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The Persuasive Nature of Web Personalization on Online Users' Product Perceptions: A Mental Accounting Perspective

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Abstract:

E-commerce firms strive to enhance engagement by providing augmented experiences to online users. This research focuses on one such shopping experience enhancement technique—Web personalization. In this study, we examine how personalization affects online users' perceptions and how different personalization levels differentially impact those perceptions. Drawing on mental accounting theory, we argue that personalization, by providing convenience in online buying, increases transaction utility and, thus, influence online users' product perceptions. We conducted a laboratory experiment in a public university in Southern India where users took buying decisions at four different personalization levels: zero, low, medium, and high. The findings from this study suggest that product prices affect users' perceived product quality, which, in turn, affects their perceived product values and, subsequently, their final purchase decision. Web personalization plays a moderating role in all cause-effect relations above. This study contributes to the existing literature on the Web personalization strategy and online user behavior. We find empirical evidence to show that personalization plays a moderating role in the relationship between user perception and intention to purchase.

Keywords: Web Personalization, Product Perception, Transaction Utility, Perceived Value, Personalization Level

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1 Introduction

While the availability of information makes online buying attractive, the multidimensional and uncertain nature of online information and the many alternatives on the market make buying online complex. In this study, uncertainty refers to conflicting information in reviews about different attributes of a product, while multidimensionality refers to the different types of information that one can find online, such as product ratings, product reviews, seller reviews, seller information, review helpfulness scores, and frequently asked questions (Balan & Mathew, 2015). Information overload increases online users' information processing (Ho & Bodoff, 2014; Tam & Ho, 2006). We searched Amazon.com and found that the top-selling products had an average of 3,350 reviews. Information relevant to a given online user gets subsumed under a plethora of other information. To help users digest multidimensional information available online, e-commerce platforms have adopted various strategies, such as review summarization, Web personalization, sentiment classification, and word clouds of frequently used words. In this study, we examine the impact of one particular approach—Web personalization—on online users' perceived expensiveness, perceived quality, perceived value, and purchase intention.

The Web personalization strategy involves adapting Web content to meet users' specific needs to maximize sales (Korper & Ellis, 2001); thus, the approach treats each online user as a unique user. Web personalization makes product information available online to help users make buying decisions. As online users have multiple options to choose from in online commerce, Web personalization increases online users' switching costs (Lynch & Ariely, 2000). As a result, many online commerce retailers have adopted Web personalization as a differentiation strategy. Prior research has shown strong evidence to suggest that Web personalization impacts various aspects of online users' shopping experience, such as confidence in their shopping decisions (Ho & Bodoff, 2014) and ease of shopping (Tam & Ho, 2005).

On the demand side, Web personalization efforts contribute to online users experiencing non-monetary benefits (e.g., convenience and ease of use) when shopping online (Chung & Koo, 2015). Online users consider transaction utility in their decision-making process (Thaler, 2008). Higher convenience in a transaction relates to higher transaction utility (Gupta & Kim, 2010) and influences product perception (Chung & Koo, 2015). Drawing on mental accounting theory (MAT) (Thaler, 2008), we argue that Web personalization increases transaction utility in online shopping and, hence, influences users' perceptions of products. We also examine whether different personalization levels influence online users' product perceptions. Prior work in this area has focused on the influence of Web personalization on online users' buying decisions and less on understanding how different personalization levels influence buying decisions in an online context. Personalization has become a commodity today in the e-commerce context. It is a significant way for businesses to differentiate themselves from their competitors (e.g., offering different degrees and types of personalization). The degree and type of personalization may depend on the contextual information on a product page because products with rich attributes have more contextual information than products with fewer attributes. In this study, we control for both personalization level and product attribute richness to assess the influence of Web personalization on users' perceptions of products.

This paper proceeds as follows: In Section 2, we review related literature on Web personalization and how users form perceptions of products. In Section 3, we provide background information about MAT. In Section 4, we present our research model and hypotheses based on MAT. In Section 5, we discuss our research methodology and how we designed the experiments we conducted. In Section 6, we discuss the analyses we conducted to test our hypotheses. In Section 7, we discuss the implications of the findings, the limitations of the study, and directions for future work. Finally, in Section 8, we conclude the paper.

2 Background and Literature Review

In this section, we review the extant literature on Web personalization. Specifically, we discuss the recent research work related to Web personalization and describe the process in which users perceive expensiveness, quality, and value, as well as form purchase intention. Next, we describe how Web personalization guides online users to form perceptions about recommended products.

2.1 Acquisition and Transaction Utility in Online Buying

Online users in an online environment maximize their total utility in their mental accounting and view of the products and how much effort they expend when making buying decisions online (Thaler, 2008). Although a product may have an equivalent value across different online stores, its acquisition utility may differ as the same product may be selling at different prices across these stores. Hence, one cannot easily conceptualize acquisition and transaction utility due to the difficulty in distinguishing them. Considering the empirical and conceptual complexity in distinguishing acquisition and transaction utility, prior studies have measured only transaction utility and total utility (Chung & Koo, 2015; Gupta & Kim, 2010). Similarly, in our study, we consider only transaction utility and total utility; we do not consider acquisition utility. Transaction utility has monetary and non-monetary components. Although prior research has mostly focused on the monetary aspect of transaction utility, its non-monetary aspects could also be vital in online users' buying decisions. Researchers have typically measured the monetary aspect of transaction utility as the difference between the objective price and an online user's reference price. In contrast, the non-monetary aspect of transaction utility is dependent on factors such as accessibility to information, convenience, and ease of use (Chung & Koo, 2015).

2.2 Web Personalization

Web personalization has gained much attention in IS research during the last decade. Web personalization refers to adapting Web content to meet users' specific needs (Korper & Ellis, 2001). In an early study on understanding Web personalization, Tam and Ho (2006) conducted a multi-factor experiment and reported that Web personalization influenced online users' cognitive processes and purchase decisions.

Sheng et al. (2008) conducted a study to examine the impact of personalization and content relevance on online users' privacy concerns. Ho et al. (2011) evaluated the effect of adaptive Web personalization at various points in online shopping using experimental studies that manipulated recommendation type and presentation timing. They reported that the recommender system's quality improved over time as it gained more information about a user but the likelihood that the user would accept the recommended product decreased over time. IS research on web personalization has also studied its relation to user acceptance (Krishnaraju et al., 2016), location preferences (Ho, 2012; Ho & Lim, 2018), and product preferences (Balan & Mathew, 2019, 2020).

According to Tam and Ho (2006), Web personalization comprises two factors: self-reference and content relevance. Self-reference refers to personalizing Web content according to one's self or past episodic experience (Tam & Ho, 2006). Self-referent Web content provides cues related to oneself; examples include personalized messages that address the user's name, the user's most recent purchase, banners related to the user's browsing history, and categorized boxes that recommend products with captions such as "personalized recommendations for you" or "unique offers specially for you." Prior research has shown that the human brain can functionally dissociate information related to the self from other semantic information (Kelley et al., 2002). In contrast to self-reference, content relevance refers to the extent to which Web content matches users' browsing goals (Tam & Ho, 2006). Some examples of content relevance include personalized product rankings based on users' preferences and personalized banner ads based on the purchasing goal of users.

Another research stream related to Web personalization has addressed how online users construct their preferences. Liu and Karahanna (2017) showed that the characteristics of information influence users' preferences. The more the attribute-level information provided in a review, the more likely the review contains conflicting information about attributes, which in turn sways online users' construction of preferences. Similarly, Balan and Mathew (2019) showed that personalization has a swaying effect on the preference construction of online users and that different personalization levels result in varying levels of swaying effect. They noticed that online users' product preferences change after being exposed to personalized content; they called this change the swaying effect (Liu & Karahanna, 2017; Balan & Mathew, 2019). Prior research has also shown the importance of location-based personalization and how it influences online users' engagement (Ho, 2012) and mood (Ho & Lim, 2018) in the mobile commerce context. In contrast, some studies have also examined the phenomenon's dark side, such as reduced search and cross-selling opportunities due to personalization (Fong, 2016).

We further seek to understand how personalization influences online users' perceived expensiveness, perceived quality, perceived value, and purchase intention, which drive them to make decisions from a mental accounting perspective.

2.3 Product Perception

Online users usually have prior beliefs about a product before they enter a website, and they update these beliefs after reading information about it on the website (Archak et al., 2011). With help from Web personalization, online users browse the product list on a website, evaluate the information on each product, and identify a product subset for closer examination. Online users assess various product attributes and then develop an overall evaluation of each product before making a final decision. In this context, Hauser and Wernerfelt (1990) proposed the consideration set theory to analyze a rational consumer's trade-offs between decision costs and the incremental benefits that they gain from choosing among a larger set of alternatives. This theory relates to Web personalization and its impact on users' attitudes and behavior (Ho & Bodoff, 2014). Gupta and Kim (2010) and Chung and Koo (2015) modeled online users' decision process from a mental accounting perspective in terms of acquisition utility and transaction utility (Thaler, 1985). Acquisition utility refers to the value of received goods compared to the outlay or, in other words, the additional benefit that users perceive they receive from a product after accounting for the opportunity cost that they invested in buying it; transaction utility captures the perceived merits of transactional experience (Thaler, 2008; Gupta & Kim, 2010).

