Privacy concerns and justice perceptions with the disclosure of biometric versus behavioral data for personalized pricing tell me who you are, I'll tell you how much you pay. Consumers' fairness and privacy perceptions with personalized pricing

TELL ME WHO YOU ARE, I'LL TELL YOU HOW MUCH YOU PAY. CONSUMERS' FAIRNESS AND PRIVACY PERCEPTIONS WITH PERSONALIZED PRICING

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PRIVACY CONCERNS AND JUSTICE PERCEPTIONS WITH THE DISCLOSURE OF BIOMETRIC VERSUS BEHAVIORAL DATA FOR PERSONALIZED PRICING

Abstract

This research investigates whether consumers express different levels of store patronage intention and expected amount of discount depending on the type of data they have to disclose to obtain a personalized price. Findings from two experiments—manipulating the type of data along with the type of incentive (Study 1) and the level of effort (Study 2)—reveal that behavioral (vs. biometric) data make customers perceive the outcome of the price personalization more equitable, thus lowering the privacy concern, and enhancing their sense of entitlement to receiving a benefit from the retailer. The impact of the type of data on perceptions of distributive justice changes as a function of the type of incentive provided to customers (Study 1) and the level of effort required to see the personalized price (Study 2). The collection of biometric data should be counterbalanced by a higher amount of personalized discount to lower consumers' privacy concerns.

Keywords

Personalized Prices; Distributive Justice; Privacy; Consumer Entitlement

1. Introduction

Thanks to advances in digital technologies, retailers can collect a huge amount of information about customers' preferences and purchase behaviors over time (Kannan & Kopalle, 2001). As a consequence, retailers are increasingly relying on algorithmic pricing approaches to set the optimal price for assorted products at the customer level (Buhmann, Paßmann, & Fieseler, 2020; Esteves & Resende, 2019). Although the literature has intensively focused on uncovering the best algorithms for price personalization, there is limited research on how consumers react to retailers' requests for personal data that feed price personalization algorithms (Seele et al., 2021). Therefore, the present research investigates consumers' reactions to having to disclose different types of data in order to receive personalized prices from the retailer. These findings can help orient retailers around capturing consumer data that does not incur a negative reaction.

Indeed, the allure of better prices may be undermined by consumers' perceived concern over the loss of their personal information, as posited by the personalization–privacy paradox (Bornschein, Schmidt, & Maier, 2020; Lee & Rha, 2016). The severity of consumers' privacy concerns can be ascribed to the type of information requested (Phelps, Novak, & Ferrell, 2000), with biometric data triggering higher concerns than behavioral data (Ioannou, Tussyadiah, & Lu, 2020). Typically, retailers use biometric data such as fingerprint scans and palm, eye, and face recognition to obtain customers' physiological information (Clodfelter, 2010). For example, Saks Fifth Avenue uses facial recognition to recognize VIPs and prevent shoplifting; Microsoft Dynamics 365 Connected Store uses in-store sensors to track consumers' movements inside the store, and Amazon Go provides a seamless payment experience thanks to facial recognition tools that can log customers and track the products put into their carts (De Keyser et al., 2021).

Granted, the retail industry does not commonly use biometric data to set personalized prices. However, research has demonstrated that technologies based on biometric data—such as AI-enabled facial recognition cameras—can help retailers gather information for customizing in-store messages (Garaus, Wagner, & Rainer, 2021). In fact, scholars anticipate that biometric data will

eventually be used to customize the entire marketing mix (De Keyser et al., 2021). Thus, we seek to add to this stream by empirically testing whether and to what extent a price personalization strategy, based on biometric data, affects consumers' perceptions and behavioral intentions. Our results provide initial evidence that the downsides of gathering biometric data can be offset through more generous price personalization.

Furthermore, prior literature has found that customers' willingness to share their behavioral and biometric data depends on non-monetary incentives, such as the level of product/service personalization they receive in exchange (Ioannou, Tussyadiah, & Lu, 2020). In this vein, price personalization can be conceived as monetary incentives—in the form of personalized discounts (Liu & Zhang, 2006)—that add extrinsic value to consumers' intrinsic motivation (Gneezy, Meier, & Rey-Biel, 2011). To the best of our knowledge, no prior studies have attempted to compare how consumers' reactions to disclosing behavioral and biometric data vary as a function of the type of incentive (monetary versus nonmonetary) provided in exchange for said data. Accordingly, the present study attempts to address recent studies' call for further research exploring the impact of biometric data on individuals and how companies can overcome biometric-related privacy concerns (De Keyser et al., 2021).

Meanwhile, the literature on price personalization has provided initial evidence that consumers display a higher sense of entitlement toward receiving personalized prices as a function of the efforts required to obtain the personalized price (Xia, Kukar-Kinney, & Monroe, 2010). However, to the best of our knowledge, prior studies have mostly overlooked the relationship between consumer entitlement and the fairness of the retailer's adopted procedures for gathering customers' personal data in exchange for personalized prices. This is not a trivial issue, since recent studies have found that customers display higher patronage intentions (due to high justice perceptions) when they willingly share their data (Schmidt, Bornschein, & Maier, 2020). Accordingly, the present work empirically tests the relationship between the type of data disclosed

by customers, the perceived justice of what customers receive from the retailer in exchange for their data, and the consumer entitlement derived from receiving personalized treatment.

The remainder of this paper is organized as follows: We first review the relevant literature in order to develop our theoretical model. Second, we report and discuss the results of two experiments that were conducted to empirically test the research hypotheses underlying our theoretical model. Finally, we provide a general discussion highlighting the theoretical and managerial implications of our findings.

2. Theoretical Background and Hypothesis Development

2.1 Personalized Pricing and Digital Technologies

Choudhary and colleagues (2005) defined personalized pricing as the strategy "whereby firms charge different prices to different consumers based on their willingness to pay" (p. 1120). Personalized pricing has its roots in the literature on dynamic pricing (i.e., Haws & Bearden, 2006). Dynamic pricing is referred to as yield (or real-time) pricing that entails dynamically changing prices in order to maximize revenues in light of demand fluctuations in the current market (Chen & Gallego, 2019). Although the existing literature considers dynamic and personalized pricing to be almost synonymous (Seele et al., 2021), personalized pricing can be conceived as first-degree price discrimination, which differs from dynamic pricing in its purpose, that is, charging different price levels to different customers based on each customer's willingness to pay (Choudhary et al., 2005). To date, most existing research on personalized pricing has taken the seller perspective (Chen & Chen, 2017): seeing algorithmic pricing as a suitable approach for optimizing the prices of products in an assortment at the customer level (Buhmann, Paßmann, & Fieseler, 2019). Such algorithms need to be fed a considerable amount of data to deliver an accurate price estimation (Fisher, Gallino, & Li, 2018; Miklós-Thal & Tucker, 2019). Technology may help retailers generate the information needed to classify whether a customer is profitable or may become profitable in the future (Inman & Nikolova, 2017).

In this vein, recent studies have usefully shown that Big Data can be profitably adopted to estimate customers' price elasticity at the individual level (Bradlow et al., 2017). Looking at the possible data sources, the recent literature has demonstrated that biometric data (collected by means of facial recognition tools that monitor consumers' paths inside the store) provide more fine-grained information (Garaus, Wagner, & Rainer, 2021). By feeding such data into algorithms, retailers can customize in-store communication and prices.

In this regard, existing research has argued that delivering an accurate personalized pricing strategy improves retailers' profitability (Sahay, 2007), but can also activate customers' privacy concerns (Miettinen & Stenbacka, 2015).

