the paradox of privacy perceptions and actual online shopping behaviors. Prior research argues that a customer's intention to purchase online involves a cost-benefit calculus (Culnan & Armstrong, 1999) in which there are countervailing influences stemming from inhibitors and enablers of online shopping behavior (Dinev & Hart, 2006; Dinev et al., 2006; Gu et al., 2017). Customers shop online when, based on their calculus, the cumulative effects of enablers outweigh that of inhibitors of transactions (Dinev & Hart, 2006; Sun et al., 2015; Trepte et al., 2020). Prior work in the privacy calculus literature has studied inhibitors (e.g., privacy concerns) and enablers (e.g., trust) of transactions (which we will refer to as privacy inhibitors and enablers). These works have not examined the effect of retailers' cutting-edge technologies, such as sophisticated product recommendations and discounts, on customers' privacy calculus. Such technologies can be incorporated in shopping sites through advanced machine learning algorithms (Meinl, 2020) by creating an optimal discounting strategy that together can boost sales and profits of retailers (DeCuba, 2017).

We suggest that product recommendations and discounts can have an effect on the privacy calculus because algorithms based on machine learning can not only propose useful recommendations and discounts for customers, but also inhibit their shopping intentions by invoking privacy concerns triggered by perceptions of and fears associated with surveillance. First, the process of online shopping begins with a search for products—when customers encounter system recommendations. Recommendations, which are typically personalized, assist customers in choosing from products. Customers receiving such personalized recommendations are likely to react positively to recommendations that match their preferences. As a result, the privacy calculus will be positively influenced involving privacy inhibitors and enablers and their effects on purchase intentions. Second, discounts may also affect the influence of inhibitors and enablers on purchase intention. Discounts encourage customers to buy online by increasing monetary and non-monetary values of online shopping (Joo, 2015; Luk & Yip, 2008). We argue that customers are susceptible to monetary incentives and discounts affect customers' privacy perceptions and may influence the effects of inhibitors and enablers on purchase intention (see Acquisti, 2004; Aloysius et al., 2016, 2018; Spiekermann et al., 2001). Our objective is thus to investigate how the effect of inhibitors and enablers can be enhanced or dampened by recommendations and discounts that customers encounter during online shopping. We draw on the privacy calculus model to investigate the cost-benefit calculus and extend the model by incorporating the moderating effects of recommendations and discounts on the effects of privacy inhibitors and enablers on purchase intention.

Our work contributes to the literature on e-commerce privacy by taking a more holistic view of privacy calculus and testing the nomological network of privacy inhibitors and enablers with the moderating effect of common retailer interventions stemming from machine learning algorithms in a single research model. Specifically, we provide insights into how three common recommendation interventions of shopping sites can decrease and increase the effects of privacy inhibitors and enablers, respectively, on purchase intention. Specifically, we study three recommendation systems interventions, namely (1) recommendations based on product relatedness, (2) language describing product recommendations, and (3) product discounts. Finally, through an examination of the three common interventions and their interplay, we can offer insights to firms selling online on how to best deploy and leverage these strategies.

In Section 2 that follows, we briefly review the relevant literature on online privacy concerns. In Section 3, we present our research model and associated hypotheses development. We also describe our research method and present our empirical analysis and results. In Section 4, we discuss our findings, present our contributions to theory, and draw managerial implications for practice. Finally, in Section 5, we present our conclusion.

2. LITERATURE REVIEW

2.1 Relationship between Privacy and Online Shopping

Prior research on online shopping has used different theories and methodologies to examine the relationship between privacy and online purchasing. Much work in this domain has studied individuals' control over their personal information when others collect personal data related to online shopping environments (Gutierrez et al., 2019; Inman & Nikolova, 2017; Jeong & Kim, 2017; Jordaan & van Heerden, 2017). For example, George (2004) used the theory of planned behavior to examine how privacy and trustworthiness of Internet shopping affected customer intentions to make online purchases and found that trustworthiness positively affected attitudes and purchasing behavior. Lian and Lin (2008) argued that the determinants of online shopping acceptance were not the same for different products or services and found different levels of negative effects of privacy concerns on attitudes toward online shopping in the context of four products: books, TV gaming systems, online news or magazines, and computer games. In contrast, other studies found that privacy concerns were not a significant factor in some online activities. For instance, Spake et al. (2011) investigated the determinants of online customer spending and found that while online shopping experience and level of comfort with providing personal information were significant predictors of the amount spent online, surprisingly, privacy concerns did not have a significant effect on online spending. Finally, based on a meta-analysis of 166 studies, Baruh et al. (2017) found that customers who were concerned about privacy were less likely to use online services and share information, and were more likely to use privacy protection measures.

2.2 Privacy Paradox and Calculus

The inconsistency between customers' privacy attitudes and privacy-related behaviors is termed the privacy paradox and has been extensively discussed in the privacy literature (Trepte et al., 2020; Yun et al., 2019). Norberg et al. (2007) found that people with concerns about disclosing specific personal information will disclose that information when requested and argued that contextual factors, such as physical location, social factors, such as the relationship between the customer and the institution collecting the information, and cognitive factors help to explain this paradox. Beresford et al. (2012) conducted a field experiment to examine the effect of monetary value on information disclosure and found that while participants had concerns about disclosing sensitive information, they disclosed sensitive information to buy DVDs for a one Euro discount. This finding suggests that monetary value offered to customers influences the privacy paradox.

Privacy researchers have used privacy calculus to explain the privacy paradox (Alsmadi et al., 2018; Chen et al., 2017; Ketelaar et al., 2018; Lankton et al., 2017; Liu, 2020). Privacy calculus is a cognitive/mental evaluation that weighs privacy costs and benefits of the online transaction and helps to explain why customers conduct online transactions despite privacy concerns (Cavusoglu et al., 2016; Culnan & Armstrong, 1999; Distler et al., 2020). Privacy calculus analyzes the sets of inhibiting and enabling factors to weigh the cumulative effects of these competing sets of factors and the net effect determines behavior. Inhibiting factors hinder and enabling factors encourage customers to disclose information and purchase online (Culnan & Armstrong, 1999; Desimpelaere et al., 2020; Hallam & Zanella, 2017). Therefore, IS researchers have used privacy calculus in different contexts and examine different privacy inhibitors and enablers that affect privacy-related behaviors. Dinev and Hart (2006) found that privacy concerns and privacy risk have negative effects and trust and personal Internet interest have positive effects on willingness to disclose information in an e-commerce setting. Xu et al. (2009) used privacy calculus in a mobile location-based services context and found that perceived risk decreases, and locatability and personalization increase intention to disclose personal information. In a social networking sites context, Krasnova et al. (2012) argue that, in addition to privacy concerns and trust, enjoyment plays a role as an enabler of self-disclosure.

3. RESEARCH FRAMEWORK AND HYPOTHESES DEVELOPMENT

As the infrastructure of online shopping sites hinges upon information technologies, those shopping sites that develop, customize, and use cutting-edge, disruptive technologies make progress in the competitive world of e-retailing. Although studied for a few decades now (see Tam & Kiang, 1992; Setiono & Thong, 2004; Setiono et al. 1998), machine learning algorithms is a cutting-edge technological approach that shopping sites use to differentiate their services and to provide a better shopping experience to customers (Schuetz & Venkatesh, 2020; Rathod, 2019). Machine learning algorithms are based on artificial intelligence (AI) that automatically learn from data and improve from experience to create optimized models. Shopping sites use machine learning algorithms to leverage recommendation systems that learn and analyze from past customer's behavior and to offer appealing discounts by analyzing millions of customers' profiles (Brady, 2020).