Online users develop their perceptions about a product based on various product attributes. Examples of the product attributes of a digital camera include battery life, camera quality, and value for money. Online users draw on many product attributes to form an overall product perception. Therefore, the literature considers product attribute information as pieces of disaggregated information that are used to form an overall perception of product quality (i.e., an outcome based on the perception of various product attributes in aggregate) (Chang & Wildt, 1994; Myers & Shocker, 1981; Olson & Jacoby, 1972; Zeithaml, 1988). In this context, disaggregated information refers to product information that a website does not group or categorize based on the attributes and that may appear anywhere on the website. Prior research has shown that product attribute information influences perceived quality (Chang & Wildt, 1994). During the judgment process of decision-making, providing rich information about the product attributes will make it easier for online users to evaluate these attributes and hence, focus less on the prices of the products. In contrast, if a website lacks attribute information, online users do not find much value from it and hence, will focus more on the product prices in making decisions (Chang & Wildt, 1994). These arguments imply that personalization based on preferences influences online users' perceptions of products with respect to price, quality, value, and purchase intention.

In summary, although we found much work in the literature that has examined the influence of personalization on online users' decision process (Balan & Mathew, 2020; Ho & Bodoff, 2014; Ho et al., 2011; Krishnaraju et al., 2016; Tam & Ho, 2005, 2006), research has scarcely examined the influence that personalization has on how online users perceive a product. We address this gap in this study. We need to study the impact of personalization on the decision process to understand what kind of information influences the decision outcome (i.e., the buying decision). Since personalization has become ubiquitous and most online platforms use it today, organizations compete by offering different forms of personalization. Recent research has also shown that different product categories have different information needs and personalization requirements due to how consumers respond to product segments that differ in attributes (Balan & Mathew, 2019; Liu & Karahanna, 2017). Hence, we need to understand the influence of personalization and product segments (i.e., from the perspective of attribute richness) on consumers' decision-making process. In this study, we focus on understanding the influence of Web personalization on the decision process, which is a function of evaluating different choice sets based on product perceptions. We further conceptualize product perceptions based on four constructs: perceived expensiveness, perceived quality, value, and purchase intention.

3 Theoretical Foundations

In this section, we review MAT and how researchers have applied MAT to study online user behavior. By understanding online users' mental processes when making decisions, we can further explore the role that Web personalization plays in online users' decision-making process for theory development.

3.1 Mental Accounting Theory (MAT)

Thaler (1985) first proposed MAT as an extension of prospect theory. According to MAT, online users' transaction decision-making involves a two-stage process: 1) judgment process and 2) decision process. The judgment process involves evaluating potential transactions, while the decision process involves approving and disapproving potential transactions (Thaler, 2008). Since online decision-making involves multiple factors such as convenience, risk, and various alternatives (Chung & Koo, 2015; Gupta & Kim, 2010), MAT provides a conceptual lens to understand how online users perceive value in online transactions (Huang et al., 2007). Users evaluate potential transactions based on two types of utility: acquisition utility and transaction utility (Thaler, 2008). Acquisition utility refers to a product's value compared to how much one spent on it. Transaction utility refers to the perceived benefits that users expect from a transaction (Thaler, 2008). Finally, total utility refers to the sum of acquisition utility and transaction utility.

As an alternative to MAT, consideration set theory closely resembles MAT (Hauser & Wernerfelt, 1990). According to consideration set theory, online users browse through products (consideration set), process the details, and create a small product subset (choice set). They subsequently evaluate the products in the choice set to make their final decision. In MAT, the judgment process equates to the consideration set and the decision process to the choice set. However, consideration set theory does not explicitly consider price perception and utility. Therefore, we adopt MAT in this research to develop our hypotheses related to perceived expensiveness, perceived quality, perceived value, and purchase intention.

Online users evaluate the outcomes during the judgment process and then approve or disapprove the evaluations in the decision process. Since MAT has multiple outcomes (i.e., unlike prospect theory), online users have multiple ways to evaluate the outcomes and the evaluations differ based on the method used. Users can evaluate the outcomes jointly (integrated) or separately (segregated)—whichever produces maximum utility (Thaler, 1985). For example, if a joint outcome $(x,\ y)$ exists, online users can value the outcome either jointly as $v(x+y)$ or separately as $v(x)\ +v(y)$. The former constitutes an integrated outcome and the latter a segregated outcome. Thaler (1985) proposed four ways to consider joint outcomes: multiple gain, multiple loss, mixed gain, and mixed loss. Online users want to avoid losses (Von Neumann & Morgenstern, 1953) and, hence, they defer making a transaction when they have losses in all the outcomes. Online users make transactions when they have either all gains or larger gains and smaller losses in combination. Thaler (1985) found that online users adopt a segregation model when they have gains in all the outcomes (multiple gain scenario) and when they have smaller gains and larger losses (mixed loss scenario), and that online users adopt an integration model when they have larger gains and smaller losses (mixed gain scenario). In summary, MAT describes online user transaction decision-making as a two-stage process and explains how they evaluate potential transactions or outcomes and make their decisions.

4 Research Model and Hypotheses

We employ MAT as a theoretical lens to examine the influence of Web personalization on online users' perceptions of products. We follow Chang and Wildt (1994) and DeLone and McLean (1992) in conceptualizing product perception as perceived expensiveness, perceived quality, perceived value, and purchase intention. We show our proposed research model in Figure 1.

Online users choose an outcome that maximizes their transaction utility and acquisition utility. Although the price of a product could be the same across multiple online stores, the transaction utility derived from various components such as convenience (Gupta & Kim, 2010) and information reliability (Chung & Koo, 2015) during online buying could vary among online stores, resulting in different perceptions of expensiveness. In contrast to product price, perceived expensiveness refers to the online users' perceptual representation or subjective perception of a product's objective price (Chang & Wildt, 1994). In the online buying context, convenience refers to how much time and effort users perceive themselves saving by shopping at an online store (Gupta & Kim, 2010). Online stores can provide convenience in various ways, such as making searching for products easy, presenting information based on user preferences, and ensuring users can navigate websites easily. Such convenience increases online users' transaction utility. In the IS discipline, information reliability is an important aspect of information quality, which refers to the accuracy, timeliness, and completeness of information (DeLone & McLean, 1992). Users perceive information quality as a key factor that contributes to information value. As Emery (1971, p. i) states: "information has no intrinsic value; any value comes only through the influence it may have on physical events. Such influence is typically exerted through human decision makers." Hence, we define information value as a function of information quality. As with convenience, the greater the information quality, the higher the transaction utility derived from the online store. Prior IS research has also studied the relationship that transaction utility has with perceived price (Ho et al., 2017; Huang et al., 2019), perceived quality and perceived value (Li & Hitt, 2010; Mithas et al., 2016), and purchase intention (Animesh et al., 2011; Tan et al., 2019; Wells et al., 2011). In line with the above studies and findings, we believe that personalization increases transaction utility by providing greater convenience and, thus, leads to reduced search costs and higher information quality.

Perceived value in the IS context refers to online users' perception of what they receive in terms of quality and convenience and what they give in terms of cost, time, and effort (DeLone & McLean, 1992; Zeithaml, 1988). Thus, perceived value represents a trade-off between costs and benefits. Transaction utility measures the trade-off between costs and benefits; when transaction utility increases, perceived value also increases and vice versa. Perceived value influences purchase intention (Chang & Wildt, 1994). Perceived value and purchase intention are related, except that purchase intention involves the intent to have a transaction under process. Prior studies have reported that convenience and information quality influence purchase intention (Chung & Koo, 2015; Gupta & Kim, 2010).

