The Impact of Perceived Availability of Consumer Data on Loyalty in Retail Channels: A Relational Exchange Perspective

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Abstract

Purpose – By building on social exchange theory, this study investigates the role of perceived availability of consumer sensitive data in shaping consumer loyalty by proposing and testing a conceptual model that considers both a negative (through perceived risk) and a positive (through perceived convenience and perceived inspiration) mechanism underlying this phenomenon. The study also explores the moderating role of purchase channel (online vs. offline) in the relationship between perceived availability of consumer sensitive data and perceived risk, perceived convenience, and perceived inspiration.

Design/methodology/approach – A field study with 923 retail consumers was carried out across 13 UK grocery retailers from both online and offline channels (e.g., Tesco, Asda, Morrison's, Ocado, Aldi, Waitrose, and Lidl). The statistical analysis was conducted using a partial least squares approach.

Findings – Results show that perceived availability of consumer sensitive data impacts consumer loyalty towards the retailer through the mediating mechanisms of perceived risk, convenience, and inspiration, which help shape consumer relationships with retailers. Our findings suggest that the online channel can improve the retail shopping experience and thus contribute to consumer acceptance of data disclosure.

Implications - Through the availability of consumer sensitive data, retailers could improve consumers' perceived convenience and inspiration by showcasing how their products or services provide consumers with a sense of meaning, purpose, and connection. Additionally, retailers should empower consumers with control over their personal data and its use, enabling them to manage their data preferences effectively, and they should be aware of the varying levels of sensitivity in personal data and so tailor consumer data collection strategies accordingly.

Originality – By advancing on the social exchange theory, we demonstrate the moderating effect that online versus offline channels can have on the relationship between perceived availability of consumer sensitive data and the three mediators regarding perceived risk, perceived convenience, and perceived inspiration. Managerial relevance of this study is evidenced through the reciprocated exchange orientation, whereby availability of sensitive data that consumers may perceive as either high (online data disclosure beyond demographic information) or low (offline interaction associated with the exchange of demographic information) can offset the perceived risk and gain perceived convenient and inspirational experience.

Keywords: inferred availability of sensitive data, privacy, benefits, relationship marketing.

Introduction

In today's retail environments, gathering and processing consumer information, as well as transforming it into superior offerings, is increasingly being taken over by consumer relationship management technology (Bleier and Eisenbeiss, 2015a; Palmatier and Crecelius, 2019; Brüggemann and Olbrich 2022; Grewal et al 2022), for example through artificial intelligence (AI) powered algorithms that collect and combine personal data (e.g., historical purchasing and browsing behaviour) from collaborative efforts of suppliers, other retailers, and end-users. One illustration is Kellogg's and Tesco sharing data to identify purchase patterns by using predictive modelling and machine learning to personalize customer interactions, predict customer needs, and provide tailored product recommendations (e.g., Grewal and Roggeveen, 2020; Knijnenburg and Kobsa, 2013; Zhang et al., 2010).

However, these technological developments bring new complexities into the consumer experience, with advances in AI having undoubtedly altered the retail landscape. When shopping both online and in-store, consumers have got used to explicitly or implicitly providing sensitive data; that is, information which goes beyond demographic data and that is more personal, such as financial or medical records (GDPR, 2016). For example, webrooming, digital payment systems, and mobile shopping have become the norm, and have left a trail of consumer behaviours and actions behind them (MacDonald, 2019). Both online and offline shopping channels thus provide retailers with data that have become a source of power through which to deliver highly personalized loyalty programmes such as incentives, rewards, products, and services that contribute to customers' quality of life and well-being –concepts that are attracting increasing attention in retail marketing (Roggeveen and Sethuraman, 2020).

Collecting consumer data is a form of reciprocal exchange that evolves over time into mutually trusting, loyal, and committed long-term relationships (Emerson, 1981). The Social Exchange Theory (SET) posits that when deciding whether to participate in the exchange, people assess the worth of a social exchange through a subjective comparison of benefits and costs (Blau, 1964; Molm et al., 2000). As stated by Blau (1964), costs are negative outcomes of the exchange that can be intangible (e.g., making one's personal data available to companies), while benefits are the rewards received from social exchange and that can also be intangible (e.g., customized interactions with companies (see Urbonavicius et al., 2021). The costs and benefits of the social exchange could therefore be identified from the context itself.

For example, Nespresso uses the huge amount of data collected from its customers to improve consumer interactions with the brand. Nespresso collects as much information as it can about each individual customer, thereby fulfilling the first assumption of the SET (Cook et al., 2013); that is, consumers' desire to increase gains and to avoid losses during the exchange. Nespresso then uses this knowledge to recognize and inspire customers at every touch point across the various online and offline channels, and even e-mails customers a reminder to decalcify their Nespresso coffee machine at specific intervals after a purchase. This ties in with the second assumption of the SET, where the exchange is structured by mutual dependence, in this case with through Nespresso encouraging customers to share detailed information by joining the Espresso Club. In return, members gain free access to a broad array of services, such as the Nespresso Boutique pick-up service, automated online ordering, and Nespresso Assistance. This links to the third assumption of the SET; namely, that exchange and mutual benefits require long-term cooperation, while the perceived value of the exchange will diminish following the law of marginal utility. Nespresso's aim is to stimulate customer engagement, increase perceived value, and strengthen the customer-retail relationship that is built through trust, commitment, and loyalty.