When shopping online, most customers view different products, compare prices, and evaluate the value of purchase before deciding to buy a product. As a result, online shopping is a dynamic behavioral and cognitive process in which customers go through different shopping stages, such as searching for a product, evaluating the product, and evaluating the purchase, to finally make the purchase decision (Cheung et al., 2017; Hong et al., 2004a, 2004b). Customers hold general inhibiting and enabling perceptions of online shopping, but customers' perceptions may change in different stages of the shopping process when customers are exposed to shopping sites interventions. We incorporate three common shopping site interventions, namely recommendations (two different types) and discounts, and argue that they moderate the effects of privacy inhibitors and enablers on purchase intention during shopping activity, as depicted in Figure 1.

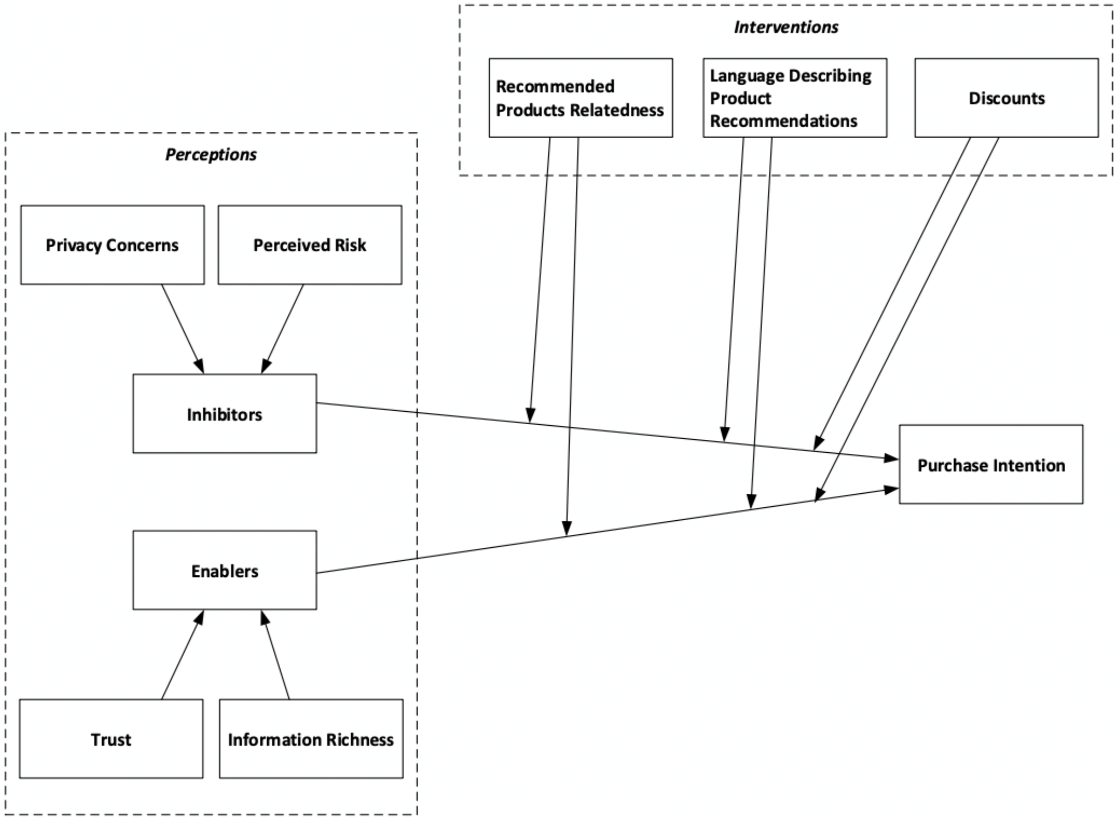


Figure 1. Research Model

When visiting a shopping site, customers first begin searching for the products that they need. In this stage, shopping site recommendation systems help the customers to find appropriate products with personalized recommendations. Recommendations have social influence on customers, decrease cognitive search effort, and leverage personal information and preferences (Häubl & Trifts, 2000; Lee et al., 2011). The recommended product will be displayed based on the customer's initial product selection. Next, during the product evaluation, customers evaluate the potential item to purchase from the shopping site by doing a cost-benefit analysis and if customers perceive the benefits of the purchase to be greater than the costs, they buy the product from the shopping site (Hong et al., 2004c, 2007). We use a privacy calculus model to examine the effect of recommendations and discounts on customers' cost-benefit analysis. Figure 1 shows that perceptions of online shopping consist of two contrasting sets: privacy inhibitors and privacy enablers. Privacy inhibitors are those perceptions that prohibit customers from shopping and privacy enablers are the perceptions that drive customers to buy online.

In presenting the notion of privacy calculus, it is clear that a customer's decision to shop online is simultaneously influenced by a set of contrary factors that incorporate the perceptions that inhibit customers and the perceptions that enable customers to purchase online (Dinev et al., 2006). *Privacy inhibitors* are the perceptions that deter customers from disclosing information and purchasing online—two key inhibitors, which we use in our conceptualization, are *privacy concerns* and *risk* (Choi et al., 2018; Dinev & Hart, 2006; Dinev et al., 2006; Keith et al., 2016; Taddaei & Contena, 2013). Privacy concerns are defined as customers' concerns about possible loss of privacy due to information disclosure to a specific shopping site (Xu et al., 2011a). Prior research argues that the main privacy concerns about information disclosure are collecting excessive information about customers without their awareness, unauthorized access to customers' information that are saved on shopping sites, unauthorized secondary use of customers' information, for example, by selling the customers' information to other parties, and deliberate and accidental errors in personal data collected by shopping sites (Hong & Thong, 2013; Malhotra et al., 2004; Smith et al., 1996). In sum, prior research finds that those customers who have privacy concerns about the control of their information in online transactions have lower willingness to purchase online (Dinev & Hart, 2006; Dinev et al., 2006; Keith et al., 2016; Wu et al., 2012). Perceived risk, which is a second major inhibitor, is defined as the possibility of the seller's opportunistic behavior that leads to a loss for customer (Ganesan, 1994; Vinhal Nepomuceno et al., 2014; Van Slyke et al., 2006). There are some risks of an online purchase, such as receiving defective or low-quality products, that in turn may cause customers to be reluctant to buy online (Chakraborty et al., 2016; Dinev & Hart, 2006; Kim et al., 2009; Li et al., 2010). Perceived risk has found to have a direct negative effect on customers' intention to purchase online in the prior research (e.g., Mamonov & Benbunan-Fich, 2018; Lemay et al., 2017; Van Slyke et al., 2006).

Privacy enablers are the other set of perceptions that drive customers to make an online purchase—the two key enablers, which we use in our conceptualization, are *trust* and *information richness*. Trust in the seller is considered one of the enablers that can offset customers' concerns about shopping online and is the belief that the seller does not behave opportunistically (Shah et al., 2013; Malhotra et al., 2004; Thongpapanl et al., 2018; Van Slyke et al., 2006). Trust as a cornerstone of behavior has been established in a variety of contexts because higher levels of trust provide the buyer a sense of security and safety in engaging in a target behavior, especially when the person/entity with whom they are interacting is unfamiliar, which can sometimes be the case with shopping online (Chakraborty et al., 2016; Ozdemir et al., 2017; Vance et al., 2008). Consistent with this logic, prior studies have found a direct positive relationship between trust and intention to purchase online (e.g., Dinev & Hart, 2006; Dinev et al., 2006; Kim et al., 2009; Pavlou & Gefen, 2004; Vance et al., 2008). Information richness is defined as the capability of the information on shopping sites to facilitate understanding of products and services (Simon & Peppas, 2005; Hoehle & Venkatesh, 2015; Venkatesh et al., 2017). Information richness helps buyers to feel more comfortable with various aspects of buying online ranging from the features of the product to the price to receiving a quality product to returns and exchanges. When customers perceive online shopping to be more like in-store shopping, their willingness to purchase from a shopping site and disclosing information to such shopping site increases.

We argue that, although privacy inhibitors and enablers have negative and positive effects respectively on purchase intentions, these effects are moderated by recommendations and discounts engage in shopping online and encounter interventions.