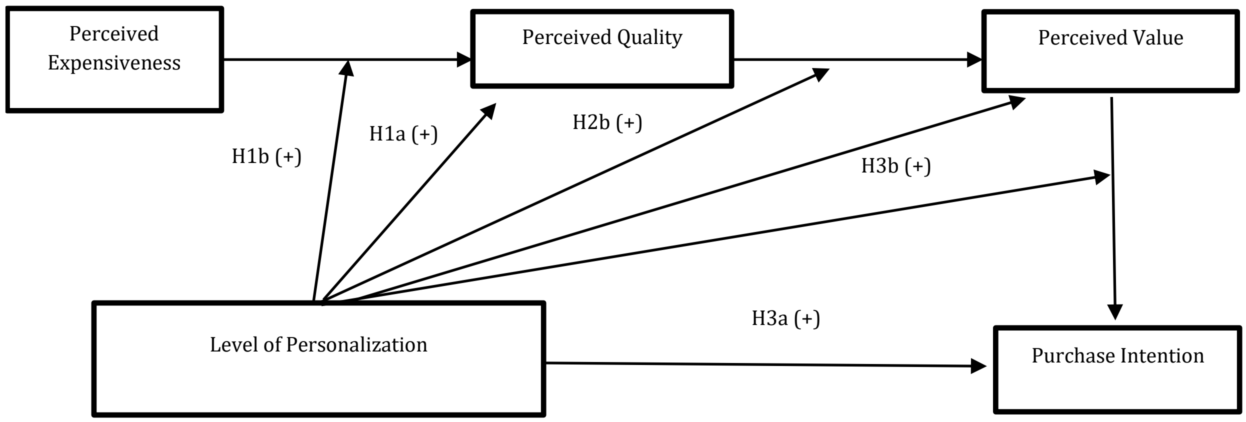

Figure 1. Research Model

Drawing on MAT, we argue that Web personalization increases ease of use (Tam & Ho, 2006), search convenience (Balan & Mathew, 2020; Tam & Ho, 2005), and information quality through content relevance (Tam & Ho, 2006), and they, in turn, influence product perception. We conceptualize online users' decision process before making a transaction as a two-stage process as proposed by Thaler (1985) and empirically tested by Gupta and Kim (2010), Kim et al. (2012), and Kim et al. (2007). First, in the judgment stage, users evaluate the costs and benefits. Second, in the decision stage, they approve or disapprove these evaluations. Based on understanding benefits as convenience in terms of ease of searching (Gupta & Kim, 2010), transaction experience (Kim et al., 2012), and information reliability (Chung & Koo, 2015), we argue that personalization involves benefits that users receive when making their buying decisions and that different personalization levels will make users perceive different levels of benefits. Previous research has conceptualized Web personalization in terms of self-reference and content relevance (Tam & Ho, 2006). Self-reference refers to personalizing Web content according to one's persona (Tam & Ho, 2006). Content relevance refers to the extent to which Web content pertains to an online user's processing goals (Tam & Ho, 2006). Furthermore, different self-reference and content relevance combinations would lead to different Web personalization levels (Tam & Ho, 2006; Balan & Mathew, 2019, 2020).

Research has also shown information reliability to influence online users' product perceptions (Kim et al., 2012; Gupta & Kim, 2010; Kim et al., 2007). Information reliability is an important aspect of information quality (DeLone & McLean, 1992), and personalization increases information quality in terms of content relevance (Tam & Ho, 2006) and timeliness (Ho et al., 2011). We further argue, based on MAT, that personalization influences how users perceive products and that different personalization levels give rise to different online users' perceptions.

According to MAT, convenience (in terms of ease of search) and information quality (in terms of relevance, timeliness, and completeness) increase transaction utility and, hence, influence perceived value and purchase intention. Perceived value in the IS context refers to the net benefit that online users perceive a product to offer (Chung & Koo, 2015; Gupta & Kim, 2010; Zeithaml, 1988). During the judgment stage in the decision process, online users choose the transaction with the maximum benefits. Furthermore, personalization is one of the benefits that online users receive in an e-commerce environment, and it increases the transaction utility of online users.

4.1 Personalization Level, Perceived Expensiveness, and Perceived Quality

Research has found that information quality and attribute richness moderate the influence of perceived expensiveness on perceived quality (Chang & Wildt, 1994). As we discuss above, we define information quality as the accuracy, timeliness, and completeness of information (DeLone & McLean, 1992). Attributes indicate a product's manufacturer-specified features or affordances that online users identify and describe in their feedback (Balan & Mathew, 2019, 2020). Perceived quality refers to a user's overall perceptions about a product's attribute information in terms of how useful the product would be for the user (Zeithaml, 1988; Myers & Shocker, 1981; Olson & Jacoby, 1972). Chang and Wildt (1994) found that product attribute information had a moderating effect on the influence of perceived expensiveness on product quality. Web personalization increases the richness of product attribute information (Balan & Mathew, 2020).

Integrating key concepts from Web personalization with MAT, we further argue that Web personalization will have a positive effect on perceived quality due to the higher information quality offered, which, in turn, influence online users' perceptions during mental accounting (Chung & Koo, 2015; Thaler, 2008). Further, Web personalization can be delivered at different levels (e.g., a self-reference level, a middle level that offers more content relevance, or a higher level that combines both self-reference and content relevance) (Tam & Ho, 2006; Balan & Mathew, 2019, 2020). Content-relevance based personalization impacts user decisions (Tam & Ho, 2006), increases the user's ability to comprehend information (Severin, 1967), and improves the congruence of information presented with the user's processing goals (Tam & Ho, 2006), an important constituent of information quality (DeLone & McLean, 1992). In situations with low personalization, online users will find it harder to understand the benefits of a product and, thus, may focus on the price (quantifiable and easy-to-understand information). Hence, when personalization is low, online users' perception of price will weakly affect perceived quality due to relatively lower information quality. In contrast, when personalization is high, their perception of price will strongly correlate with perceived quality due to higher information quality. Thus, we hypothesize:

> **H1a:** Web personalization has a positive effect on perceived quality.

> **H1b:** Personalization level positively moderates the impact of perceived expensiveness on perceived quality.

4.2 Personalization Level, Perceived Value, and Purchase Intention

Perceived value is a primary factor influencing purchase decision (Chung & Koo, 2015; Gupta & Kim, 2010; Chang & Wildt, 1994). According to MAT, online users choose an option that maximizes the total utility of a transaction as measured by the sum of acquisition utility and transaction utility. Transaction utility depends on factors such as convenience, ease of product search, and information quality (Chung & Koo, 2015; Gupta & Kim, 2010).

Personalization increases the ease of product search and information quality of the website by providing relevant content. Online users in a personalized environment expend less cognitive effort to make buying decisions due to fewer clicks and shorter time spent (Balan & Mathew, 2020), which, in turn, improve ease of use. Further, research has found that the human cognitive system exhibits a higher learning effect when provided with relevant content (Severin, 1967). When exposed to relevant content, online users have a higher recall and hold the information in their working memory for a longer time (Tam & Ho, 2006). Prior research has shown that transaction utility moderates the influence of perceived quality on perceived value (Chung & Koo, 2015). As personalization enhances ease of use (Balan & Mathew, 2020) and ease of use leads to higher transaction utility (Chung & Koo, 2015; Thaler, 2008), we argue that personalization will have a positive effect on perceived value (Chung & Koo, 2015; Gupta & Kim, 2010). Furthermore, as transaction utility is a function of Web personalization, personalization level is expected to moderate the effect of perceived quality on perceived value (Chung & Koo, 2015). When personalization is low, online users' perception of quality will weakly affect perceived value due to relatively lower transaction utility. In contrast, when personalization is high, perception of quality will strongly affect perceived value due to higher transaction utility.

> **H2a:** Web personalization has a positive effect on perceived value.

> **H2b:** Personalization level moderates the impact of perceived quality on perceived value.

In a similar vein, since transaction utility has a positive effect on purchase intention, we further argue that personalization will have a positive impact on purchase intention based on prior studies that have shown that higher transaction utility influences purchase intention (Chung & Koo, 2015; Gupta & Kim, 2010). Furthermore, according to Chung and Koo (2015), transaction utility will moderate the relationship between perceived value and purchase intention. Therefore, when personalization is low, users' perception of value will weakly affect purchase intention due to relatively lower transaction utility. In contrast, when personalization is high, their perception of value will strongly affect purchase intention due to higher transaction utility.

H3a: Web personalization has a positive effect on purchase intention.

H3b: Personalization level moderates the impact of perceived value on purchase intention.

5 Research Methodology

We adopted an experimental methodology to address our research objectives. The methodology involved a multi-group laboratory experiment that examined the effect of personalization on online users' perceptions of price, quality, value, and purchase intention. Other IS scholars have also conducted behavioral experiments to study the impact of personalization on online users' behavior (Balan & Mathew, 2016b, 2019, 2020; Ho & Bodoff, 2014; Ho et al., 2011; Krishnaraju et al., 2016; Tam & Ho, 2005, 2006). The experimental part of our study comprised four parts: summarizing reviews to extract attribute-rich content, operationalizing personalization, designing websites, and describing the experimental procedure.

The experiment involved four different groups exposed to four separate websites that we designed to operationalize different levels of personalization. We manipulated personalization levels using two factors: self-reference and content relevance (Tam & Ho, 2006). The four groups comprised different levels of personalization, i.e., low, medium, high, and a no personalization group as the control group. The low personalization group had self-referent web content and no relevant content personalization; the medium personalization group had content-based personalization and no self-referent content; the high personalization group had both self-referent Web content and content-based personalization. We adopted Balan and Mathew's (2016a) review-based personalization approach to operationalize content relevance. To control for product attribute richness, we used two completely different products, as suggested by Chang and Wildt (1994) who used two extremely different types of products (i.e., a personal computer and an apartment) to obtain more generalizable results. Following this approach, we considered two different products: one high-value and attribute-rich product (a digital camera) and one low-value and less attribute-rich product (a trolley bag).

5.1 Web Personalization based on Product Reviews

We used the personalization algorithm that Balan and Mathew (2016a) used in their review-based personalization approach. In this approach, they developed and empirically tested a method based on attribute-level review information. They reported that, when exposed to personalization based on preferences, online users expended lower cognitive effort due to a lower number of clicks and shorter time to make their online buying decision. Motivated by these findings, we choose this personalization approach for the content-relevance personalization using product review information.

The personalization approach based on product reviews followed a three-stage process. First, we applied parts of speech (PoS) tagging to the reviews to extract product attributes—a widely used technique to extract entities from text. The PoS output comprises part of speech tags for every word in its use context. We considered the top 20 percent of the most frequently occurring nouns and noun phrases as the product attributes, an approach used by Archak et al. (2011). Second, we then computed a sentiment score for every phrase that discussed a particular attribute and considered the average sentiment score for a particular attribute as the review summary of the respective attribute as Balan and Mathew (2016a) did. We used this summary to personalize the product listing on the website according to online users' preferences.