(TABLE 1 ABOUT HERE)

2.2. Type of Data, Patronage Intention and Personalized Pricing

The recent literature has reported that innovative retail technologies can significantly improve personalization (Riegger et al., 2021), thanks to the considerable amount of biometric and/or behavioral data collected on customers who interact with retail technologies (North-Samardzic, 2020). That said, consumers can react differently depending on the type of data they are asked to disclose (Phelps, Novak, & Ferrell, 2000). Behavioral data refer to the "collection of behavioral information of individuals related to individual's activity, personal interests, location-based data, browsing patterns and search history (e.g., cookies)" (Ioannou, Tussyadiah, & Lu, 2020, p. 5). In retail settings, behavioral data are used to gain deeper insights into the actions that consumers take inside the store, such as POS data and/or location-based data (Aloysius, Hoehle, & Venkatesh, 2016). Instead, biometric data are related to individuals' unique physical characteristics and are therefore more suitable for unequivocally identifying a person's identity (Morosan, 2018; Mothersbaugh et al., 2012). Overall, the relevant literature has highlighted that customers are more reluctant to use technologies that require the disclosure of biometric data (Clodfelter, 2010). Indeed,

prior studies have suggested that consumers perceive biometric data disclosure as more sensitive because it deals with the "perceived intimacy level of information" (Lwin, Wirtz, & Williams, 2007, p. 575). Thus, consumers asked to disclose sensitive data may feel that the material benefits do not outweigh the perceived risk of their information being outside of their control (Ioannou, Tussyadiah, & Lu, 2020).

However, customers may find more value in sharing personal information that is specifically intended to facilitate personalized offers (Riegger et al., 2021). In this regard, the personalization privacy paradox posits that personalization can trigger both positive and negative outcomes that are connected, respectively, to the benefit of receiving customized treatment and to concerns about data loss (Awad & Krishnan, 2006). Accordingly, when the benefits of personalization outweigh the concerns over the type and collection of data, consumers generally display higher levels of engagement with the firm (Aguirre et al., 2016). Although the existing literature has not provided empirical evidence regarding consumers' different behavioral intentions in response to disclosing behavioral vs. biometric data, research has documented that the sensitivity of the data requested affects customers' responses (Smith, Dinev, & Xu, 2011). Specifically, disclosing sensitive data that relate to sharing intimate information to retailer may lower individuals' behavioral intentions (Okazaki et al., 2020). Accordingly, we posit that:

H1a: Customers will display a lower patronage intention when the retailer gathers biometric versus behavioral data.

Furthermore, the literature has shown that higher levels of personalization (represented as a personalized discount) can encourage consumers to engage with the firm (Aguirre et al., 2016), especially when they cannot easily delineate a cost-benefit trade-off (Kim & Kim, 2018). Accordingly, when customers are asked to disclose more sensitive data, they may expect to receive

a greater incentive in order to counterbalance such a trade-off. Thus, we argue that consumers' acceptance of the personalized discount depends on the kind of data being requested. Formally:

H1b: Customers will display a lower acceptance of the personalized discount when the retailer gathers biometric versus behavioral data.

2.3 Type of data and distributive justice

Consumers' different reactions to the type of data may be rooted in the idea of distributive justice: the degree of proportionality between what customers are asked to give and what they receive in exchange (Cropanzano et al., 2001). Exchanges are perceived as equitable when this proportionality is achieved (Seiders & Berry, 1998).

Building on equity theory (Adams, 1965), we can extend this logic to companies: Customers who receive preferential treatments will perceive said treatments as fair so long as the requested input (e.g., more sensitive data) is accompanied by an appropriate output in exchange (Mayser & von Wangenheim, 2013).

The existing literature has documented considerable heterogeneity in the extent to which customers interact with shopper-facing retail technologies—that is, technologies that provide an in-store technological interface between the customer and the retailer (Inman & Nikolova, 2017)-especially if they require an excessive amount of information compared to the benefit they receive (Wünderlich, Wangenheim, & Bitner, 2013). Prior studies have found that consumers incorporate the potential losses of privacy and confidentiality into their decisions to disclose data (Featherman, Miyazaki, & Sprott, 2010; Michaelidou and Micevski, 2019). Thus, in line with the notion of distributive justice, consumers need to perceive the benefits of data disclosure as outweighing the risks in order to engage with the firm's offer (Milne et al., 2017). On this point, different technologies can shift the cost-benefit ratio in favor of either the consumer or the retailer (Pizzi & Scarpi, 2020): the higher the data sensitivity, the higher the psychological cost for the consumer

(Mothersbaugh et al., 2012). Consistent with Ioannou et al. (2020), consumers might expect that disclosing behavioral data will provide them with more benefits and be less subject to risks than biometric data. Indeed, the disclosure of behavioral data is associated with receiving more personalized products and services, tailored to fulfill the specific needs of each individual (Riegger et al., 2021). Accordingly, we expect that biometric data will seem like a more sensitive output and thereby lower perceptions of distributive justice. Formally:

H2a: Customers will display lower distributive justice perceptions when the retailer gathers biometric versus behavioral data.

2.3.1 The moderating effect of type of incentive

As discussed above, the distributive justice principle states that there should be proportionality between inputs and outcomes (Maxham & Netemeyer, 2003). A corollary of this principle is that consumers providing an input expect to receive a higher output (Mayser & von Wangenheim, 2013). Therefore, retailers can counterbalance their requested input by offering consumers a higher output in exchange. In this regard, prior literature has addressed the use of incentives to compensate customers for personal disclosures (Premazzi et al., 2010). Indeed, retailers might offer non-monetary incentives such as personalized assortments that are tailored to consumers' specific tastes and needs based on gathered data (Godek & Eveland, 2018). Indeed, prior research has shown that consumers perceive the shopping experience as easier and more effective when assortments align with their expectations (Morales et al., 2005; Rooderkerk & Lehmann, 2021). In a similar vein, En and colleagues (2006) found that monetary incentives exert a positive effect on consumers' perception of an equitable exchange with a retailer, especially when they are asked to disclose more sensitive data. In fact, prior research in related fields has found that monetary incentives are generally more effective than nonmonetary incentives in shaping consumers' behavioral intentions (Reimer & Benkenstein, 2016). Accordingly, we contend that

consumers asked to disclose biometric data will perceive the exchange as more equitable if they are offered monetary incentives (Goodwin, 1991). Thus, we hypothesize that:

> *H2b: The type of incentive moderates the relationship between the type of data and distributive justice perceptions so that customers perceive the exchange to be more equitable if they receive a monetary rather than a nonmonetary incentive to disclose biometric data.*

2.3.2 The moderating effect of perceived effort

Existing research on consumer behavior has documented a positive relationship between customers' perceived effort and their reactions (Roggeveen, Micheal, & Grewal, 2012). Specifically, consumers prefer to invest less effort into their shopping activities and thereby save time. On this point, different retail technologies may require various levels of customer effort, depending on the complexity of the technology itself (Adapa et al., 2020) or the need to acquire new shopping habits (Wang, Harris, & Patterson, 2013). Unsurprisingly, the literature has also established that consumers will more readily adopt technologies that are easy to use (and thus require minimal effort) (Davis, 1989).