3.1 Moderating Role of Recommendations

Shopping sites use recommendation systems to customers finding the desired products they want during the search phase of the shopping process. Recommendation systems refer to online tools that tailor vendors' products and services to customers' needs and preferences and have other terms, such as personalization, recommendation agents, and interactive decision aid systems (Ku et al., 2016; Li & Karahanna, 2015), to refer to the idea of suggesting products and services to customers.

Adomavicious and Tuzhilin (2005) discuss that personalization is an iterative process based on the three stages of the understand-deliver-measure cycle: (a) understanding the customer that requires collecting information about a customer and conversion into a customer profile; (b) delivering personalized offerings for the customer based on information in the customer profile; (c) measuring personalization impact to find how satisfied the customer is with the recommended offerings and to receive the associated feedback. Adjusting vendors' products and services using customers' information and preferences is called matchmaking and is the first step in delivering personalized offerings (Adomavicious & Tuzhilin, 2005).

Xiao and Benbasat (2007) elaborate on three matchmaking techniques of recommendations. The first technique is content filtering wherein recommendations are based on the product features that customers liked in the past. The second technique is collaborative filtering wherein recommendations are the items that other customers with similar interests and preferences liked or purchased in the past. For example, Amazon's recommendation feature, "customers who bought this item also bought the following items," is collaborative because it reflects other customers' historical shopping activities. The third technique is hybrid filtering that combines content filtering and collaborative filtering to recommend items to customers. Finally, Li and Karahanna (2015) add a fourth type of recommendation named "social network" that provides recommendations based on what the customer's friends on social media (e.g., Facebook) have bought in the past. However, customers are typically unaware of these matchmaking techniques and usually do not distinguish across these techniques; they encounter language used to introduce the recommendation that suggests either the source of the recommendation is other customers' preferences or that the source is the retailer. Thus, from the customers' side, all four matchmaking approaches are categorized into two sources based on the language used to introduce the recommendation: (a) shopping site inference about customer preferences, and (b) other customers' preferences. Table 1 shows that the statements used in content-based filtering and hybrid filtering are perceived to be shopping site inference about the customer's preferences and the statements used in collaborative filtering and social network filtering seem to be other customers' preferences. Each of these recommendation sources thus represents the output of recommendation systems.

Table 1. Recommendation Sources Based on Language

Recommendation Source	Matchmaking Approach	Statement Example
Shopping site inference about preferences	Content-based, Hybrid	You might also like these items
Other customers' preferences	Collaborative, Social network	Other customers have purchased these items

As discussed earlier, privacy enablers are perceived by customers before or immediately after visiting a shopping site and the high level of privacy enablers enhances customers' intention to purchase from a specific shopping site (Dinev et al., 2006, 2015; Xu et al., 2014). However, customers' perceptions of shopping sites are not static and change during the shopping process when customers encounter different interventions such as recommendations. The positive effect of privacy enablers on purchase intention is amplified through recommendations during the search phase of shopping and these benefits can be understood from two perspectives.

First, prior studies underscore that the opinions of others influence people during online shopping (Zhu & Zhang, 2010). In online shopping settings, customers get opinions through product recommendations (Wind & Rangaswamy, 2001) and such influence becomes more important because customers have time constraints, possess limited knowledge, or lack interest in making the decision (Lee et al., 2011). Second, recommendations reduce customers' cognitive effort to purchase from a shopping site (Aljukhadar et al., 2012; Benlian et al., 2012; Häubl & Trifts, 2000). In the complex decision-making situations in which many alternatives are available, recommendation systems help customers to reduce the cognitive burden associated with the product selection process because they facilitate identifying a subset of desirable products (Xiao & Benbasat, 2007).

We argue that product recommendations will enhance customers' intention to shop online. Recall that trust provides the buyer a sense of security and safety in engaging in a target behavior. We argue that recommendations, by providing more interaction with the retail site, will enhance that sense of security and will lead to an amplification of the overall effect of trust on purchase intention. Likewise, recall that information richness affects purchase intentions by reducing equivocality. We argue that product recommendations will help the customer to develop more of a sense of the alternative products that are available along with the comparative product attributes associated with those products. This additional information will reduce uncertainty and thereby strengthen their purchase intention. Thus, we hypothesize:

H1: Recommendations moderate the relationship between privacy enablers and purchase intention such that with recommendations, the effect is stronger than it is without recommendations.

Historic purchases of products recommended to customers can be correlated or uncorrelated to purchases of the product that a customer is evaluating. Recommended products for which historic purchases are uncorrelated to the focal product picked by the customer may not mirror customer preferences to the same degree as products for which historic purchases are correlated to historic purchases of the focal product picked by the customer. Therefore, correlated recommendations are likely to be perceived as personalized more than uncorrelated recommendations.

When the effect of privacy enablers on customers' intention to purchase is in conjunction with recommendations, the joint effect will be stronger with correlated recommendations than uncorrelated ones because correlated recommendations provide personalized offerings. Personalized offerings are more influential on customers' perceptions, as prior research shows that when a recommended product harmonizes with a customer's preferences, the customer is expected to conform more to the recommendation (Fitzsimon & Lehman, 2004). This customer will encounter a lower level of cognitive dissonance and make the purchase decision with greater comfort (Aljukhadar et al., 2012). When the benefits of correlated recommendations are juxtaposed with privacy enablers, the customers will display greater purchase intentions. In the case of correlated recommendations, in comparison to uncorrelated recommendations, the interaction with the retail site provided by the product recommendations will be more of a sense of safety and less equivocality, as discussed in our arguments for H1. Consequently, we expect the logic of amplification—here, applied to correlated recommendations in comparison to uncorrelated recommendations—to apply. Thus, we hypothesize:

H2: Recommendations moderate the relationship between privacy enablers and purchase intention such that with correlated recommendations, the effect is stronger than it is with uncorrelated recommendations.

Prior work has established that that privacy inhibitors decrease customers purchase intentions in online shopping environments. The influence of privacy inhibitors on purchase intention can be affected during the shopping process as customers encounter recommendations. This is due to the fact that recommendation systems elicit customers' preferences from explicit and implicit inputs to provide personalized recommendations. Explicit input is direct feedback from customers that clearly show their interests and preferences such as product ratings and movie critiques. In contrast, implicit input is information gathered from customers through browsing history, purchase history, clicking behaviors, and search patterns to make future recommendations (Pu et al., 2012; Zhang et al., 2014). Recommendation algorithms use explicit and implicit inputs to cluster information based on preferences and provide personalized offerings. However, prior studies argue that customers are concerned about how online companies use their private information by analyzing explicit and implicit inputs (Chellappa & Sin, 2005; Li & Unger, 2012; Rao & Upadhyaya, 2009; Tam & Ho, 2005). Kobsa (2007) posited that information collection by recommendation systems make customers wary of price discrimination, unauthorized access to accounts, or government surveillance. Customers also worry that their habits and interests can be predicted by the analytical algorithms used by recommendation systems (Kobsa 2007; Li & Unger, 2012).

The fact that personalized recommendations are based on customer attributes, preferences, and choices will cause customers to worry about what and how much personal information is collected by shopping sites. Therefore, heightened awareness of potential risks about recommendations may enhance the effect of latent privacy inhibitors on purchase intention. For instance, when a customer is reluctant to purchase from a shopping site because of concerns about the sharing of secure information, the customer's intention to purchase from the shopping site decreases further with encountering recommendations due to the aforementioned increased concerns about personal information collection of recommendation systems. In effect, we expect an exacerbation effect such that concerns surrounding privacy inhibitors will heighten in their importance when recommendations, which will also be viewed as a privacy intrusion, exist. Thus, we hypothesize:

H3: Recommendations moderate the relationship between privacy inhibitors and purchase intention such that with recommendations, the effect is stronger than without recommendations.