5.2 Design and Manipulation

We followed Tam and Ho (2006) to manipulate the personalization level using two factors: self-reference and content relevance. Although both self-reference and content relevance stimulate individuals to cognitively process personalized content, which should lead to higher recall, self-reference stimulates poorer recall than content relevance (Tam & Ho, 2006) because, when exposed to self-referencing Web content, online users hold information related to self in the working memory for a shorter duration. However, online users have better recall as they cognitively process personalized content offered to them by both self-reference and content relevance together. Based on these arguments, we consider self-reference-based personalization low personalization, content relevance-based personalization medium personalization, and both self-reference and content relevance-based personalization high personalization. Thus, we had four groups with four different personalization levels.

We developed four different websites with four different personalization levels using HTML, PHP, and MySQL. The websites had four personalization levels: no, low, medium, and high personalization. The four websites had all the information that a typical website provides, such as product rating, product reviews, product price, helpfulness score, a product image, and a product description. The no personalization group received generic (i.e., non-personalized) Web content. The low personalization group received self-referent Web content (high self-reference) in the form of personalized background in online users' favorite color, Indian Premier League cricket banners of the online users' favorite team, personalized messages with the online users' name in the home page, and personalized message alerts with the online users' name throughout the shopping period from login to checkout (e.g., messages while signing up/in, adding a product in the cart, clicking the checkout button). The medium personalization group received relevant Web content according to their purchasing goal (high content relevance). This group had a review summary-based personalization as we describe above to personalize the product listing according to their preferences. The high personalization group received both self-referent Web content (high self-reference) and relevant Web content according to their purchasing goal (high content relevance).

Based on the approach that Chang and Wildt (1994) followed, we chose two completely different products: a digital camera as a high-value, attribute-rich product and a trolley bag as a low-value, less attribute-rich product. All four websites had 25 products (12 digital cameras and 13 trolley bags). They had a sign-up page that elicited users' stated preferences and demographic details. We developed the websites in such a way that they mimicked a professional shopping website. The websites had an elegant user interface design that resembled other major Indian shopping websites. We also made sure that the design matched the basic structure that prior work involving e-commerce experiments has followed (Balan & Mathew, 2019, 2020; Ho & Bodoff, 2014; Jiang & Benbasat, 2007; Liu & Karahanna, 2017; Tam & Ho, 2005, 2006). The information that we used on the website mimicked the original content from a major Indian e-commerce retailer. All four websites had a search bar to help users search for a product. The product cart page had a "buy" button that, once clicked, would trigger the completion of the transaction. After the users completed the sign-up process, we directed them to an instructions page that provided the guidelines along with a scenario asking them to buy one digital camera and one trolley bag. All groups received the same instructions and scenario. We placed the banner ads associated with Indian Premier League (IPL) for low and high personalization groups at the top of the website and the IPL fan posters vertically on the left and right margins.

5.3 Pilot Test

We conducted two pilot tests before the actual experiment to test the website's usability, aesthetics, and functionality; check the quality of the data we recorded; and understand users' preference to personalize the self-referent Web content. Each pretest involved 15 participants. In the first pilot test, we collected feedback on the website's aesthetics and conducted a survey to determine how many participants watched television series or sports leagues. If they answered "yes" to any of the above questions, we collected more details, including their favorite sports leagues, favorite sports league teams, and favorite television series. We used this information to design the self-referent Web content for the actual experiment. The first pilot study revealed that most participants (graduate students) watched both television series and the IPL. We used this information to narrate a scenario based on a famous television series to add more flavor to the experiment and keep the participants motivated and engaged in doing the task. We also used IPL banner ads and fan posters as a cue for the self-referent Web content. We incorporated these changes in the second pilot test and checked the website's functionality and the quality of the data recorded at the backend. All the websites we used in this study adopted a similar registration process to sign up. We did not use the sign-up information at all for the no personalization group, but we used it for the other three groups to personalize based on self-reference (first name for personalized messages, favorite IPL team for banner ads and fan posters, favorite color for personalized background layout) or content relevance (ranking products on the home page based on users' preferences) or both.

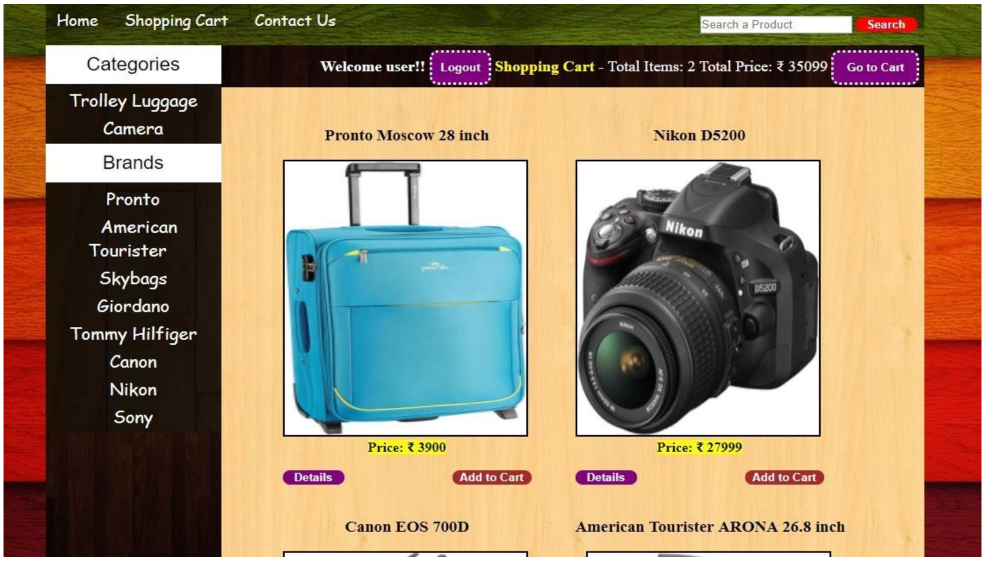

Figure 2. Home Page with No Personalization

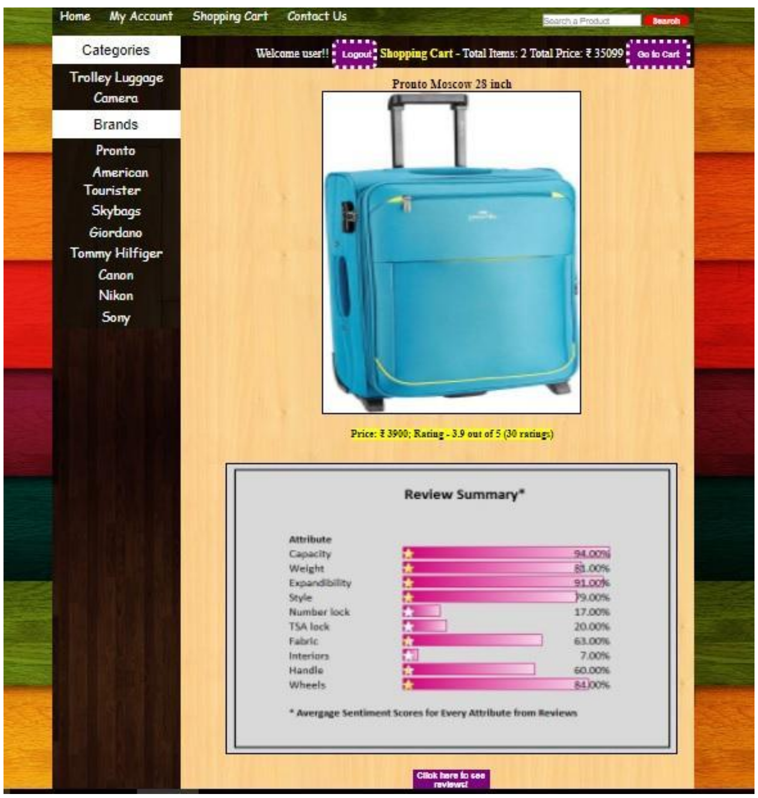

Figure 3. Attribute-level Review Summaries in all Groups

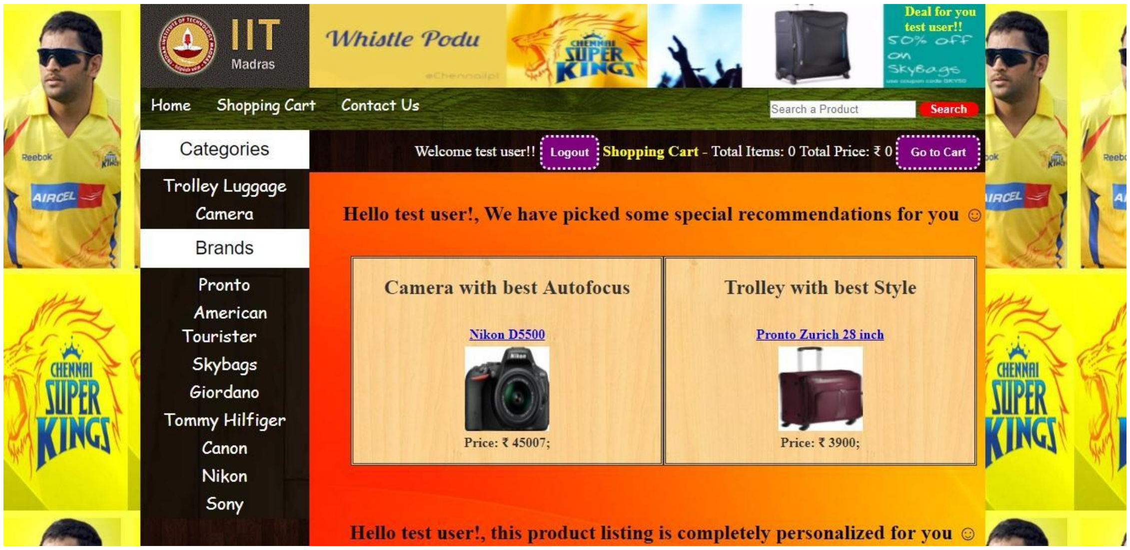

Figure 4. Home Page with Self-referent (Personalized Ad Banners, IPL Team Banners, and Favorite Color Background) and Relevant Content (Personalized Recommendations)