Notably, consumers often conceive effort as a non-monetary input in an exchange, which influences their distributive justice perceptions (Oliver & Swan, 1989). In this vein, Xia and colleagues (2010) found that customers' negative feelings in response to a required amount of effort can be offset by increasing the distributive justice of the exchange (in the form of price discounts). This is to say, if customers need to devote high effort to discovering the type and/or amount of benefit offered by the retailer in exchange for the information collected, they will expect to receive greater benefits. In other words, customers may conceive both the data disclosure and the difficulty of detecting the personalized benefit as nonmonetary efforts imposed by the retailer: the former due to privacy risks and the latter due to time losses (Klein & Ford, 2003). Accordingly, a high

nonmonetary effort to disclose more sensitive data might be compensated for by making it easier to detect the benefit provided by the retailer. Specifically, we hypothesize that:

> *H2c: The level of effort moderates the relationship between the type of data and distributive justice perceptions so that customers perceive the exchange to be more equitable if they experience low rather than high levels of effort in uncovering the benefit offered by the retailer in exchange for their biometric data.*

2.4 Distributive justice and privacy concern

Martin and colleagues (2017) documented a "growing concern by consumers about their privacy and potential harm when firms try to collect and use customer data" (p. 37). The existing literature suggests that personalization might exert both positive and negative effects on consumers' perception toward the retailer (Son & Kim, 2008), depending on consumers' perception that they are actually receiving a personalized treatment (Song, Lim, & Oh, 2021). On the positive end, personalization has been found to improve the interactivity between retailers and customers (Song & Zinkhan, 2008). On the negative end, personalization has been found to increase consumers' concerns about the collection of personal information (Awad & Krishnan, 2006).

The present work adheres to the definition of privacy concerns as customers' apprehension about information being collected from them (Cloarec, Meyer-Waarden, & Munzel, 2021). Accordingly, privacy disclosure can be conceived as consumers' behavioral response to perceiving a relatively low level of concern about their collected information (Pizzi & Scarpi, 2020). In this regard, the Privacy Calculus Model posits that consumers decide whether to disclose their personal information by balancing the risks and benefits of information disclosure (Dinev and Hart, 2006). More precisely, personal information is more likely to be disclosed by individuals when the benefits offset the risks (Sun et al., 2015; Maseeh et al. 2021; Massara, Raggiotto, and Voss, 2021). Recent studies on consumers' privacy disclosure behaviors have found that shopper-facing technologies

can shift the willingness to disclose based on two factors: the level of distributive justice in the input-output exchange (Aiello et al., 2020) and consumers' personality traits (e.g., mindfulness, as in Ioannou, Tussyadiah, & Marshan, 2021). In this vein, Schmidt, Bornschein, and Maier (2020) found that consumers—even if they are aware and concerned about how their personal information is used—are more likely to disclose their data as long as they perceive the exchange with the retailer to be fair. Consistent with this notion, the recent literature has addressed the role of consumers' information collection concerns as an antecedent of their willingness to disclose information for personalization purposes. Specifically, Cloarec, Meyer-Waarden, and Munzel (2021) proposed that reciprocity in the social exchange between the customer and the retailer lowers customers' information collection concerns, and may even mitigate those concerns entirely (Grewal et al., 2011). Accordingly, we hypothesize that:

H3: Distributive justice exerts a positive impact on privacy disclosure.

2.5 Privacy Disclosure and consumer entitlement

Consumer entitlement can be defined as "the extent to which a customer expects special treatment in retail environments" (Boyd & Helms, 2005, p. 271). In other words, consumers feel entitled when they perceive themselves to be special customers of the firm (Butori, 2010; Zboja, Laird, & Bouchet, 2016). As a recent example, Polyakova, Estes, and Ordanini (2020) found that customers receiving preferential treatments by a service provider display higher levels of entitlement. Note that the existing literature distinguishes between psychological and effortful entitlement. The former refers to a chronic sense of deservingness related to individuals' personality traits (Campbell et al., 2004; Neave, Tzemou, & Fastoso, 2020); the latter is situational and reflects individuals' belief that their entitlement is rooted in their personal effort (Martin, Strong, & O'Connor, 2018).

In the domain of price personalization, the literature has found initial evidence that consumers develop a higher sense of deservedness when they undertake greater effort to obtain the personalized price (Xia, Kukar-Kinney, and Monroe, 2010). We argue that this might be because customers perceive personal information disclosure as a type of cost (Culnan & Bies, 2003): one that reflects the effort to cope with the risks of their disclosure (Dinev & Hart, 2006). Accordingly, when consumers are asked to share their personal data, they might feel more entitled to a dedicated offer (in terms of monetary rewards). Although there is scarce research relating privacy disclosure to consumer entitlement, it seems reasonable that customers would feel entitled to a benefit in exchange for disclosing their personal information to retailers. Thus, we hypothesize that:

H4: Privacy disclosure exerts a positive impact on consumer entitlement.

2.6 The consequences of consumer entitlement

The existing literature has provided mixed results on the consequences of consumer entitlement. Some studies have focused on the negative consequences, showing that preferential treatments might lead entitled customers to adopt opportunistic behaviors (Polyakova, Estes, & Ordanini, 2020), feel embarrassed (Jiang, Hoegg, & Dahl, 2013), and display lower future intentions toward the retailer or service provider (Zhang & Hanks, 2015). Overall, these findings apply well to contexts where customers can receive variable treatment. Taking a different tack, other studies has demonstrated that low levels of consumer entitlement might produce a strong feeling of injustice (Martin, Strong, & O'Connor, 2018) as a response to unmet customer expectations (Oliver & Swan, 1989). Instead, when expectations are met, consumer entitlement contributes to improving customers' overall assessment of the shopping or service experience (Harvey & Martinko, 2009; Xia, Kukar-Kinney, & Monroe, 2010). In this vein, prior research has observed that consumer entitlement favors the development of more positive attitudes and repatronage intention toward the retailer (Sirakaya-Turk, Ekinci, & Martin, 2015; Terblanche, 2018;

Van Steenburg, Spears, & Fabrize, 2013; Xia & Kukar-Kinney, 2014). This effect can be ascribed to the fact that high levels of consumer entitlement are associated with a better fulfillment of consumers' expectations (Zboja, Laird, & Bouchet, 2016). Accordingly, we predict a positive relationship between a sense of entitlement and store patronage intention:

H5a: Consumer entitlement exerts a positive impact on customers' intention to repatronize the store.

Furthermore, since high levels of consumer entitlement reflect customers' beliefs of deserving superior or personalized treatment (Boyd & Helms, 2005), we expect that the level of consumer entitlement will shape customers' expectations about the degree of personalized price reduction. The existing literature has well documented that consumers display different levels of elasticity to price cuts (Shankar & Krishnamurthi, 1996), which has been explained in both probabilistic (Han, Gupta, & Lehmann, 2001) and consumer-related terms (Mulhern, Williams, & Leone, 1998). With regard to the latter, the literature has shown that consumer entitlement sets higher expectations (in terms of deserving special treatment) due to raising customers' perceived importance for the retailer (Wetzel, Hammerschmidt, & Zablah, 2014; Nguyen & Shi, 2018). Thus, we argue that the expected amount of price discount will depend on how entitled consumers feel to the retailer's special treatment. Specifically, we hypothesize that:

H5b: The higher consumer entitlement is, the higher the amount of personalized discount expected by the customer.

Figure 1 summarizes the theoretical model that encompasses our hypothesized relationships:

(FIGURE 1 ABOUT HERE)

3. Overview of the Studies

The goal of this research is twofold: First, it aims to assess how consumers react—in terms of a) store patronage intention (Study 1) and b) expected amount of discount (Study 2)—to the type of data they are asked to disclose by a retailer implementing an in-store technology that can set personalized prices. Our examination of these causal relationships unfolds along a mediation path that includes distributive justice, privacy disclosure, and consumer entitlement.

Second, this research aims to assess the role of two potential moderators: type of incentive (Study 1) and level of effort (Study 2). Specifically, Study 1 investigates whether consumers will react more favorably if the retailer collects data to provide them with personalized discounted prices (monetary incentive) rather than for profiling purposes (nonmonetary incentive). That is, Study 1 examines whether and to what extent the causal path—from the type of data used to the store patronage intention—changes as a function of the benefit provided to customers in exchange for their personal information. Study 2 builds on the findings of Study 1 by further exploring the actual amount of personalized discount that consumers perceive as fair, based on the type of data gathered and the level of effort required to obtain the personalized price.