3.2 Moderating Role of Discounts

Sales promotions are an effective marketing strategy to encourage customers to purchase and have an impact on the purchase decision-making process (Kotler & Keller, 2012; Kwok & Uncles, 2005). The most common form of sales promotion is a discount (Palazon & Delgado-Ballester, 2009) that is employed as another intervention by shopping sites. Discounts refer to a direct stimulus that sellers offer through extra values or incentives that are usually reduced prices for a product or set of products to attract customers (Haugh, 1983; Lee & Stoel, 2014; Xu & Huang, 2014). Prior studies argue that discounts provide customers either utilitarian benefits or hedonic benefits. Utilitarian benefits of discounts are monetary savings (Blattberg & Neslin, 1990; Chandon et al., 2000), search cost reduction (Darke & Dahl, 2003), decision cost reduction (Chandon et al., 2000; Wansink et al., 1998), and quality improvement (Chandon et al., 2000; Luk & Yip, 2008). In contrast, hedonic benefits are more intrinsic, subjective, and intangible and result from fun and playfulness (Kwok & Uncles, 2005).

Customers encounter discounts in two ways. First, when customers visit a shopping site they typically search for products and browse for the various offerings the shopping site displays. The browsing process is primarily a search process in which customers can get an overall view of the products being offered. Second, when customers choose a specific product after searching and select it to read product information. In this case, the search process is more focused and the customer is mainly interested in finding out information related to a specific product. In either of these two scenarios, the utilitarian and hedonic benefits of discounts add value to the focal product, increase value of shopping, decrease purchase decision time, and encourage customers to purchase from the shopping site (Lee & Chen-Yu, 2018; Luk & Yip, 2008; Park & Lennon, 2009).

When customers are already experiencing the positive feelings tied to higher information richness and/or trust, providing discounts will create a sense of greater overall value that spans across both hedonic and utilitarian benefits. We expect this to lead to an amplification tied to combination of hedonic and monetary benefits that in turn will contribute to higher levels of purchase intention. Thus, we hypothesize:

H4: Discounts moderate the relationship between privacy enablers and purchase intention such that with discounts, the effect is stronger than it is without discounts.

As mentioned earlier, recommendations have been found to have negative effects on online shopping as customers are concerned about the collection of personal information by recommendation systems (Kobsa, 2007). The negative effects of recommendations discourage customers from purchasing in online settings and online shops strive to find ways to decrease such negative effects.

Recommendation and discount interventions can have an effect such that discounts mitigate the negative effect that recommendations cause. Customers encounter recommendations during the search phase and face discounts when they evaluate the chosen product. Because discounts provide a monetary benefit, it can offset the harm that recommendations cause. Discounts appear after recommendations and their positive effects can impact the negative effects of recommendations. Prior studies have found that discount benefits counteract concerns about personal information collection and information disclosure to shopping sites. For instance, Acquisti (2004) argues that the monetary benefits of privacy protection and privacy intrusions can be easily quantified by discounts. Hui et al. (2007) also discuss the lack of privacy assurances and information requests can be offset by monetary incentives such as discounts. We argued earlier that there can be an exacerbation effect of recommendations on the relationship between inhibitors and intention—discounts can offset and ameliorate this negative effect due to the monetary benefits it provides. Thus, we hypothesize:

H5: Discounts moderate the positive moderating effect of recommendation systems on the relationship between inhibitors and purchase intention such that with discounts, the effect is weaker than it is without discounts.

4. METHOD

4.1 Participants

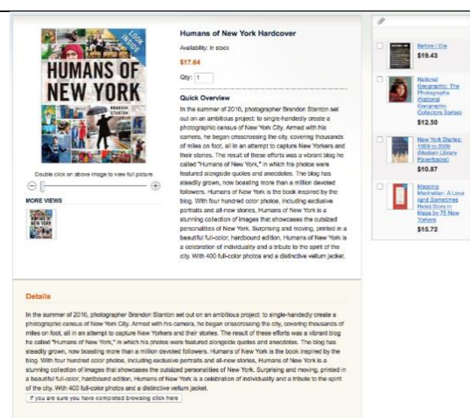
We collected the data from online customers in the U.S. who were recruited from a consumer panel of a research firm to ensure that our participants were representative of online customers in terms of gender, age and other demographics. We removed the responses that were completed in a very short time (i.e., under five minutes) and those that did not correctly answer reverse-coded filler items. In total, we had 496 usable responses and used these responses for further analyses. Appendix A summarizes the respondent demographics and shows that income figures represent a reasonable spread across salary levels.

4.2 Data Collection Procedure

The participants completed (1) an online consent form to participate in the study; (2) a browsing task in which they were exposed to one of the 18 different online stores, each of which had one combination of the interventions; and (3) a survey that captured the measures in our model. Each of these separate components were connected via URL links so that the participants had seamless transitions from one component to the next.

The participants were randomly assigned to one of the 18 independent shopping sites to experience shopping with different conditions. The browsing task instructions required the participants to inspect the 16 books displayed on level 1 of the online store and to identify the most interesting book. We also informed the participants that they could return to level 1 at any given time so that: (1) participants could identify the book that truly intrigued them; (2) our shopping site provides ecological validity as it mimics browsing behavior in a real-world e-commerce environment. We also required the participants to go to level 2 once they finished browsing the books on level 1 of the sites. We provided buttons on all pages of level 2 and level 3 of the sites labeled “If you are sure you have completed browsing click here” (see Table 2 for screenshots). Finally, participants responded to a survey with measures of perceptions of privacy inhibitors and enablers, intention to purchase from the shopping site, and demographic information.

Table 2. Shopping Site Designs

Level 1	Level 2	Level 3
		

4.3 Design of the Browsing Experience

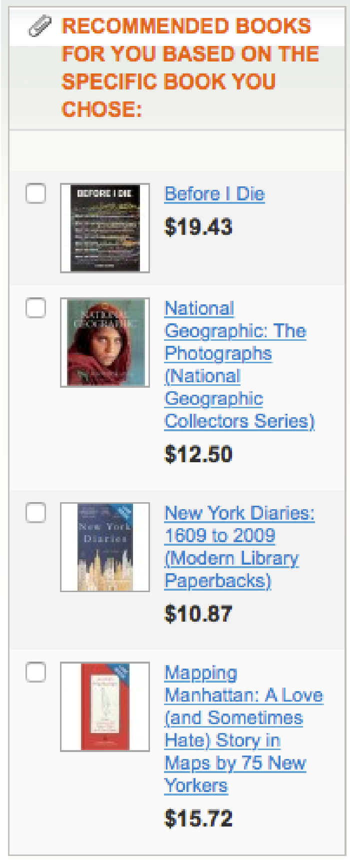
We developed 18 different online stores using the Magento[1] platform and downloaded product data from the book category of the Amazon website and transferred the data into the Magento application. We downloaded focal products as well as (1) products for which historical purchases were correlated and (2) products for which historical purchases were uncorrelated to the focal product. We developed the 18 separate shopping sites to operationalize all possible combinations featured in our research design, namely recommendations—no recommendation/language suggesting retailer recommendation/language suggesting other customers' preference—historic purchase correlations (correlated/uncorrelated)—and discounts (no discount/ discount/ bundle discount).

Our browsing experience consisted of multiple levels that were consistent with what typical shopping sites provide to their customers. Books included in the first level of our application were bestsellers in Amazon's book categories such as arts and photography, biographies and memoirs, business and investing, along with computer and technology. In total, 16 bestselling books from 16 categories were displayed on the first level of each of our e-commerce stores. We presented the books on a single page in a tabular format that was the same across all different conditions that the participants experienced (see Table 3). Participants were instructed to click on the book that interested them most and when they followed this instruction the application took them to the second level of the bookstore.