Figure 5. Home Page with Self-referent (Personalized Ad Banners, IPL Team Banners, and Favorite Color Background) and Relevant Content (Personalized Product Ranking)

5.4 Experimental Procedure

We conducted the experiment in the information technology lab of a premier technology institute in India. Following Balan and Mathew (2016a), the participants' working memory was cleared before the start of the experiment by having them partake in some entertainment activities and play fun videos for ten minutes. Since people have limited working memory, this exercise enabled participants to maximize the extent to which they used their working memory in our study.

We gave all participants a scenario that asked them to buy one digital camera and one trolley baggage for an old man traveling abroad. The scenario gave them a fixed budget of INR 75,000 to limit how much they could spend and to add more reality to the experiment. We designed the scenario with the utmost care and asked the participants to step into the shoes of an old man to ensure all the participants had the same goal and to control how much information they needed to process in completing the task. We did not restrict the amount of time that participants could take to complete the task. Each batch of the experiment comprised around 40 participants, and we completed six batches. We took several control measures in the experiment.

For example, we used the same lighting conditions and environment for all the participants. We controlled for the same products, user interface design, aesthetics, and functionalities on the four websites, i.e., one website for each experimental condition (please see Appendix B for more details about the website).

5.4.1 Participants

Our participants comprised graduate students at the academic institute. The participants were active users of the Internet (we had a pre-criterion that they had to have bought a minimum of five products online a priori) and were between 25 to 35 years of age. The participants completed the experiment voluntarily. We gave fixed incentives to all participants (i.e., snacks, beverages, and mobile recharge vouchers). In addition, there was a lucky draw for gift vouchers after each batch of the experiment. The lucky draw was completely independent of the task to be executed by the participant.

Table 1. Measurement Items (for Trolley Bag/Digital Camera)

Construct	Code	Item	Definition
Perceived expensiveness	PT1	To what extent do you perceive the price of this trolley bag to be high or low?	Online users' perceptual representation or subjective perception of the objective price of the product (Chang & Wildt, 1994).
	PC1	To what extent do you perceive the price of this camera to be high or low?	
Perceived quality	PT2	To what extent do you perceive the overall quality of the trolley bag to be high or low?	Online users' judgment of the overall experience with a product. Perceived quality refers to a user's overall perceptions about all the attributes of a product in terms of how useful the product would be for the user (Chang & Wildt, 1994).
	PC2	To what extent do you perceive the overall quality of the camera to be high or low?	
Perceived value	PT3	To what extent do you perceive the trolley bag to be useful?	Online users' perception of benefits in terms of quality and convenience and losses in terms of cost, time, and effort (DeLone & McLean, 1992; Zeithaml, 1988).
	PC3	To what extent do you perceive this camera as worth it?	
Purchase intention	PT4	How do you rate your intention to purchase the trolley bag?	Online users' perception of completing a pending transaction (Chang & Wildt, 1994).
	PC4	How do you rate your intention to purchase the camera?	
Note: interval scale: 9: high, 1: low (Chang & Wildt, 1994)			

5.5 Experimental Data

We obtained experimental data from two sources: the survey instrument and website log files. Following Chang and Wildt (1994), we developed and used a self-reported questionnaire to capture perceived expensiveness, perceived quality, perceived value, and purchase intention. We measured perceived expensiveness on a single item with a nine-point scale that assessed the extent to which the users perceived the price as low (1) or high (9). Similarly, we measured perceived quality, perceived value, and purchase intention on a single item with a nine-point scale (1 = low, 9 = high). We also recorded the clickstream data in a MySQL database, i.e., including the clicks made by each user and the time that each user took to purchase a product.

5.6 Manipulation Check

We checked our experimental manipulation during the pilot test and the actual experiment (Balan & Mathew, 2019). We did two pilot tests in which we asked users to enter two scores on a nine-point scale regarding the degree to which they perceived the website as being personalized to them and the information richness of the attributes of the digital camera and trolley bag (to check for attribute richness). We show the details in Appendix A. We also asked them to provide feedback (as open-ended text) about how difficult they found searching for the products they intended to buy. The pilot tests further involved a group discussion with the participants to obtain open-ended feedback to enhance the website's design. The results showed that users in the personalized environment could perceive the website's personalization and that the digital camera had higher attribute richness than the trolley bag. Finally, during the actual experiment, before signing off, we asked the users to enter a score (as in the pilot test) on a nine-point scale to indicate how much they perceived the website as being personalized to them. We considered their score a metric for our personalization's effectiveness and used it for our manipulation check (Tam & Ho, 2006). The participants in the medium and high group (third and fourth groups) had higher scores (Medium personalization: M: 7.838, SD: 1.028; high personalization: M: 7.789, SD: 1.004) relative to the no personalization and low personalization groups (low personalization: M: 4.265, SD: 1.98; no personalization (control): M: 3.411, SD: 0.95). As such, we verified the effectiveness of the manipulations.

6 Analyses

Our initial sample comprised 154 data points. We reduced the sample size to 148 data points after cleaning the data. During cleaning, we removed incomplete records (6), which included participants who did not complete the experiment (4) and participants who completed the experiment but did not enter the data after making the purchase (2). The final dataset contained 78 male and 70 female participants. The no (control), low, medium, and high personalization groups had 35, 37, 38, and 38 participants, respectively. In the analyses, we focus on direct relationships before examining the interaction effects. We show the results in Tables 2, 3, 4, and 5.

6.1 Perceived Quality

We conducted a between-subjects one-way ANOVA to compare the effect of personalization on perceived quality in the no personalization, low personalization, medium personalization, and high personalization conditions. We conducted the ANOVA independently for both products. We found that personalization had a significant effect on the perceived quality of the trolley bag across the four conditions ($F(3, 145) = 3.176$, $p = 0.026$). However, personalization did not significantly affect the perceived quality of the digital camera across the four conditions [$F(3, 145) = 0.280$, $p = 0.840$].

Since we found a significant effect for the trolley bag, we further evaluated the differences in perceived quality among the four groups for the trolley bag in post hoc comparisons using the Tukey HSD test. The results showed that the mean perceived quality for the no personalization condition (M = 6.51, SD = 1.358) significantly differed from the medium personalization condition (M = 7.37, SD = 1.410) and the high personalization condition (M = 7.13, SD = 1.324). However, the mean perceived quality of the no personalization condition did not significantly differ from the low personalization condition (M = 6.67, SD = 1.339). The mean perceived quality was the highest for the medium personalization group (7.37) followed by the high personalization group (7.13), low personalization group (6.67), and no personalization group (6.51).

The results show that personalization has a direct effect on the perceived quality of low value products with few attributes (trolley bag). Thus, we found partial support for H1a.

6.2 Perceived Value

We conducted a between-subjects one-way ANOVA to compare the effect of personalization on perceived value in the no personalization, low personalization, medium personalization, and high personalization conditions. We conducted the ANOVA independently for both products. We found that personalization had a significant effect on the perceived value of the trolley bag across the four conditions ($F(3, 145) = 10.449$, $p < 0.001$). However, personalization did not significantly affect the perceived value of the digital camera across the four conditions ($F(3, 145) = 0.297$, $p = 0.828$).

Since we found a significant effect for the trolley bag, we further evaluated the differences in perceived value among the four groups for the trolley bag in post hoc comparisons using the Tukey HSD test. The results showed that the mean perceived value for the no personalization condition (M = 6.46, SD = 1.721) significantly differed from the medium personalization condition (M = 7.68, SD = 1.350) and the high personalization condition (M = 7.95, SD = 1.319). However, the mean perceived value of the no personalization condition did not significantly differ from the low personalization condition (M = 6.48, SD = 1.523). The mean perceived value was the highest for the high personalization group (7.95) followed by the medium personalization group (7.68), low personalization group (6.48), and no personalization group (6.46).

Overall, we found that personalization has a direct influence on users' perceived value of low value products with few attributes (trolley bag). Thus, we found partial support for H2a.