3.1 Method

3.1.1 Procedure

In both studies, individuals were gathered via Prolific and invited to participate in an online experiment. We limited participation to native English speakers in order to prevent any potential misunderstanding of the scenarios and accompanying videos, which were in English. We adopted a scenario-based approach in line with prior studies that have investigated fairness-related topics (e.g., Collie, Bradley, & Sparks, 2002; Xia, Kukar-Kinney, & Monroe, 2010). After seeing a brief introductory section, participants were randomly exposed to one of four scenarios resulting from a 2

(type of data: behavioral vs. biometric) × 2 (in Study 1, type of incentive: nonmonetary vs. monetary; in Study 2, level of effort: low vs. high) between-subjects design. Each scenario asked participants to imagine themselves shopping in a grocery store equipped with a technology that could outfit customers with personalized prices on all the assorted products. After reading the written description of the scenario, participants were shown a short video (30 seconds) that described how the technology works. The purpose of the video was to increase the vividness and effectiveness of the experimental manipulation (Russell, 2002). Participants had to wait a set amount of time (represented via an on-screen timer) in order to ensure they read the written text and watched the scenario's video before moving on. After being exposed to the scenario, participants were redirected to the respective section of the questionnaire where they could complete the measures for each key construct. Distributive justice was measured through a 7-point Likert scale (3 items) adapted from Blodgett, Hill, and Tax (1997); consumer entitlement was measured through a 7-point Likert scale (3 items) taken from Xia, Kukar-Kinney, and Monroe (2010). Next, participants were asked to rate the extent to which they felt confident with disclosing their personal information based on the technology depicted in the scenario (7-point Likert scale, seven items adapted from Wolfinbarger & Gilly, 2003, as in Pizzi & Scarpi, 2020). Then, as a dependent measure, participants in Study 1 were asked to rate their future intentions toward the retailer by means of a 7-point bipolar scale (3 items adapted from Inman & Nikolova, 2017). Participants in Study 2, instead, were asked to assess the expected amount of discount from the retailer in exchange for the data, as well as the effort required to obtain a personalized discounted price. This latter measure involved a single-item scale purposely developed for this study: Participants could freely move the thumb of a horizontal slider, ranging from a 0% to a 50% discount (with unitary increases allowed), until they reached the desired value. Finally, participants were thanked and debriefed.

3.1.2 Stimuli

The experimental stimuli in the above scenarios were selected based on a pretest conducted

on a convenience sample (n = 100), which helped to ensure the effectiveness of the manipulations. These individuals were recruited on social media groups associated with shopping topics. Specifically, participants in the pretest were presented with alternative descriptions of retailers implementing in-store technologies to track customers' behaviors. This description was displayed to each participant and was randomized by Qualtrics. Then, participants were asked to assess whether they felt that the technology required access to their behavioral or biometric data (or both); whether the technology provided more benefit to the retailer or the consumer (7-point bipolar scale, three items adapted from Maxham & Netemeyer, 2003), and whether they believed that the technology required them to offer a high or low level of input effort in order to reap the associated benefit. Finally, pretest participants rated their perception of the realism of their read scenario.

Based on the pretest results, we identified two data sources with the greatest amount of difference (Behavioral: scanner data from previous purchases; Biometric: in-store cameras equipped with AI for image recognition); these served as an experimental manipulation of the independent variable in both Study 1 and Study 2. Specifically, consumers correctly identified that the technologies presented in the scenario required different access to their information ($M_{biometric} = 4.67$ vs. $M_{behavioral} = 4.05$; $F(1,98) = 3.66$, $p = .05$), as well as perceived higher benefits from disclosing their behavioral rather than their biometric data ($M_{biometric} = 4.16$ vs. $M_{behavioral} = 4.91$; $F(1,98) = 5.87$, $p = .02$). The pretest also allowed us to identify two different types of incentives (nonmonetary: the retailer collects data for statistical purposes; monetary: the retailer collects data to provide customers with personalized discounted prices), which served as an experimental manipulation in Study 1. We also considered two different levels of effort required by customers to benefit from personalized prices (Low: the personalized discounted price is displayed as a pop-up when the customer scans the product with the self-scanner; High: the customer needs to check in the "my current balance" section to see what price the retailer has charged for each scanned product). Specifically, participants in the pretest perceived that the two conditions described significantly different levels of effort ($M_{low} = 3.45$ vs. $M_{high} = 4.60$; $F(1,40) = 6.06$, $p < .05$). Finally, we

performed a realism check to compare whether participants felt that the retailer collecting biometric data for the purpose of charging personalized prices was more unrealistic than collecting behavioral data. The results from the pretest did not yield significant differences in the levels of realism associated with the disclosure of either data type ($M_{biometric} = 4.23$ vs. $M_{behavioral} = 4.30$; $F(1,98) = .04$, $p = .83$).

3.1.3 Model estimation

The conceptual model, graphically represented in Figure 1, was estimated by means of the PROCESS macro 3.5 for SPSS (customized Model 83; Hayes, 2018). A moderated mediation analysis was carried out to estimate the conditional indirect effect of type of data on patronage intention (Study 1) and expected discount amount (Study 2) through distributive justice, privacy disclosure, and consumer entitlement, moderated by type of incentive (Study 1) and level of effort (Study 2). A total of 5,000 bootstrap samples were used to obtain bias-corrected confidence intervals (CIs; 95%) and thereby assess the significance of the effects.

3.1.4 Construct Reliability and Validity

Factor analysis confirmed the factorial structure of the original scales in both Study 1 and Study 2, except for Item 7 of the Privacy Disclosure scale, which was removed from both studies due to the significant improvement of Cronbach's alpha after its deletion. The reliability for all scales was satisfactory, with Cronbach's alpha ranging between .87 (Distributive Justice) and .97 (Privacy Disclosure and Future Intentions). A confirmatory factor analysis provided support for the measures' convergent validity, with all factor loadings exceeding the recommended 0.6 threshold (Bagozzi & Yi, 1988), while the composite reliability (CR) and the average variance extracted (AVE) were greater than the recommended 0.7 and 0.5 thresholds, respectively (Fornell & Larcker, 1981). Accordingly, we averaged the items from the aforementioned scales to define the factors for the subsequent analyses. Table 2 below reports the scale items, Cronbach's alpha, CR and AVE

values.

(TABLE 2 ABOUT HERE)

3.2 Study 1

A total of 360 individuals (mean age = 36; 70% females) participated in Study 1. The goal of Study 1 was to estimate the theoretical model presented in Figure 1 and assess the moderating role of distributive justice. Accordingly, respondents were randomly exposed to one of the four experimental conditions resulting from a 2 (type of data: behavioral vs. biometric) × 2 (type of incentive: nonmonetary vs. monetary) between-subjects design.

Each of the four scenarios portrayed a shopping experience in a grocery retailer that had implemented a program for collecting data on customers visiting the store. Backed by the pretest results, the four scenarios differed in terms of the type of data collected by the retailer, as well as the benefit offered to customers in exchange for their data (i.e., distributive justice). In the behavioral data condition, participants were informed that the retailer was collecting POS data from all their transactions; in the biometric data condition, participants were told that the retailer installed ceiling cameras that used AI software to track each customer's in-store movements. In the nonmonetary condition, participants were informed that the retailer would use the data for statistical purposes to profile its customers and customize its offerings; in the monetary incentive condition, participants were told that the retailer would use their personal data to provide each customer with personalized, discounted prices on preferred products. As in the pretest, the written description of the scenario was accompanied by a short video (30 seconds) describing the situation in order to increase the vividness of the experimental manipulation.

3.2.1 Results

A confirmatory factor analysis supported the underlying dimensional structure of the constructs, which achieved high reliability values (all Cronbach's alphas > .90).