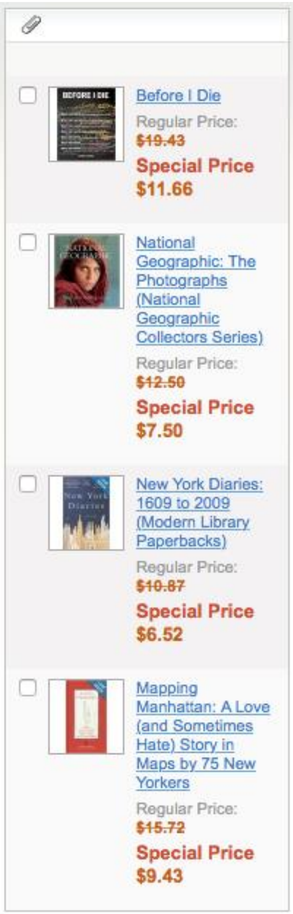
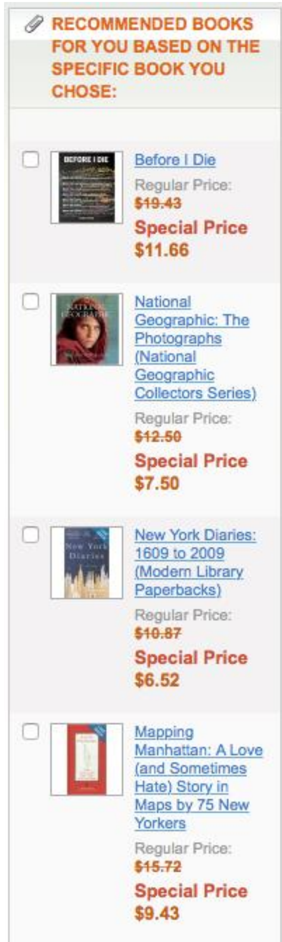
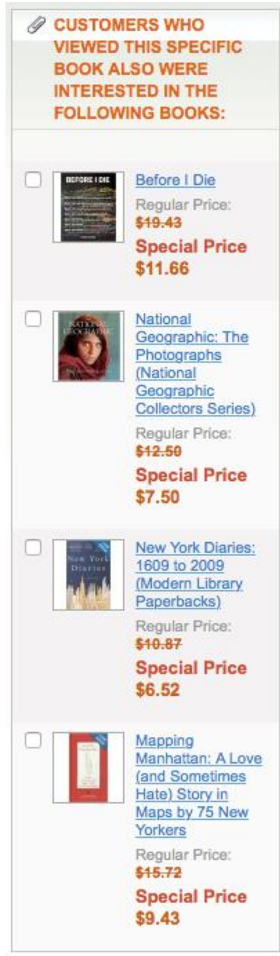
[1] Magento is an open source application platform which provides online merchants with dynamic and flexible shopping cart system and enables the developers to manage the appearance, functionality, and content of their online stores.

Table 3. Different Conditions of Shopping Experience

<table>
<tr><td></td><td>No recommendation</td><td>Recommendations using language suggesting retailer inferences about customer preferences</td><td>Recommendations using language suggesting other customer preferences</td></tr>
<tr><td>No discount</td><td>Condition 1

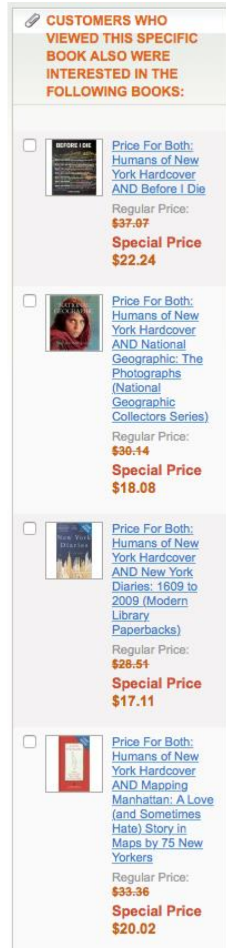
</td><td>Condition 2

</td><td>Condition 3

</td></tr>
</table>

<table>
<tr>
<td>Regular discount</td>
<td>Condition 4

</td>
<td>Condition 5

</td>
<td>Condition 6

</td>
</tr>
</table>

<table>
<tr><td>Bundle discount</td><td>Condition 7

</td><td>Condition 8

</td><td>Condition 9

</td></tr>
</table>

In the second level of the bookstore, the participant saw detailed information (downloaded from Amazon) about the specific book they selected on the first level. We chose to download the product information from Amazon because we wanted to provide a realistic shopping environment including actual prices and a quick overview of the product as well as more detailed book descriptions. The second level also displayed four more books that were displayed on the right-hand side of the site. Above these four recommended books, depending on their assigned configuration, participants either saw no message, saw a message “recommended books for you based on the book that you chose” or saw a message “customers who viewed this book were also interested in the following books”. The four books that participants saw were best-selling books in the same book category on Amazon as the focal book selected by the participant but depending on the assigned configuration, they were either known to have correlated purchases with the focal book selected by the participant[2] or they were not known to have correlated purchases with the focal book. Finally, depending on the assigned configuration there was either no discount offered for purchase of each one of the four recommended books, there was a discount offered for the purchase of each one of the four recommended books, or there was a bundle discount for each one of the four recommended books (requiring purchase of the focal book as well). Based on the average discount offered on Amazon on the date of download of the book information, the regular discounts used were 40% off the list price of the book and the bundle discounts were 40% off the sum of the list prices of the two books.

Each of these displayed books linked the customer to level 3 that had information such as price, a quick overview, and a detailed overview of each recommended book that was displayed. The screenshots taken of the three levels of our shopping artifacts are shown in Table 2.

4.4 Measurement

We adapted the scales for the constructs in the model from prior literature (see Appendix B). Privacy inhibitors and enablers have a multi-dimensional structure as prior studies found that different constructs form the inhibitors and enablers (e.g., Dinev & Hart, 2006; Xu et al., 2009). For the privacy inhibitors, we drew the items for privacy concerns from Bart et al. (2005) and for perceived risk from Kim et al. (2009). We used trust and information richness as the dimensions of privacy enablers and we adapted their items from Van der Heijden (2003) and Froehle and Roth (2004), respectively. If conceptualized as a hierarchical model, the second-order construct is at a more general level compared to the first-order constructs. Petter et al. (2007) identify the

[2] Based on Amazon recommendations.

decision rules for measuring constructs as formative or reflective and indicate that if the indicators of a construct are not interchangeable, formative measurement is appropriate. Following Petter et al. (2007), we conceptualize privacy inhibitors as a second-order construct that is formed by privacy concerns and perceived risk. Privacy concerns and perceived risk are modeled as formative dimensions because both concepts are not interchangeable but together they act as privacy inhibitors. Likewise, trust and information richness form privacy enablers and both constructs form the second order privacy enabler construct. The items for purchase intention were adapted from Wells et al. (2011). All items were measured on 7-point scales.

Before conducting our primary survey, we conducted a pilot study by asking Ph.D. students and administrative staff of a U.S. university to participate in the survey and provide feedback. They gave us minor suggestions and confirmed that the instructions were clear and easy to follow. Then, we invited two researchers who were IS faculty members to read the instructions and give us feedback on the measures and the structure of the survey in general. The researchers held a Ph.D. degree from U.S. universities and were unfamiliar with our study. Both researchers confirmed the instructions to be clear.

5. RESULTS

As described previously, our study consisted of 3 levels of recommendation source languages x 3 levels of discounts x 2 levels of recommended products correlations. Due to the small size of each sub-sample and the number of items in the measurement model, covariance-based structural equation modeling (CB-SEM) was not appropriate for our study. As a result, we estimated the structural model with partial least squares (PLS) because (1) when the sample size is small and the variables do not follow a normal distribution, PLS can examine the relationships of the model better (Zhang et al., 2011); and (2) PLS is also well-suited for testing the models with formative constructs and maximizing variance explained (Cenfetelli & Bassellier, 2009; Dijkstra & Henseler, 2015).

We used Smart-PLS 3.0 to conduct the PLS analysis in two stages. In the first stage, we tested whether the measures used as operationalizations of the model constructs are reliable and valid (the measurement model). After establishing the adequacy of measurement model, we proceeded to the second stage and estimate the path coefficients of the research model (the structural model) and compared path coefficients across multiple groups. The subsequent sections report the results for each of these two stages.