6.3 Purchase Intention

We conducted a between-subjects one-way ANOVA to compare the effect of personalization on purchase intention in the no personalization, low personalization, medium personalization, and high personalization conditions. We conducted the ANOVA independently for both products. We found that personalization had a significant effect on purchase intention for the trolley bag across the four conditions ($F(3, 145) = 8.272$, $p < 0.001$). However, personalization did not have a significant effect on purchase intention for the digital camera across the four conditions ($F(3, 145) = 0.205$, $p = 0.893$).

We further evaluated the differences in purchase intentions among the four groups for the trolley bag in post hoc comparisons using the Tukey HSD test. The results indicated that the mean purchase intention for the no personalization condition (M = 6.37, SD = 1.784) significantly differed from the medium personalization condition (M = 7.39, SD = 1.579) and the high personalization condition (M = 7.82, SD = 1.107). However, the mean purchase intention of the no personalization condition did not significantly differ from the low personalization condition (M = 6.42, SD = 1.601). The mean purchase intention was the highest for the high personalization group (7.82) followed by the medium personalization group (7.39), low personalization group (6.42), and no personalization group (6.37).

Overall, we found that personalization has a direct influence on users' intention to purchase low value products with few attributes (trolley bag). Thus, we found partial support for H3a.

Table 2. ANOVA Results for Impact of Personalization on Perceived Quality, Perceived Value, and Purchase Intention

Product	Measurement	F	Sig.	Mean difference	Std. error	Results
Trolley bag	Perceived quality	3.176	0.026	5.869	17.607	H1a Partially Supported
Digital camera	Perceived quality	0.280	0.840	0.554	1.661	
Trolley bag	Perceived value	10.449	0.000	22.751	68.254	H2a Partially Supported
Digital camera	Perceived value	0.297	0.828	0.408	1.225	
Trolley bag	Purchase intention	8.272	0.000	19.269	57.807	H3a Partially Supported
Digital camera	Purchase intention	0.205	0.893	0.498	1.493	

Table 3. Multiple Linear Regression with Interaction Terms for Influence of Perceived Expensiveness on Perceived Quality

Product	Model	R square	Std. error	Change statistics			Results
				R square change	F change	Sig. F change	
Trolley bag	1a	0.062	1.359	0.062	3.176	0.026	H1b not supported
	1b	0.100	1.345	0.038	2.015	0.115	
Digital camera	1a	0.006	1.407	0.006	0.280	0.840	H1b not supported
	1b	0.047	1.392	0.041	2.085	0.105	

[A] Predictors: (constant), high, medium, low (personalization)
[B] Predictors: (constant), high, medium, low, high personalization * perceived expensiveness, medium personalization * perceived expensiveness, low personalization * perceived expensiveness

Table 4. Multiple Linear Regression with Interaction Terms for Influence of Perceived Quality on Perceived Value

Product	Model	R square	Std. error	Change statistics			Results
				R square change	F change	Sig. F change	
Trolley bag	2a	0.178	1.476	0.178	10.449	0.000	H2b supported
	2b	0.489	1.176	0.311	28.771	0.000	

Table 4. Multiple Linear Regression with Interaction Terms for Influence of Perceived Quality on Perceived Value

Digital camera	2a	0.006	1.173	0.006	0.297	0.828	H2b supported
	2b	0.352	0.956	0.346	25.823	0.000	

[A] Predictors: (constant), high, medium, low (personalization)
[B] Predictors: (constant), high, medium, low, high personalization * perceived expensiveness, medium personalization * perceived expensiveness, low personalization * perceived expensiveness

Table 5. Multiple Linear Regression with Interaction Terms for Influence of Perceived Value on Purchase Intention

Product	Model	R square	Std. error	Change statistics			Results
				R square change	F change	Sig. F change	
Trolley bag	3a	0.146	1.526	0.146	8.272	0.000	H3b supported
	3b	0.398	1.295	0.252	19.765	0.000	
Digital camera	3a	0.004	1.558	0.004	0.205	0.893	H3b supported
	3b	0.275	1.343	0.271	18.050	0.000	

[A] Predictors: (constant), high, medium, low (personalization)
[B] Predictors: (Constant), high, medium, low, high personalization * perceived expensiveness, medium personalization * perceived expensiveness, low personalization * perceived expensiveness

6.4 Moderating Effect of Level of Personalization

We followed Baron and Kenny (1986) in studying the moderating effect of personalization on the influence of perceived expensiveness on perceived quality. According to Baron and Kenny (1986), a significant interaction effect for the moderator and predictor variables indicates a moderating relationship.

6.4.1 Personalization Level and the Influence of Perceived Expensiveness on Perceived Quality

To study the moderating effect of personalization on the influence of perceived expensiveness on perceived quality, we used a moderated multiple linear regression to predict perceived quality based on the three personalization groups and the interaction between perceived expensiveness and the three personalization groups.

Following Baron and Kenny (1986), we built two multiple regression models: 1) perceived quality with the low, medium, and high personalization groups as predictors, and 2) perceived quality with the low, medium, and high personalization groups and the interactions of perceived expensiveness with the low, medium, and high personalization groups as predictors. We used the no personalization group as the reference group and dummy coded the low, medium, and high personalization groups. We applied these two multiple linear regression models independently to both the products (i.e., the digital camera (high value, attribute rich) and trolley bag (low value, less attribute rich)). The R2 did not change significantly from the first model without interactions to the second model with interactions for the trolley bag ($F(3, 142) = 2.015$, $p = 0.115$) and for the digital camera ($F(3, 142) = 2.085$, $p = 0.105$). Consistent with the findings from the ANOVA, the first model without interactions was significant for the trolley bag ($F(3, 145) = 3.176$, $p = 0.026$) but not for the digital camera ($F(3, 145) = 0.280$, $p = 0.840$).

The results indicate that personalization has a direct effect on perceived quality but no moderation effect on the influence of perceived expensiveness on perceived quality. Thus, we did not find support for H1b.

6.4.2 Personalization Level and the Influence of Perceived Quality on Perceived Value

We tested the moderating effect of personalization on the influence of perceived quality on perceived value by employing a moderated multiple linear regression to predict perceived value based on the three personalization groups and the interaction between perceived quality and the three personalization groups.

We built two multiple regression models: 1) perceived value with the low, medium, and high personalization groups as predictors and 2) perceived value with the low, medium, high personalization groups and the interactions between perceived quality and the low, medium, and high personalization groups as predictors. We used the no personalization group as the reference group and dummy coded the low, medium, and high personalization groups. We applied these two multiple linear regression models independently to both products: the digital camera (high value, attribute rich) and the trolley bag (low value, less attribute rich). We found a significant R2 change from the first model without interactions to the second model with interactions for the trolley bag ($F (3, 142) = 28.771$, $p < 0.001$) and for the digital camera ($F (3, 142) = 25.823$, $p<0.001$). Consistent with the findings from the ANOVA, the first model without interactions was significant for the trolley bag ($F (3, 145) = 10.449$, $p < 0.001$) but not for the digital camera ($F (3, 145) = 0.297$, $p = 0.828$).

For the trolley bag, the regression coefficient for the interaction between perceived quality and the personalization groups was the highest for the high personalization group ($\beta = 0.808$, $p < 0.001$) followed by the medium personalization group ($\beta = 0.752$, $p < 0.001$) and the low personalization group ($\beta = 0.721$, $p < 0.001$). For the digital camera, the regression coefficient for the interaction between perceived quality and the personalization groups was the highest for the medium personalization group ($\beta = 0.547$, $p < 0.001$) followed by the low personalization group ($\beta = 0.534$, $p < 0.001$) and the high personalization group ($\beta = 0.532$, $p < 0.001$).

Overall, we found that personalization has a moderating effect on the influence of perceived quality on perceived value for both the trolley bag and the digital camera. Thus, we found support for H2b. We also found that personalization has a significant direct effect on the perceived value of the trolley bag.

6.4.3 Personalization Level and the Influence of Perceived Value on Purchase Intention

We built two multiple regression models: 1) purchase intention with the low, medium, and high personalization group as predictors, and 2) purchase intention with the low, medium, and high personalization groups and the interactions that perceived value had with the low, medium, and high personalization groups as predictors. We used the no personalization group as the reference group and dummy coded the low, medium, and high personalization groups. We applied these two multiple linear regression models independently to both the products. We found a significant R2 change from the first model without interactions to the second model with interactions for the trolley bag ($F (3, 142) = 19.765$, $p < 0.001$) and the digital camera ($F (3, 145) = 18.050$, $p < 0.001$). Consistent with the findings from the ANOVA, the first model without interactions was significant for the trolley bag ($F (3, 142) = 8.272$, $p < 0.001$) but not for the digital camera ($F (3, 145) = 0.205$, $p = 0.893$).

For the trolley bag, the regression coefficient for the interaction between perceived value and the personalization groups was the highest for the low personalization group ($\beta = 0.744$, $p < 0.001$) followed by the medium personalization group ($\beta = 0.728$, $p < 0.001$) and the high personalization group ($\beta = 0.540$, $p = 0.001$). For the digital camera, the regression coefficient for the interaction between perceived value and the personalization groups was the highest for the medium personalization group ($\beta = 0.861$, $p < 0.001$) followed by the high personalization group ($\beta = 0.815$, $p < 0.001$) and the low personalization group ($\beta = 0.635$, $p < 0.001$).