The results from the moderated mediation model confirmed the model robustness, as the 95% CI of the moderated mediation index does not contain zero (Index = -.095; 95% CI [-.236; -.008]).

As advanced in H2a, the biometric data lowered distributive justice (Effect = -.811; $p < .001$; 95% CI [-1.199; -.422]), which in turn positively affected privacy disclosure (Effect = .749; $p < .001$; 95% CI [.697; .802]), supporting H3. As hypothesized in H4, privacy disclosure improved consumer entitlement (Effect = .394; $p < .001$; 95% CI [.188; .601]), which was also influenced by distributive justice (Effect = .281; $p = .003$; 95% CI [.094; .467]). Finally, consumer entitlement exerted a positive impact on patronage intention (Effect = .075; $p = .021$; 95% CI [.011; .139]), thus supporting H5a. A significant direct effect emerged between behavioral versus biometric data on patronage intention (Effect = -.664; $p < .001$; 95% CI [-.859; -.469]), as hypothesized in H1a. In other words, distributive justice, privacy disclosure, and consumer entitlement partially mediated the relationship between behavioral versus biometric data and patronage intention toward the retailer. Overall, these findings support the causal mediation chain advanced in our theoretical model (Figure 1).

In addition, Study 1 supports the moderating role of the type of incentive on the relationship between behavioral versus biometric data and distributive justice (Effect = -.748; $p = .008$; 95% CI [-1.298; -.198]), as advanced in H2b. Specifically, the conditional effect at the values of the moderator shows that monetary incentives strengthen the relationship (Effect = -1.558; $p < .001$; 95% CI [-1.948; -1.169]) more than nonmonetary incentives (Effect = -.811; $p < .001$; 95% CI [-1.199; -.422]); an R^2 change equal to 0.016 ($p = .008$) supports the significance of the moderation. Finally, the indirect effect from the type of data to patronage intention through distributive justice, privacy disclosure and consumer entitlement was found to be significant for both nonmonetary (Effect = -.018; 95% CI [-.041; -.002]) and monetary (Effect = -.035; 95% CI [-.075; -.005]) incentives. The results of Study 1 are summarized in Figure 2:

(FIGURE 2 ABOUT HERE)

3.3 Study 2

A total of 360 individuals (mean age = 35; 75% females) were recruited from Prolific on the condition that they had not participated in Study 1. The goal of Study 2 was to estimate the theoretical model presented in Figure 1 and assess the moderating role of effort level. Accordingly, respondents were randomly exposed to one of the four experimental conditions resulting from a 2 (type of data: behavioral vs. biometric) × 2 (level of effort: low vs. high) between-subjects design. Similar to Study 1, the four scenarios portrayed a shopping experience in a grocery retailer that had implemented a program for collecting either behavioral or biometric data from customers visiting the store. In contrast to Study 1, all participants in Study 2 were informed that the retailer intended to use the data to provide each customer with personalized discounted prices that would be shown to customers on their self-scanning devices. However, Study 2 also manipulated the level of effort required from customers to visualize this personalized price. In line with the pretest, the low-effort condition involved customers seeing the personalized price on the screen of the self-scanner when scanning the related product; the high-effort condition required customers to scroll to the "my current balance" section of the self-scanner to see the retailer's personalized price for each scanned product. As in Study 1, the written scenario was accompanied by a short video (30 seconds) that described the situation in order to increase the vividness of the experimental manipulation.

3.3.1 Results

A confirmatory factor analysis supported the underlying dimensional structure of the constructs, which all achieved high reliability values (all Cronbach's alphas > .83). The results again support the robustness of the conceptual model (Index = .123; 95% CI [.006; .322]). As in Study 1, biometrics lowered distributive justice (Effect = -1.382; $p < .001$; 95% CI [-1.706; -1.057]), which increased privacy disclosure (Effect = .650; $p < .001$; 95% CI [.578; .721]) and in turn boosted consumer entitlement (Effect = .214; $p = .013$; 95% CI [.046; .382]). Finally,

consumer entitlement positively affected the expected discount amount (Effect = 1.584; $p < .001$; 95% CI [.674; 2.495]), as hypothesized in H5b. In Study 2, we found that the direct effect of behavioral versus biometric data on the expected discount amount was not significant (Effect = .681; $p = .610$; 95% CI [-1.939; 3.300]); instead, we uncovered a full mediation that runs counter to what was hypothesized in H1b.

The test for the moderation by level of effort showed a significant effect on the relationship between type of data and distributive justice (Effect = .558; $p = .017$; 95% CI [.101; 1.015]), as advanced in H2c. Specifically, the conditional effects at the values of the moderator show that low levels of effort strengthened the relationship (Effect = -1.382; $p < .001$; 95% CI [-1.706; -1.057]) more than high levels (Effect = -.824; $p < .001$; 95% CI [-1.146; -1.502]); an R^2 change equal to .013 ($p = .017$) supports the significance of the moderation.

Finally, the indirect effect from the type of data on the discount amount through distributive justice, privacy disclosure and consumer entitlement was found to be significant at both low (Effect = -.305; 95% CI [-.695; -.040]) and high (Effect = -.182; 95% CI [-.433; -.024) levels of effort.

The findings from Study 2 are summarized in Figure 3 below. Meanwhile, Figure 1 illustrates the overall increase in the ecological validity of the results from Study 1 for the causal mediation chain.

(FIGURE 3 ABOUT HERE)

4. General Discussion

Our research examines how consumers react to different types of data requests from retailers in terms of store patronage intention (Study 1) and the expected amount of personalized price reduction (Study 2). With regard to the type of data, our research compared behavioral and biometric data, finding that consumers react more favorably to requests for the former (such as POS data about their in-store purchases) than the latter. Specifically, customers perceive the request for behavioral data as more fair, which increases both their confidence about disclosing their data and

their sense of entitlement toward the retailer. These factors ultimately lead to higher patronage intentions (Study 1) and shape the amount of discount that customers will accept in exchange for their data (Study 2).

Furthermore, our research illuminated whether and to what extent the retailer's data collection purpose affects consumers' reactions. Indeed, the results from Study 1 support the hypothesis that providing customers with personalized, discounted prices significantly improves their reactions, as they perceive that incentive as a fair compensation for their data. In other words, personalized pricing strategies can be an effective tool for encouraging customers to share their data with the retailer.

Study 2 built on this finding by identifying consumers' ideal level of discount based on the data being exchanged. Specifically, Study 2 investigated how the type of data works alongside the level of effort required to obtain the personalized price to shape customers' expectations about the discount amount. The results from Study 2 corroborate Study 1 about the positive effects of behavioral data collection on perceptions of fairness: Procedures with fairer perceived outcomes mitigate customers' privacy concerns while increasing their sense of entitlement about receiving a benefit from the retailer. In addition, Study 2 showed that allowing customers to see the personalized prices with a low level of effort increases their distributive justice perceptions.

4.1 Theoretical Contribution

The present research aims to contribute to the existing literature in several ways. First, our research contributes to the growing literature on price personalization (Chen & Chen, 2017) by exploring how consumers react to requests for different types of data (i.e., biometric versus behavioral). Prior studies in separate domains have demonstrated that consumers display different levels of confidence toward these two types of data disclosure (e.g., Ioannou, Tussyadiah, & Lu, 2020; Phelps, Novak, & Ferrell, 2000). However, to the best of our knowledge, this is the first time that consumers' reactions to the disclosure of biometric versus behavioral data have been examined

by considering what retailers offer consumers in exchange for their data (e.g., personalized prices). In this vein, our study helps to advance scholarly knowledge by proposing and empirically testing a comprehensive theoretical model—one that compares consumers' reactions to retailers' requests for access to biometric versus behavioral data in order to customize prices. In this way, the present research addresses recent calls for a quantitative account of the drivers and barriers of success for technology-enabled pricing strategies (e.g., Riegger et al., 2021).