5.1 Measurement Model

In accordance with prior research that argues reflective and formative latent variables require different measurement adequacy tests (Petter et al., 2007), we performed several different tests to assess reflective and formative latent variables of our study. We first estimated the means, standard deviations, and correlations among the variables with pooled data, as shown in Table 4. Purchase intention is the only reflective latent variable in the model and we found that its values of Cronbach alpha and composite reliability were 0.93 and 0.96, respectively—this exceeds the recommended threshold of 0.70, thus supporting reliability (Nunnally, 1978).

Convergent validity of purchase intention was supported as the average variance extracted (AVE) was above the threshold of 0.50 and the loadings of items were above 0.70 (Bagozzi & Yi, 1988; 2012), as shown in Appendix B. Results also show that discriminant validity of purchase intention was supported as square root of the AVE value of purchase intention was higher than all inter-variable correlations (Segars, 1997). We followed the guidelines of Petter et al. (2007) to assess the second-order formative constructs—privacy inhibitors and enablers. We found that for privacy inhibitors and enablers, the variance inflation factor (VIF) was below 2.0 and the weight of the associated first-order latent variables—perceived privacy concerns and perceived risk were 0.83 and 0.45, respectively for privacy inhibitors and trust and information richness were 0.63 and 0.58, respectively for privacy enablers was significant**,** and the weight range of indicators was 0.14 to 0.39 and significant (see Appendix C).

Table 4. Descriptive Statistics, Reliabilities, Average Variance Extracted, and Correlations

	Mean	S.D.	Cor	Others	Retailer	Reg	Bun	Gender	Age	Inhibitor	Enabler	PI
Cor	0.51	0.50	NA									
Others	0.37	0.48	0.50	NA								
Retailer	0.33	0.47	-0.06	-0.22***	NA							
Reg	0.33	0.47	-0.02	0.00	0.03	NA						
Bun	0.33	0.47	0.04	0.00	-0.02	-0.25***	NA					
Gender	0.41	0.49	0.01	0.00	0.00	0.00	-0.02	NA				
Age	2.69	1.10	-0.01	0.02	0.01	-0.05*	0.01	0.00	NA			
Inhibitor	3.55	0.99	-0.02	-0.01	0.00	0.00	-0.02	0.03	-0.01	NA		
Enabler	3.87	1.12	0.02	0.00	-0.01	0.01	0.02	0.00	0.00	-0.41***	NA	
PI	4.58	1.50	0.01	0.02	0.00	0.00	0.01	-0.02	0.01	-0.49***	0.38***	0.94

*Note. Diagonal is square root of average variance extracted (AVE). S.D.= standard deviation; Cor= Correlated Products; Others= Recommendations with other customers' preferences source; Retailer= Recommendations with retailer source; Reg= Regular discounts; Bun= Bundle discounts; Inhibitor= Privacy inhibitors; Enabler= Privacy enablers; PI= Purchase intention. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; NA: Not applicable.*

5.2 PLS Path Modeling in Multiple Groups

We conducted multigroup analysis (MGA) to test the moderation effects of our study because prior research argues that MGA is the appropriate method to estimate the moderating effects when the moderator variable is a *discrete* variable (Eberl, 2010; Henseler, 2007; Sarstedt et al., 2011). In MGA, the discrete variable divides the sample data into a group of sub-samples and in each of separate sub-samples, the same PLS path model is analyzed (Eberl, 2010; Henseler, 2007). The moderators are discrete variables, leading us to analyze the PLS path model using MGA. We divided our sample data into groups of sub-samples based on different types of recommendations, discounts, and recommended products correlations. As the hypotheses focus on recommendations and discounts in general, we combined two recommendation source languages and two types of discounts to test hypotheses, as shown in Table 5. Thus, we compared A1 with (BX1+BY1) to test hypothesis 1 and 3, BX1 with BX2 to test hypothesis 2, A1 with A2 to test hypothesis 4, and (BX1+BY1) with (BX2+BY2) to test hypothesis 5.

Table 5. Structure of Data for Hypotheses Testing

	No Recommendation (A)	Recommendations (B)	
		Uncorrelated (X)	Correlated (Y)
No Discount (1)	A1	BX1	BY1
Discounts (2)	A2	BX2	BY2

5.3 Structural Model and Hypotheses Testing

We ran MGA to test the significance of differences in the path estimates across groups. We first estimated an overall model inclusive of pooled data from all different conditions that the participants experienced. The results of structural model estimates for the groups that we compared to test the hypotheses are shown in Table 6, and the results of MGA and hypotheses testing are shown in Table 7.

Table 6 shows that privacy inhibitors had a negative effect and privacy enablers had a positive effect on purchase intention in the overall model. However, these effects were not significant in some of other groups that represent different conditions of shopping experience. This difference indicates that various interventions that customers encounter when visiting a shopping site can affect purchase intention. We tested H1 by comparing the “no recommendation with no discount” condition with the “recommendation with no discount” condition to examine whether recommendations without the effect of discounts can strengthen the relationship between privacy enablers and purchase intention. Table 6 shows that in the “no recommendation with no discount condition”, the effect of privacy enablers was not significant in contrast to the “recommendation with no discount” condition. Table 7 confirms the difference in privacy enablers path coefficients of the two conditions was significant. Thus, H1 is supported.

Table 6. Structural Model Estimates

	Overall model	No recommendations with no discounts	Recommendations with no discounts	Uncorrelated recommendations with no discounts	Correlated recommendations with no discounts	No recommendations with discounts	Recommendations with discounts
Sample size	496	42	83	40	43	90	143
Age	0.01	-0.19	-0.04	-0.12	-0.01	0.18^{*}	0.01
Gender	0.00	0.03	0.01	-0.12	0.06	0.13	0.13
Privacy Inhibitors	-0.50^{***}	-0.66^{***}	-0.42^{***}	-0.46^{***}	-0.36^{*}	-0.37^{**}	-0.07
Privacy Enablers	0.26^{***}	0.05	0.41^{***}	0.31	0.47^{**}	0.44^{***}	0.21^{***}
R^2	0.49	0.54	0.47	0.60	0.65	0.57	0.07

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 7. Multigroup Comparisons

	Comparing samples	Privacy inhibitors	Privacy enablers	Supported?
		Δ	Δ	
H1	No recommendation with no discounts— Recommendations with no discounts	Not hypothesized	-0.36^{*}	Yes
H2	Uncorrelated recommendations with no discounts— Correlated recommendations with no discounts	Not hypothesized	-0.16	No
H3	No recommendation with no discounts— Recommendations with no discounts	0.14	Not hypothesized	No
H4	No recommendation with no discounts— No recommendations with discounts	Not hypothesized	-0.39^{*}	Yes
H5	Recommendations with no discounts— Recommendations with discounts	0.35*	Not hypothesized	Yes

* $p < 0.05$

The results of structural model estimates and multigroup comparison show that the effect of privacy enablers on purchase intention was significant in both the “uncorrelated recommendation” condition and the “correlated recommendation” condition, and there was no significant difference between the path coefficients. The effect of privacy enablers on purchase intention was not stronger in the “correlated recommendation” condition than the “uncorrelated recommendation” condition. Thus, H2 is not supported. We found that privacy inhibitors negatively affect purchase intention in the “no recommendation with no discount” condition and the “recommendation with discount” condition. The results of multigroup comparison on Table 7 also show that there was no significant difference between the path coefficients of these two conditions that suggests implies recommendations do not positively moderate the relationship between privacy inhibitors and purchase intention. Thus, H3 is not supported.