Overall, we found that personalization has a moderating effect on the influence of perceived value on purchase intention for both the trolley bag and the digital camera. Thus, we found support for H3b. In addition, we also found that personalization has a significant direct effect on purchase intention for the trolley bag.

6.5 Summary

Our results indicate that the level of personalization positively moderates relations between perceived quality and perceived value and between perceived value and purchase intention for both low-value, less attribute-rich products (trolley bag) and high-value, attribute-rich products (digital camera), which supports H2b and H3b. However, we found that personalization level did not have a moderating effect on the influence of perceived expensiveness on perceived quality for both the low-value, less attribute-rich product (trolley bag) and the high-value, attribute-rich product (digital camera), which does not support H1b.

Our results concur with Chung and Koo (2015) who showed that convenience in a website influences perceived value and purchase intention, with Gupta and Kim (2010) who showed that information reliability on a website influences perceived value and purchase intention, with Tam and Ho (2006) and Balan and Mathew (2020) who showed that personalization influences buying decisions (purchase intention), and with and Chang and Wildt (1994) who showed that product attribute information influences perceived quality. In the present study on online shopping, personalization provides benefits such as convenience, information reliability (an aspect of information quality) (DeLone & McLean, 1992), rich attribute information, and relevant content. Convenience makes it easier for users to search for the products they want (e.g., through personalized product listings that depend on users' preferences). More accurate, timely, and complete information improve information quality and content relevance in a personalized environment (DeLone & McLean, 1992). All these factors increase the transaction utility and, thus, increase perceived value and users' purchase intention (Thaler, 1985, 2008).

As online users have prior beliefs about a product before entering a website (Archak et al., 2011), they update their beliefs as they navigate through online stores. The online store environment moderates online users' product perceptions (Mazumdar et al., 2005). Lynch and Ariely (2000) found that online users' quality perceptions increased when they faced lower search costs for quality information. As perceived quality refers to overall perceptions about a product's attributes (Chang & Wildt, 1994), it is also affected by website usability and information reliability. According to Chang and Wildt (1994, p. 18):

> *It is expected that, in general, the greater the number of information cues the more influence these cues have on quality perceptions (assuming they are consistent in terms of content). Further, product attributes differ in importance, and it may be expected that information on more important attributes has higher information value and thus greater influence on quality perceptions.*

The high content relevance-based personalization adopted in this study provides attribute-rich information based on product reviews; hence, online users update their perceptions after reading the information. The relevant attribute information provides more cues about the attributes that users look for and, hence, influences their quality perception (which Chang and Wildt (1994) have also reported). Other incentives of personalization, such as reduced search costs, might influence users' perceived value and purchase intention (Gupta & Kim, 2010; Lynch & Ariely, 2000), which potentially explains why personalization influences perceived value and purchase intention as well as transaction utility.

Online users construct their preferences based on the interaction between their information processing system and the information environment (Liu & Karahanna, 2017). Online users elicit different preferences in the same environment even if they adopt the same rules and strategies (Bettman et al., 1998). The extent to which users evaluate an attribute as essential depends on various information environment characteristics such as conflicting values in information, procedural variance with the individual (e.g., choice versus matching), information framing, and presentation of information (Payne et al., 1992). The more attributes there are in a product, the more likely online users in an attribute-rich information environment will encounter conflicting information in the reviews; as such, the information environment will influence their preferences.

We also used the clickstream data to corroborate our findings. The clickstream data provide the number of clicks users made on the website and the time spent making buying decisions. Prior studies have demonstrated rigor by triangulating findings from perceptual data with click data (John et al., 2017). We found that the high personalization group made the fewest clicks (M: 8.25, SD: 8.088) and spent the least time making buying decisions (M: 232.25, SD: 274.160). These findings concur with prior studies indicating that online users click less and spend less time making buying decisions in a personalized environment (e.g., Balan & Mathew, 2016a, 2016b). We also computed the average time spent per product as the total time spent on the product details page divided by the number of product clicks, which can be considered a way to assess information processing depth (following Ho & Bodoff, 2014). Online users follow two different routes for information processing: the central and peripheral routes (Petty & Cacioppo, 1986). According to the elaboration likelihood model (ELM), information processing depth is high when users face relevant content because their cognitive system adopts the central information processing route (Petty & Cacioppo, 1986). We found that users in the medium personalization group spent the most time (on average) on the product details page (M: 30.91, SD: 23.67) followed by the high personalization group (M: 27.66, SD: 26.24), the low personalization group (M: 19.98, SD: 17.93), and the no personalization group (M: 13.83, SD: 10.66). The medium and high personalization groups had almost the same information processing depth. Users in the medium and high personalization groups also spent about the same time processing information. For the high-value, attribute-rich product (digital camera), we found the highest regression coefficient for the interaction between perceived value and personalization for the medium personalization group ($\beta = 0.861$, $p < 0.001$) followed by the high personalization group ($\beta = 0.815$, $p < 0.001$). For the low-value, less-attribute rich product (the trolley bag), we found the highest regression coefficient for the interaction between perceived value and personalization groups for the low personalization group ($\beta = 0.744$, $p < 0.001$). These findings conclude that the depth of thinking varies with different levels of personalization. As the depth of thinking influences information processing (Ho & Bodoff, 2014; Petty & Cacioppo, 1986) and user attitude and behavior (Ho & Bodoff, 2014), different levels of personalization elicit different levels of information processing. Thus, the results from additional clickstream analyses triangulate with our findings regarding the moderating effect of personalization on the relationships of perceived expensiveness on perceived quality, perceived quality on perceived value, and perceived value on purchase intention for both high-value, attribute-rich and low-value, less attribute-rich products.

7 Discussions

7.1 Theoretical Implications

Web personalization has become ubiquitous in online platforms today and has pushed organizations to understand consumer decision-making better to differentiate themselves from competitors when designing their platform strategies. Prior IS research on Web personalization has studied the influence of Web personalization on buying decisions (Tam & Ho, 2005, 2006), user acceptance (Krishnaraju et al., 2016), location preferences (Ho, 2012; Ho & Lim, 2018), and product preferences (Balan & Mathew, 2019, 2020). However, there has been little work to examine the influence of personalization on buying decision process and product perceptions. Understanding how users perceive information in a personalized environment can be vital in explaining their decisions and helping organizations design novel personalization and product layout strategies for their online platforms to gain a competitive advantage. Our study addresses this gap by developing and testing a model on the effects of different personalization levels and product attribute richness on consumers' decision process. In doing so, we help online platforms customize their personalization strategies for different product segments.

Our study has important implications for theory. First, although researchers have studied the effect of personalization on online user behavior (Balan & Mathew, 2020, 2019; Ho & Bodoff, 2014; Ho et al., 2011; Krishnaraju et al., 2016; Tam & Ho, 2005, 2006), they have scarcely examined the influence that personalization has on online users' perceptions. Our study represents an early attempt to assess the impact of personalization on online users' perceptions of price, quality, and value and on their purchase intention. Second, we found evidence that Web personalization has a quasi-moderation effect on users' product perceptions, which opens many avenues for future research. Although previous studies have found that the store environment (Mazumdar et al., 2005) and attribute information (Chang & Wildt, 1994) moderate online users' perceptions in online shopping, the moderating effect they have in a personalized environment can be completely different. Third, we modeled personalization from a MAT perspective. Other researchers have modeled personalization using information processing theory (Tam & Ho, 2006), the elaboration likelihood model (Ho & Bodoff, 2014), and consumer search theory (Ho & Bodoff, 2014), but we bring a new perspective to study personalization based on transaction utility. Finally, we operationalized personalization in a unique way. Although we adopted two factors (self-reference and content relevance) from the literature to operationalize personalization (Tam & Ho, 2006), personalizing using self-reference and content relevance in combination represents a unique approach. We adopted a methodology to effect multi-level personalization through single or combined instances of self-referent and content relevant Web stimuli. We believe this approach could guide future research in this area.

7.2 Managerial Implications

In addition to the theoretical implications, our study has various practical implications. First, we found that personalization moderates online users' perceived value and purchase intention. Both established and emerging e-commerce companies may find the results helpful when developing personalization agents. Although most organizations believe personalization influences buying decisions, they do not view content-based personalization as that important. Second, e-commerce platforms can use attribute-based personalization to offer convenience (in terms of ease of search) and information quality (in terms of attribute information) to online users. Online users have a higher learning effect when they have relevant information (Severin, 1967). Third, all e-commerce platforms currently use the same personalization; however, our study shows that they can vary at the personal level based on self-reference and content relevance (e.g., information quality and convenience). Fourth, we found that content relevance-based personalization better suits attribute-rich products and self-reference-based personalization better suits less attribute-rich products. This finding can help online retailers design their personalization agents according to the product category and attribute richness associated with the product. Finally, e-commerce platforms can provide high-quality personalization to improve the overall buying experience and improve customer satisfaction.