Second, advances in technology provide an increasing number of opportunities for retailers to offer personalized prices to customers. Despite the potential profitability of these technologies, they require input data in order to compute prices at the customer level, which might trigger privacy concerns from the consumer perspective (Inman & Nikolova, 2017; Martin et al., 2020; Pizzi & Scarpi, 2020). Our research supports prior studies that highlight the potential benefits of technology-enabled personalized prices (Liu & Zhang, 2006) and advances prior findings by incorporating consumers' privacy concerns. In doing so, this study originally combines two streams of literature that have scarcely crossed thus far: consumers' price perceptions and their privacy concerns.

The recent literature has examined how consumers react to discounted prices in terms of justice perceptions, which reflect the effort that customers must exert to benefit from personalized prices (Priester, Robbert, & Roth, 2020; Xia, Kukar-Kinney, & Monroe, 2010). However, it has almost completely overlooked the type of data that is requested from customers. This is not a trivial issue, as prior research has already established that the type of data significantly impacts consumers' privacy concerns (Graeff & Harmon, 2002; Milne et al., 2017; Wieringa et al., 2021), which are associated with distributive justice perceptions (Pizzi & Scarpi, 2020). Our results shed new light on how the type of data can trigger different levels of distributive justice perception and privacy disclosure. Specifically, our research documents that behavioral data yield higher distributive justice perceptions and confidence in disclosing personal information than biometric data.

Third, the present research addresses the role of consumer entitlement in the domain of pricing strategies. Specifically, the findings indicate the extent to which consumers feel entitled to expect more from the retailer in exchange for their personal information. Consumer entitlement has been extensively related to consumers' reactions to service failures (Li, Ma, & Zhou, 2017; Wolter et al., 2019) and price fairness (Xia, Kukar-Kinney, & Monroe, 2010). However, the existing literature has only begun to explore the relationship between consumers' privacy concerns and their entitlement. In this regard, Xia and colleagues (2010) found that consumer entitlement can be interpreted as a subjective sense of deservedness stemming from consumers' devoted level of effort. Therefore, one might expect that consumers who perceive that they are disclosing too much information to the retailer would feel more entitled because of this sense of deservedness. Conversely, our results show that consumers feel more entitled to compensation from the retailer when they perceive the outcome of the process to be fair, which increases their comfort with sharing their personal information. This finding can be interpreted in light of Polyakova, Estes, and Ordanini's (2020) study, which reported that providing customers with preferential treatments increases their entitlement. Accordingly, our research contributes to the literature by showing that the distributive justice of the retailer's offered treatment in exchange for consumer data enhances consumer entitlement via lower privacy concerns. In other words, the higher distributive justice of the treatment leaves customers more comfortable with disclosing their data, which then increases their entitlement.

Finally, our research addresses the role of two relevant moderators: type of incentive and level of effort. The type of incentive refers to what the retailer offers consumers in exchange for their data (monetary versus nonmonetary incentives). Prior literature has documented that consumers are more likely to share their data if the retailer provides them with personalized treatments (Mayser & von Wangenheim, 2013). The present work builds on this finding and shows that personalized pricing can be conceived as a monetary incentive since it tailors the price reduction to each customer's typical shopping pattern. In other words, personalized pricing

strategies make data disclosure appear more oriented toward the customer and moderate the impact of the type of data gathered on consumers' distributive justice perceptions.

The level of effort can be conceptualized as the amount of input that consumers are required to put forth in an exchange. Prior studies have found that effort is associated with consumers' fairness perceptions (Oliver & Swan, 1989). Relatedly, Xia et al. (2010) found that the fairness of the outcome counterbalances the effort connected to the relative difficulty of obtaining a personalized price. Our research aligns with these prior findings and extends them by showing that the level of effort significantly interacts with the type of data in shaping consumers' distributive justice perceptions. The different sensitivity to disclosing biometric versus behavioral data can be counterbalanced by the retailer giving consumers a simpler procedure for viewing their personalized prices.

4.2 Managerial implications

Retailers are gaining access to increasingly large amounts of data on customers visiting their stores. The proliferation of such data has been further boosted by retailers' mounting adoption of several in-store technologies. On the one hand, these data are of paramount importance to retailers' managerial decisions; on the other hand, retailers are well aware that consumers might be discouraged from disclosing personal information. Our research suggests that personalized pricing strategies might be a viable tool for incentivizing customers to willingly accept data disclosure. Indeed, customers perceive personalized prices based on their shopping habits as a fair compensation for their disclosed data. In this regard, our results show that consumers feel increasing levels of entitlement toward compensation (in the form of personalized prices) based on amount of perceived effort invested in the exchange. Accordingly, retailers are encouraged to carefully estimate the amount of customized price reduction that consumers perceive as fair depending on the type and amount of data they are asked to disclose.

Our results highlight that not all types of data are equally effective at activating consumers' privacy concerns. Specifically, behavioral data were found to induce milder privacy concerns because consumers perceive this data type as a fairer exchange for personalized prices than biometric data. Our results suggest that, if retailers opt to collect biometric data, then they should strive to counterbalance consumers' privacy concerns by improving the degree of benefit offered in exchange. Some retailers are already exploiting biometric data to provide, for instance, quick check-out (e.g., Amazon Go relying on computer vision machine learning solutions to track customers) or seamless payment options (e.g., Apple Pay's fingerprint or Visa's face recognition authentication). Retailers might further exploit biometric data to provide their customers with a more personalized shopping experience, such as using facial recognition technology to identify consumers' emotional reactions in front of the shelf (e.g., to detect if they are experiencing difficulties in finding products). Basing on our findings, retailers should abide by the principle that more sensitive data requests should be met with higher customer benefits. Relatedly, our results suggest that monetary incentives work better than nonmonetary incentives in counteracting consumers' potential negative reactions to biometric data disclosure.

Furthermore, our results shed some light on how consumers feel about the complexity of the procedure for displaying the retailer's personalized prices. Specifically, our findings show that consumers react more favorably when they can quickly check discounts during the shopping experience. From a technological point of view, this goal can be accomplished by implementing an application that is installed either on self-scanning devices or as a mobile app on customers' smartphones. In either case, the app should offer a user-friendly interface that highlights the personalized price of each product when scanned.

Our results may also help retailers adapt to the disruptive pace of innovation stemming from emergent technologies (Grewal et al., 2021). For instance, RFID tags allow the detection of customer behavior in real-time (Landmark & Sjøbakk, 2017); similarly, in-store sensors allow retailers to track consumers' paths to infer their behaviors while shopping (Van De Sanden,

Willems, & Brengman, 2019). This is to say, technology already provides retailers with the possibility of identifying customers throughout their entire shopping path and tracking their performed activities, which can then be used to send personalized messages or even charge personalized prices. The implementation of such automatic and interactive tools could potentially improve customer satisfaction and profitability. However, since all these activities imply gathering a considerable amount of data, our results can help retailers identify the boundary between providing value to the customer and discouraging patronage intention.

Finally, we focused on the costs and benefits for customers in terms of disclosing data to get personalized prices. However, it might be worthwhile to consider the retailer's cost in offering personalized prices to obtain sensitive customer data. Accordingly, retailers need to weigh the costs and benefits of obtaining such information before implementing such strategies. Our results shed light on the amount of personalized price discount that consumers expect, which can help retailers quantify the cost of the price reduction and minimize their losses.

4.3 Limitations and future research

Our research is not without its limitations. First, the two experiments both relied on a scenario-based approach. Although prior studies acknowledge that this approach is suitable for investigating justice-related topics (Collie, Bradley, & Sparks, 2002; Xia, Kukar-Kinney, & Monroe, 2010), a field experiment would provide higher ecological validity (Viglia et al., 2019), albeit in a less controlled environment. Relatedly, price personalization might be more problematic in the context of stores that manage huge product assortments and see average basket sizes in excess of 50 items (e.g., in superstores). In this case, consumers may perceive that checking personalized prices for each item would entail a significant increase in effort, and thus be reluctant to do so. As such, future studies might attempt to replicate our findings in a real retail setting.