The results emphasize the key positive role of discounts. According to Table 6 and Table 7, in the “discount with no recommendation” condition, the path coefficient of privacy enablers was significant in contrast to the “no recommendation with no discount” condition and the difference between the path coefficients was significant. We conclude that discounts moderate the relationship between privacy enablers and purchase intention. Thus, H4 is supported. Discounts can also offset the negative effect of privacy inhibitors when recommendations are provided to the customers. As shown in Table 6, privacy inhibitors had a negative effect on purchase intention in the “recommendation with no discount” condition, but this was not significant in the “recommendation with discount” condition and the MGA results show that the difference between the coefficients was significant. Given the significant negative path coefficients of privacy inhibitors in the “no recommendation with no discount” condition and the “recommendation with no discount” condition, by providing discounts to the participants, the three-way interaction effect of discounts, recommendations, and privacy inhibitors on purchase intention was not significant. Thus, H5 is supported. We also found that the effect of control variables (age and gender) was not significant in the overall model as well as in most groups. Finally, the value of R^2 is high in the overall model and in most groups.

5.4 Post-hoc Analyses

As we provided shopping experience with different recommendation source languages and discounts to the participants, we conducted some post-hoc analyses to investigate differential effects of recommendation source languages and discounts on privacy inhibitors and enablers. Table 8 shows structural model estimates of the models with different recommendations and discounts. We also ran MGA to test the significance of difference for more interesting path coefficients.

Table 8. Structural Model Estimates of Different Recommendations and Discounts

	Retailer source with no discounts	Others source with no discounts	Uncorrelated retailer source with no discounts	Correlated retailer source with no recommendations	Uncorrelated others source with no discounts	Correlated others source with no discounts	Regular discount with no recommendations	Bundle discount with no recommendations	Retailer source with regular discount	Retailer source with bundle discount	Others source with regular discount	Others source with bundle discount
Age	-0.14	0.11	-0.34^{*}	-0.01	0.41*	-0.03	0.15	0.23^{*}	-0.11	0.46^{*}	-0.33^{*}	0.03
Gender	0.06	-0.10	-0.06	0.17	0.24	-0.11	0.14	0.08	-0.23	-0.20	0.41^{**}	-0.03
Privacy Inhibitors	-0.39^{**}	-0.47^{**}	-0.62^{**}	-0.07	-0.17	-0.72^{*}	-0.38*	-0.34^{*}	0.30	-0.04	-0.08	-0.33
Privacy Enablers	0.46^{**}	0.35^{*}	0.22^{*}	0.68^{**}	0.45	0.19	0.47^{**}	0.41^{**}	0.38^{*}	0.31	0.10	0.16
R^2	0.67	0.60	0.70	0.70	0.61	0.61	0.57	0.53	0.11	0.35	0.21	0.19

** p < 0.05; ** p < 0.01; *** p < 0.001.*

Table 8 shows that the path coefficient of privacy enablers was significant when either recommendations with retailer source or recommendations with others source were provided to customers, but when we ran MGA, we found that *only* the value of retailer source was significantly different ($p < 0.05$) from the "no recommendation with no discount" condition. This finding indicates that only recommendations with retailer source language can significantly moderate the relationship between privacy enablers and purchase intention. We also found that when correlated recommendations with retailer source were provided to customers, the negative effect of privacy inhibitors became nonsignificant. By running MGA, we found that the difference between the privacy inhibitor path coefficient in the correlated retailer source "recommendation with no discount" condition was significantly different (at $p < 0.05$) from the same path in uncorrelated retailer "recommendation with no discount" condition. Although we had found that discounts moderate the relationship between privacy enablers and purchase intention, the results of post-hoc analyses show that *only* regular discounts significantly strengthened the effect of privacy enablers on purchase intention. We also investigated H5 more with all possible combinations of two recommendation source languages and two types of discounts, as shown in Table 8. We found that the effect of three-way interaction of discounts, recommendations, and privacy inhibitors on purchase intention becomes nonsignificant *only* when the recommendation has language suggesting a retailer source and the discount is regular.

6. DISCUSSION

E-retailers are using machine learning techniques to increase their sales and profitability. They compete to attract customers by incorporating dynamic and interactive interventions (Amasiatu & Shah, 2019) based on machine learning algorithms that could boost the shopping experience, improve the likelihood of purchase, and promote cross selling of products. To introduce customers to products that better fit their preferences, sites attempt to assist customers to reduce time and search costs through online recommendations. Recommendation systems use machine learning algorithms to identify the best matches among millions of products of possible interest to the customer. Another intervention that uses machine learning to attract more customers and increase purchase likelihood are discounts that affect customers' perceptions and drive purchase behavior. Shopping sites leverage machine learning algorithms to track sales trends, customer demands, and on-hand inventory to optimize their discounting strategies and provide different types of discounts to customers. Customers see discounts tied to their recommendations and sometimes during after they see the recommendations that affect privacy perceptions as well as the effect of recommendations in the previous stage. The privacy paradox indicates that although customers express their concerns about online shopping, they purchase from shopping sites. In this work, we investigated how recommendations and discounts as shopping site interventions moderate the effect of privacy inhibitors and privacy enablers. Our findings provide give insights into how online shopping interventions can influence customers' privacy-related behaviors that provide a more holistic understanding of the impacts connected can help give a more comprehensive explanation for the privacy paradox. Specifically, we found that making explicit product recommendations and also discounts can each enhance the effect of privacy enablers on purchase intention. Further, discounts can ameliorate the negative moderating effect of recommendations on the relationship between privacy inhibitors and purchase intention.

6.1 Scientific Implications

Our work provides several scientific implications. First, we contribute to the privacy calculus literature, which in an online shopping context has examined only the direct effects of inhibitors and enablers on behavioral intention (e.g., Keith et al., 2016; Krasnova et al., 2012; McKnight et al., 2011; Xu et al., 2009), The effects of these inhibitors and enablers, however, are subject to influence by website design and shopping process features—therefore, we extend our understanding by incorporating moderators into the privacy calculus model. This is the first, study that examines the moderating effects of the language used to describe the source of recommendations (retailer inference and other customers' preferences), whether historical purchases of the recommended products are known to be correlated to purchases of the focal product (correlated and uncorrelated), and different types of discounts (regular and bundle) on the relationship between privacy costs/benefits and purchase intention. The research directly answers calls for further investigation of privacy perceptions (see Bélanger & Crossler, 2011; Culnan, 1993; Dinev et al., 2015; Shah et al., 2013). Our work sheds light on how the effect of privacy inhibitors is decreased and that of privacy enablers is moderated by recommendations and discounts.

Second, we enrich the e-commerce literature by considering the influence of retailer interventions on the effect of privacy enablers on purchase likelihood at different stages of shopping activity. We found that the effect of privacy enablers on purchase likelihood is enhanced by language suggesting recommendations either from the retailer or resulting from other customers' preferences. Our findings are consistent with informational social influence from recommendations on customers, especially customers with limited product knowledge and limited time to purchase, that encourages them to purchase online (Lee et al., 2011). Our findings are also consistent with recommendations alleviating the cognitive burden from customers, increasing customers' interest in products, and, in general, increasing purchase intention. We found that, in terms of privacy enablers and their positive effects on online shopping, only recommended products with historic purchase correlations to the focal product enhance the effect of privacy enablers on purchase intention.

Third, we contribute to the literature on recommendation systems by providing insights into the effect of the language used to describe the source of recommendations on the relationship between privacy inhibitors and enablers. Previous research found that one type of recommendations (content-filtering) increases privacy costs (Xu et al., 2011b). However, we found that the signaling effect in the language used to describe content-based and collaborative filtering that can influence purchase intentions beyond the actual products recommended were similar. Regardless of providing recommendations, the effect of privacy inhibitors on purchase intention was significant. These findings imply that recommendations that shopping sites provide to customers do not enhance the effect of privacy inhibitors, compared to when shopping sites do not provide recommendations. Another implication of this research is on the role of discounts in privacy. Customers seek to find ways to lower the cost of their purchases and try to find shopping sites that offer discounts (Bansal & Zahedi, 2014). Our work elaborates on how different types of discounts (i.e., regular discounts and bundle discounts) can increase the positive effect of privacy enablers and decrease the negative effects of privacy inhibitors on online shopping. To illustrate, we found that regular discounts (discounts for a single product) are more influential than bundle discounts. In contrast to bundle discounts, we found that regular discounts can increase the effect of privacy enablers and play a role in motivating customers to make purchases. The findings reveal that the various utilitarian and hedonic benefits of discounts interact with privacy enablers to increase intention to purchase online only when regular discounts are offered.