7.3 Limitations and Future Work

This study has several limitations. First, we conducted a laboratory-controlled experiment to study the impact of personalization on online users' perceptions. However, the effect in the real environment could be different. Hence, we need to validate our findings using field experiments. Second, we used active online shoppers in the 25-35 age bracket as subjects in our experiment. Thus, other studies need to assess the impact of personalization on passive e-commerce shoppers and older online users (> 35 years). Third, we used attribute-based personalization. However, other studies could use more sophisticated personalization agents such as collaborative filtering to study the phenomenon in the future. Fourth, we used a single item nine-point scale to measure perceived value and purchase intention for simplicity. Researchers could develop multiple-item scales to measure online user perceptions. Finally, researchers could extend our study by extracting more variables from clickstream data, which could help explain how online users form perceptions.

8 Conclusion

Our study represents an early attempt to understand the impact of Web personalization on online users' product perceptions. We found that personalization has a moderating effect on the relationships of perceived expensiveness on perceived quality, perceived quality on perceived value, and perceived value on purchase intention for both high-value, attribute-rich and low-value, less attribute-rich products.

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Appendix A: Survey Instrument (1 = Low, 9 = High)

Manipulation check on personalization level

1) To what extent do you perceive the website content to be personalized for you?

Perceived expensiveness (for trolley bag)

1) To what extent do you perceive the price of this trolley bag to be high or low?

Perceived quality (for trolley bag)

1) To what extent do you perceive the overall quality of the trolley bag to be high or low?

Perceived value (for trolley bag)

1) To what extent do you perceive the trolley bag to be useful?

Purchase intention (for trolley bag)

1) How do you rate your intention to purchase the trolley bag?

Perceived expensiveness (for digital camera)

1) To what extent do you perceive the price of this camera to be high or low?

Perceived quality (for digital camera)

1) To what extent do you perceive the overall quality of the camera to be high or low?

Perceived value (for digital camera)

1) To what extent do you perceive this camera as worth it?

Purchase intention (for digital camera)

1) How do you rate your intention to purchase the camera?

Appendix B: Website Screenshots

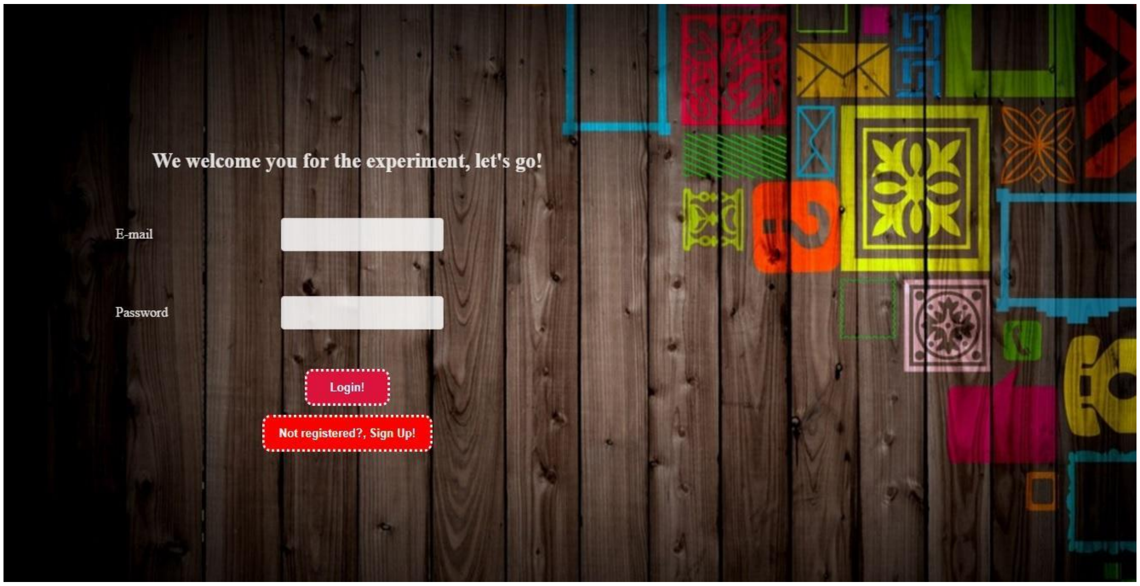

Figure B1. Login screen

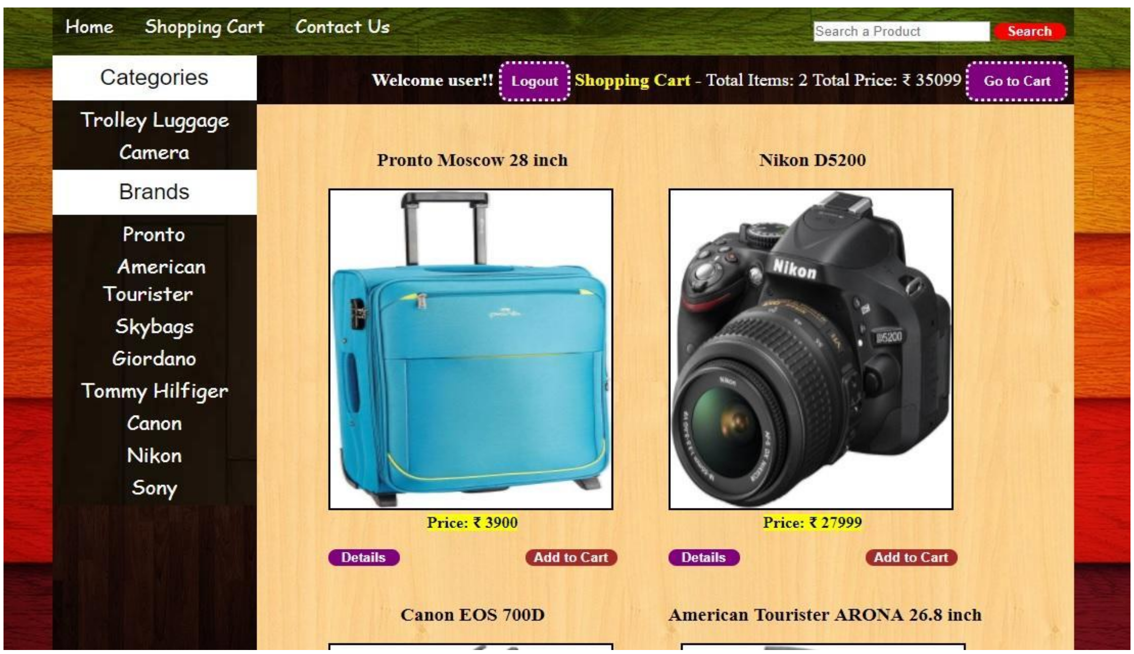

Figure B2. Home Page with No Personalization

Figure B3. Attribute-level Review Summaries in All Groups

Figure B4. Home Page with Self-referent and Relevant Content

Figure B5. Home Page with Self-referent and Relevant Content

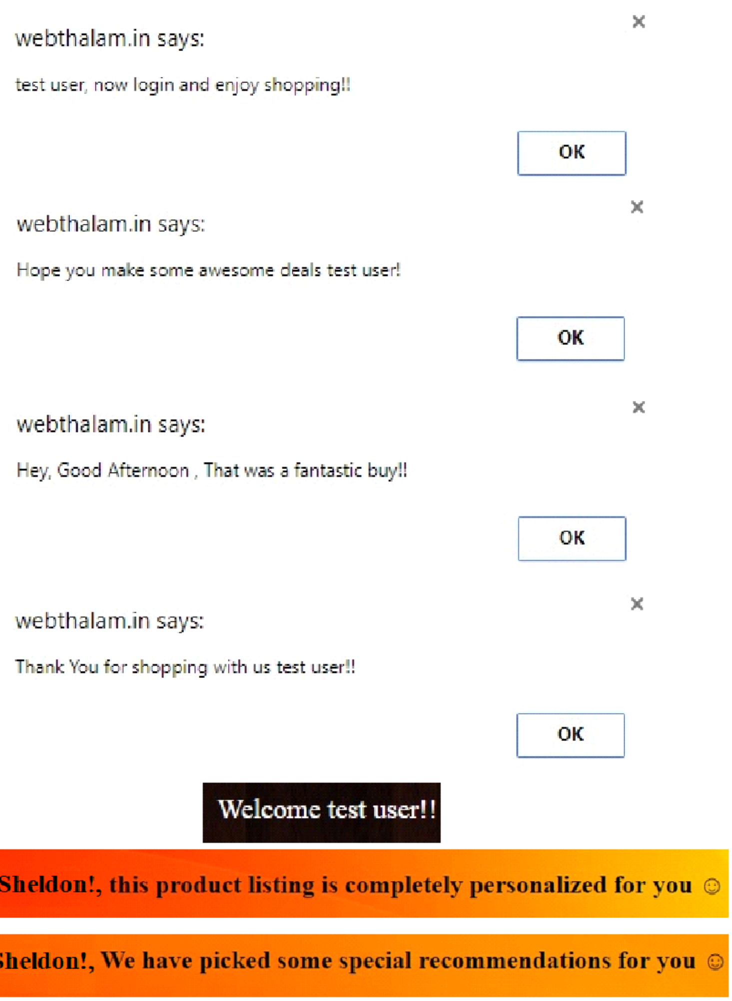

Figure B6. Personalized Self-referent Messages Displayed to the Users

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