Second, Study 1 treated the type of incentive dichotomously, comparing individuals' reactions to data disclosure for a purely profiling purpose (i.e., all the benefits are for the retailer) or

for a personalizing purpose (i.e., benefits shared between the retailer and the customer). However, this manipulation does not consider the different levels of distributive justice perceptions that would stem from the *magnitude* of the price reduction. Study 2 partially filled this gap by using the amount of expected discount as a dependent variable. However, future studies could conduct a more in-depth investigation that includes a broader range of personalized, discounted prices. In addition, participants in our study were not aware of the prices charged to other customers. However, recent literature has shown that consumers develop different price fairness perceptions based on comparisons with other customers (Lastner et al., 2019). In our study, we purposely did not manipulate the prices charged to other customers in order to isolate the effect of the type of data and incentive on each customer's distributive justice perceptions. While distributive justice and fairness are related constructs, the latter reflects a comparative judgment—which includes what is provided to other customers. For this reason, future research might supplement the theoretical model with the type of incentive provided to other customers.

Finally, our studies found a relationship between privacy disclosure and consumer entitlement that might sound a bit counterintuitive with respect to prior findings. Specifically, building on the findings by Xia et al. (2010), one might expect that consumers' sense of deservedness would increase if they perceived that they are disclosing too much information to the retailer. Conversely, in our studies, customers exhibited higher levels of entitlement as they became more comfortable with sharing their personal information (as a result of perceiving a fair process). This finding might stem from the fact that our participants did not have the chance to choose whether they were willing to share their data with the retailer. Future studies might further explore this issue, assessing whether there is a systematic difference in consumer entitlement between customers who do and do not accept the disclosure of their personal information.

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Table 1
Summary of the literature

Key issues	Description of issue	Main findings	Some key publications	Our incremental contribution
Personalized pricing	This stream of research highlights the benefits brought by personalized pricing strategies and the potential impact of customer-level data on the accuracy of price estimations.	Algorithmic pricing is a suitable approach for optimizing the prices of products in an assortment at the customer level. Algorithms need to be fed a considerable amount of data to deliver an accurate price estimation. Biometric data provide more fine-grained information to estimate customers' price elasticity at the individual level. Delivering an accurate personalized pricing strategy improves retailers' profitability but can also activate customers' privacy concerns.	Bradlow et al. (2017) Buhmann, Paßmann, & Fieseler (2019) Fisher, Gallino, & Li (2018) Garaus, Wagner, & Rainer (2021) Miettinen & Stenbacka (2015) Miklós-Thal & Tucker (2019) Sahay (2007)	The present work originally incorporates previous studies on consumers' privacy concerns which might potentially emerge as a consequence of retailers' personalized pricing strategies based on behavioral or biometric data of the customer. We empirically test whether and to what extent a price personalization strategy, based on biometric data, affects consumers' perceptions and behavioral intentions.
Privacy disclosure	This set of studies examine how consumers react when they are asked to provide personal information to companies. The relative balance between what consumers receive from the firm in exchange for their data and the sensitiveness of the information provided affects consumers' disclosure intentions.	Personal information is more likely to be disclosed by individuals when the benefits offset the risks. Consumers are more likely to disclose their data when they perceive the exchange with the retailer to be fair. Reciprocity in the social exchange between the customer and the retailer lowers customers' information collection concerns. The severity of consumers' privacy concerns can be ascribed to the type of information requested, with biometric data triggering higher concerns than behavioral data. Customers' willingness to share their behavioral and biometric data depends on non-monetary incentives, such as the level of product/service personalization they receive in exchange	Cloarec, Meyer-Waarden, & Munzel (2021) Dinev & Hart, 2006 Grewal et al. (2011) Ioannou, Tussyadiah, & Lu (2020) Martin, Borah, & Palmatier (2017) Maseeh et al. (2021) Schmidt, Bornschein, & Maier (2020) Phelps, Novak, & Ferrell (2000)	The present study attempts to address recent studies' call for further research exploring the impact of biometric data on individuals and how companies can overcome biometric-related privacy concerns. Indeed, no prior studies have attempted to compare how consumers' reactions to disclosing behavioral and biometric data vary as a function of the type of incentive (monetary versus nonmonetary) provided in exchange for their data.

Table 2
Construct measures

Items	Cronbach alpha		AVE		CR	
	S1	**S2**	**S1**	**S2**	**S1**	**S2**
Distributive Justice (adapted from Blodgett, Hill and Tax, 1997)	.91	.87	.77	.71	.91	.88
Given the investment I would need to make to receive a personalized discounted price, the final outcome that I will receive is fair						
The outcome of the retailer's implementation of personalized discounted prices would be fair for me						
Considering the inconvenience that obtaining personalized discounted prices might cause me, the outcome that I would receive would be more than fair						
Privacy Disclosure (as in Pizzi and Scarpi, 2020)	.97	.96	.86	.81	.97	.96
I feel like my privacy would be protected at this retail store						
I would feel safe in my shopping experiences with this retail store						
I would feel comfortable sharing my information with this retailer						
I would feel safe sharing my information with this retailer						
I think my benefits gained from sharing my data would offset the risk of my information disclosure						

The value I would gain from personalized prices is worth the information I give away						
I think the risks of my information disclosure will be greater than the benefits gained from the personalized prices						
Consumer Entitlement						
(as in Xia, Kukar-Kinney and Monroe, 2010)	.95	.94	.87	.84	.95	.94
I feel that I am entitled to obtain a personalized discounted price						
I feel that I deserve a personalized discounted price from the retailer						
I think I should get the personalized discounted price on the products I choose						
Future Intentions						
(adapted from Inman and Nikolova, 2017)	.97	-	.94	-	.98	-
(1- Much lower than before to 7 – Much higher than before)						
My willingness to purchase from this retailer would be						
My willingness to visit this store in the future would be						
My willingness to recommend this retailer to my friends and relatives would be						