6.2 Practical Implications

Our work can help e-retailers and any shopping site in different ways. First, we confirm the negative effect of privacy inhibitors and the positive effect of privacy enablers on purchase intention. Customers balance privacy inhibitors and enablers before deciding about the purchase and the online companies should lower customers' privacy concerns to increase their sales. We found that recommendations strengthen the positive effects of privacy enablers on purchase intention and do not increase the effect of privacy inhibitors. When shopping sites become more interactive and adopt interventions that facilitate purchase activities, customers make more purchases. We suggest that there does not seem to be a downside to the implementation of recommendation systems to provide a positive impression and influence on customers, with one caveat. These sites should be cautious about the algorithm they use to recommend products, as our findings show that only recommending products known to have historic purchase correlations with the focal product sought by a customer has a positive impact on customers' purchase intention. In practice, it is likely that retailers may recommend uncorrelated products as well in order to reduce excess inventories of these products but we suggest recommending correlated products should be prioritized over uncorrelated products recommendations.

We suggest that discounts can be used as a means to help shopping sites to address customers' concerns. However, not every type of discount strengthens privacy benefits and weakens privacy costs. Online shopping sites offer bundle discounts along with regular discounts to induce customers to buy more. Our findings indicate that only regular discounts can increase the positive effects of privacy benefits. Moreover, although the presence of recommendations is helpful to customers, it raises privacy concerns. Shopping sites can decrease privacy concerns associated with recommendation systems. Our findings assert that regular discounts can help ameliorate the effects of privacy concerns associated with recommendation systems that offer recommendations using language suggesting a retailer source. It is suggested that shopping sites prioritize regular discounts more than bundle discounts in order to lower the effect of privacy inhibitors on customers' purchase intention.

6.3 Limitations and Future Research Directions

We acknowledge key limitations of this study that provide opportunities for future research. Future research should build on our work and focus on an interplay between website and interface design and recommendation systems. A large body of research on human-computer interaction has been developed to understand how different "searching" and "browsing" tasks influence shopping tasks influence shopping outcomes (Hong et al., 2004c). In this domain, prior studies also investigated different product listing form (e.g., Hong et al., 2007, 2004a, 2004b), animated products/banner-ads (e.g., Cheung et al., 2017; Hong et al., 2004c), usability (e.g., Hoehle & Venkatesh, 2015; Venkatesh et al., 2017), trust (e.g., Thongpapanl et al., 2018), and brand equity (Xu et al., 2014) and examined the differential effects on online shopping behavior.

Such factors should be integrated in our research model to understand their influence in context of recommendation systems and associated outcomes. In addition, even though the participants we surveyed online comprised a reasonable sample of customers dealing with shopping sites, they were restricted to subjects in the United States. A more geographically diverse sample including participants from various areas may increase the generalizability of the findings. Second, we studied customers' purchase intention, but we suggest that future studies in the field examine whether purchase intention leads to actual online purchase and analyze how shopping site interventions impact the effects of privacy inhibitors and enablers on online purchase behavior. We created an e-commerce application to capture customers' online shopping activities and their perceptions of various aspects of the purchase decision process. Nonetheless, future studies can collect data about customers' purchasing activities in a field study that tracks customers' behaviors on an active shopping site.

7. CONCLUSION

We investigated how shopping sites can influence the effects of privacy inhibitors and enablers of online shopping when using recommendations and discounts powered by machine learning on their sites. Shopping sites can increase sales in multiple ways, one of which is addressing customers' privacy concerns. Based on the privacy literature, we presented a model that helps privacy researchers and retailers to better understand customers' privacy-related behaviors. We examined the roles of two common interventions and representative designs, based on recommendations and discounts, that emerged from these interventions that shopping sites commonly use to influence customers' online purchase intention. We found moderating roles for recommendations and discounts—and the emerging designs—and gained a better understanding of the manner in which these shopping site features can impact the effect of privacy inhibitors and enablers on purchase intention.

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APPENDIX A

Table A.1: Respondent Demographics

Demographic	Category	Frequency (Percent)
Gender	Male	207 (41.73)
	Female	289 (58.27%)
Age groups	Under 20	36 (7.26%)
	20-29	225 (45.36%)
	30-39	146 (29.44%)
	40-49	48 (9.68)
	50-59	26 (5.24)
	60 or older	15 (3.02)
Income (Annual, in USD)	0-10,000	53 (10.69%)
	10,000-19,000	41 (8.27%)
	20,000-29,000	69 (13.91%)
	30,000-39,000	68 (13.71%)
	40,000-49,000	56 (11.29%)
	50,000-74,000	91 (18.35%)
	75,000-99,000	49 (9.88%)
	100,000-150,000	51 (10.28%)
	Over 150,000	18 (3.63%)
Job	ICT	61 (12.30%)
	Banking and Finance	12 (2.42%)
	Insurance, Real Estate and Legal	12 (2.42%)
	Government and Military	20 (4.03%)
	Construction and Engineering	20 (4.03%)
	Retail and Wholesale	10 (2.02%)
	Education	55 (11.09%)
	Marketing and Advertising	16 (3.23%)
	Student	116 (23.39%)
	Other	174 (35.08%)

APPENDIX B

Table B.1: List of Measurement Items and Loadings

Theoretical Construct	Items	Loading
Privacy Concerns	PPC1: I would be comfortable giving personal information on this site. *	0.87
	PPC2: I would be comfortable shopping at this site. *	0.87
	PPC3: The site clearly explains how user information is used. *	0.71
Perceived Risk	Per_risk1: Purchasing from this retailer online would involve product risk (i.e., defective product).	0.84
	Per_risk2: Purchasing from this retailer online would involve financial risk (i.e., fraud, hard to return).	0.90
	Per_risk3: My overall perception of risk related to buying online from the retailer is high.	0.75
Trust	Trust_ret1: This retailer is trustworthy.	0.91
	Trust_ret2: I trust this retailer keeps my best interests in mind.	0.88
	Trust_ret3: This retailer’s behavior meets my expectations.	0.83
Information Richness	Inf_rich1: My interaction with the online site was close to an actual face-to-face interaction.	0.95
	Inf_rich2: My interaction with the online site felt like a face-to-face interaction.	0.94
	Inf_rich3: Shopping at the online site felt like an in-person interaction.	0.95
Purchase Intention	Int_pur1: Suppose you were in the market for a book. How likely would you be to purchase a book at this online site?	0.95
	Int_pur2: Suppose you were in the market for a book. How likely would you be to do business with the Online Bookstore via its website?	0.90
	Int_pur3: If you were in the market for a book, what is the likelihood that you would use this online site to purchase the book?	0.96

* Reverse-coded items

APPENDIX C

Table C.1: Second-Order Formative Constructs VIFs and Weights

Latent Variable	VIF	Dimensions	Weight	Indicators	Weight
Privacy Inhibitors	1.70	Privacy Concerns	0.83^{***}	PPC1	0.35^{***}
				PPC2	0.39^{***}
				PPC3	0.25^{***}
		Perceived Risk	0.45^{***}	Per_risk1	0.18^{***}
				Per_risk2	0.21^{***}
				Per_risk3	0.14^{**}
Privacy Enablers	1.69	Trust	0.63^{***}	Trust_ret1	0.23^{***}
				Trust_ret2	0.22^{***}
				Trust_ret3	0.21^{***}
		Information Richness	0.58^{***}	Inf_rich1	0.21^{***}
				Inf_rich2	0.22^{***}
				Inf_rich3	0.21^{***}

$* p < 0.05$; $** p < 0.01$; $*** p < 0.001$.