Figure 1: The Theoretical Model

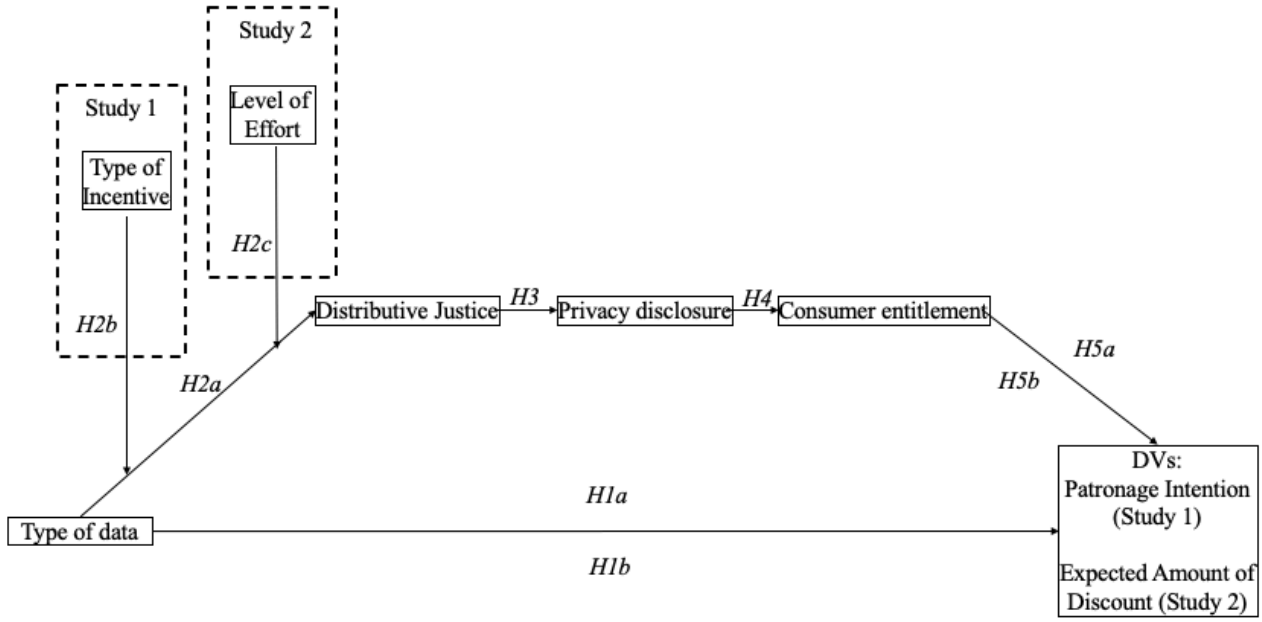
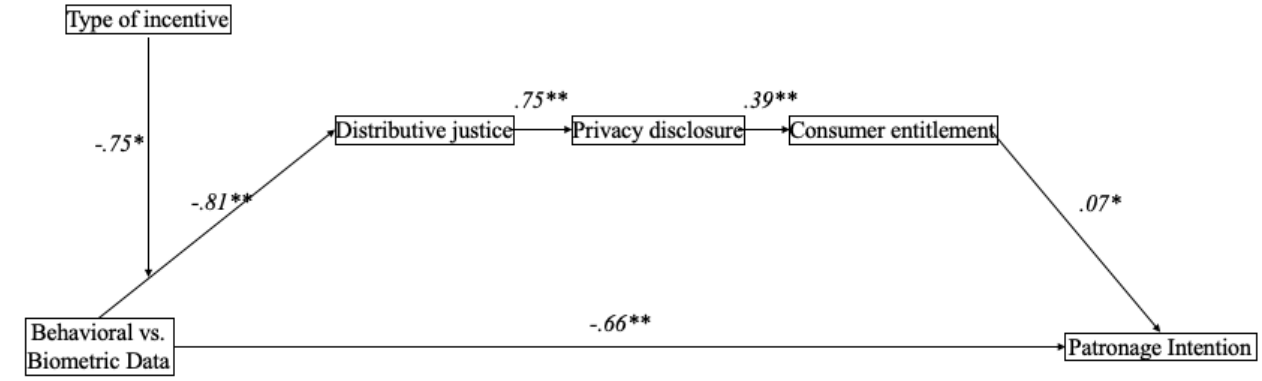
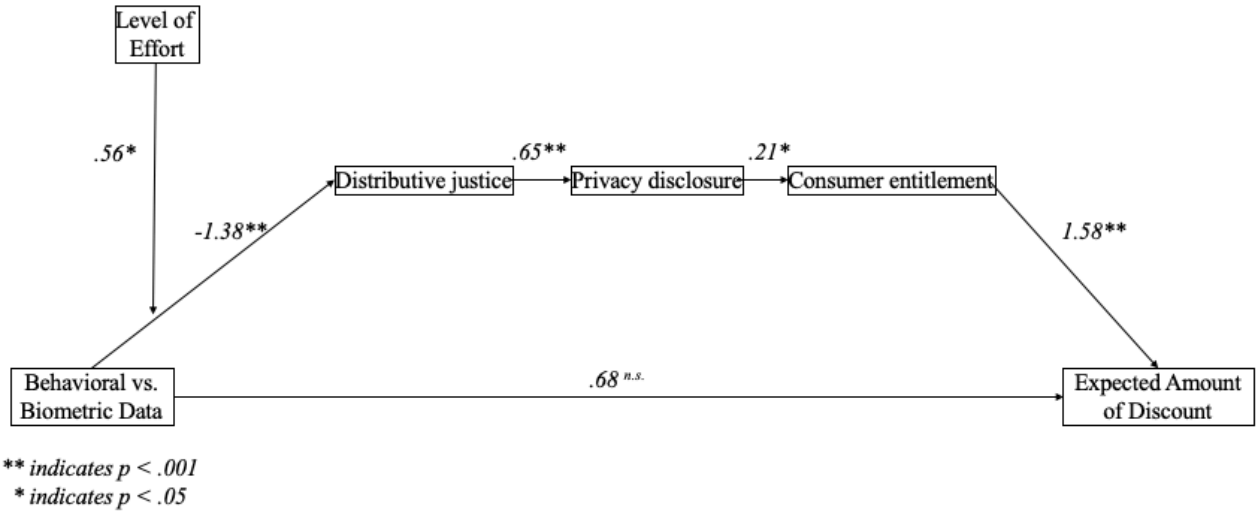


Figure 2: Results from Study 1



** *indicates* $p < .001$
* *indicates* $p < .05$

Figure 3: Results from Study 2



** *indicates* $p < .001$
* *indicates* $p < .05$

Appendix A: Scenarios used in Study 1

Behavioral Data and Nonmonetary Incentive

The retail store where you usually do your grocery shopping decided to implement a new system to **profile customers** to understand which products their customers are more interested in.

To identify your preferred products, the retailer will collect all check-out data from your previous purchases and will run some analyses on your typical basket composition.

Biometric Data and Monetary Incentive

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in.

To identify your preferred products, the retailer will install cameras across the store area to scan your movements throughout the store and identify your preferences accordingly to provide you with a personalized discount on your preferred products.

Behavioral Data and Monetary Incentive

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in.

To identify your preferred products, the retailer will collect all check-out data from your previous purchases and identify your preferences accordingly to provide you with a personalized discount on your preferred products.

Biometric Data and Non-Monetary Incentive

The retail store where you usually do your grocery shopping decided to implement a new system to **profile customers** to understand which products their customers are more interested in.

To identify your preferred products, the retailer will install cameras across the store area to scan your movements throughout the store and will run some analyses on your typical path throughout the store.

Appendix B: Scenarios used in Study 2

Behavioral Data and High Effort

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in. Personalized prices will be displayed to each customer on the **self-scanning device** used during the shopping trip.

To identify your preferred products, **the retailer will collect all check-out data from your previous purchases** and will run some analyses on your typical basket composition.

Every time you scan a product, it will be put into your basket with a personalized price**, and you will have to check in the "my current balance" section to see which price has been charged by the retailer.**

Biometric Data and High Effort

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in. Personalized prices will be displayed to each customer on the **self-scanning device** used during the shopping trip.

To identify your preferred products, **the retailer will install cameras across the store area to scan your movements throughout the store** and identify your preferences accordingly.

Every time you scan a product, it will be put into your basket with a personalized price**, and you will have to check in the "my current balance" section to see which price has been charged by the retailer.**

Behavioral Data and Low Effort

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in. Personalized prices will be displayed to each customer on the **self-scanning device** used during the shopping trip.

To identify your preferred products, **the retailer will collect all check-out data from your previous purchases** and will run some analyses on your typical basket composition.

Every time you scan a product, it will be put into your basket with a personalized price: **the self-scanner will display the personalized price that the retailer has set for you on its screen.**

Biometric Data and Low Effort

The retail store where you usually do your grocery shopping decided to implement a new system to provide customers with **personalized prices,** which include a discount on the products each customer is more interested in. Personalized prices will be displayed to each customer on the **self-scanning device** used during the shopping trip.

To identify your preferred products, **the retailer will install cameras across the store area to scan your movements throughout the store** and identify your preferences accordingly.

Every time you scan a product, it will be put into your basket with a personalized price: **the self-scanner will display the personalized price that the retailer has set for you on its screen.**