As sensitive data are becoming an increasingly important source for competitive advantage (Brown et al., 2003; Kim and Kim, 2004; Schumann et al., 2014), retailers have started to leverage consumer data across channels, to provide superior shopping experiences, and to fuel consumer loyalty (e.g., Schumann et al., 2014; Verhoef et al., 2010). Indeed, consumer loyalty is key to marketing strategy as it reflects a deeply held commitment to repeat purchase or re-patronize a retail outlet or service in the future (Oliver, 1997). Retailers have recently been adopting technologies, such as mobile apps, self-scanning, smart shelves, gravity feed shelving systems, and ‘scan and go’ for data collection purposes (Inman and Nikolova, 2017). Similarly, advances in salient retail technologies help convert data and information into superior knowledge about the consumer (Grewal and Roggeveen, 2020; Prince, 2018; Wang et al., 2016).

Leveraging consumer data beyond the individual transaction (Kim et al., 2015; Narayanan and Manchanda, 2009) implies a trade-off situation for consumers. On the one hand, complying with retailers’ direct or more subtle data requests provides opportunities to receive individualized offers with greater convenience such as personalized product offerings, prize discounts, enhanced experiences, or personalized marketing communications (Bleier and Eisenbeiss, 2015ab; Chen et al., 2021; Shankar et al., 2016). On the other hand, sensitive data in the hands of a retailer entails higher levels of risk, as data may be misused by retailers themselves or passed onto third parties (e.g., Martin et al., 2017). Leveraging consumer data thus reflects the current societal and political debate concerning the collection and use of personal information, which has resulted in marketing researchers actively addressing the risk-related facets surrounding the occurrence and role of sensitive data in consumer-business relationships

(Chen et al., 2021). In turn, this could have adverse effects for retailers, with consumers either avoiding personalized offers or engaging in switching behaviour (Gruntkowski and Martinez, 2022).

Existing studies have explored the role of perceived risk *prior to* the provision of sensitive data (Bleier and Eisenbeiss, 2015b; Krasnova et al., 2012; Martin and Murphy, 2017; Norberg et al., 2007; Wang et al., 2016). However, no research to date has investigated perceived availability of consumer sensitive data to retailers and its perceived risk and benefits on consumer-related outcomes such as loyalty. AI, augmented/virtual reality (AR/VR), smart displays, as well as mobile devices and applications (Agarwal et al., 2020) have the potential to re-invent loyalty efficiency. Examples include highly personalized incentives such as points, rewards, products, and services that are integrated into a larger network of connected objects such as wearables, smart home appliances, personal assistants (e.g., chatbots, voicebots), and other sensors that reinforce consumers' purchase behaviours and their relationship with the retailer (Chen et al., 2021). Yet these new technologies also come with new challenges (e.g., data privacy concerns), which have thus far received little attention. Exploring this area may therefore prove relevant as it may cause different cognitive reactions in terms of perceived convenience and inspiration, in addition to perceived risk, which might significantly impact consumer loyalty.

Under the lens of the SET (Blau, 1964), this research examines how the *perceived availability of sensitive consumer data* –understood as consumer perception of the availability of their sensitive data in terms of breadth and depth of both profile and personal information to retailers (Bleier & Eisenbeiss, 2015b)– affects loyalty in retail channels, with the mediating roles of perceived risk, perceived convenience, and perceived inspiration. We also test the moderating effect of purchase channel (online vs. offline) in the relationship between perceived availability of consumer sensitive data and perceived risk, perceived convenience, and perceived inspiration.

Understanding these dynamics is essential, as the magnitude of perceived data disclosure may influence consumers' channel preferences, potentially driving them towards offline channels in response to heightened risk perceptions, or segmenting the market by channel affinity (Breugelmans et al., 2023; De Keyser et al., 2015; Konus et al., 2008; Sands et al., 2016).

By addressing this gap, our study makes two primary contributions. First, we contribute to consumer experience and privacy literature by providing additional insights for retailers to maintain loyal consumers, given the acceptance of perceived availability of consumers' sensitive data through enhanced and superior services. We specifically investigate moderating and mediating variables that help to explain customers' decisions regarding whether to maintain or terminate a relationship based on the subjective benefits and the risk associated with perceived availability of consumers' sensitive data.

Second, we contribute to the development of social exchange theory (Bagozzi, 1975; Blau, 1964; Cook et al., 2013) by providing a more nuanced understating of how the perceived availability of sensitive consumer data influences loyalty through the dual pathways of the privacy calculus framework (Culnan & Armstrong, 1999), where benefits such as perceived convenience and perceived inspiration are weighed against perceived risks. Our findings clarify the reciprocal nature of consumer-retailer relationships and highlight that consumers weigh up the benefits of personalization against potential privacy risks when deciding whether or not to share sensitive data. Observed through opt-in and opt-out choices, this dynamic underscores' the importance for retailers of maintaining a careful balance between leveraging customer data to enhance loyalty offerings and protecting consumers' privacy rights. Moreover, we show that this trade-off is moderated by channel-specific exchange orientation, which is seen to be higher in online channels –where consumers perceive greater benefits but also higher risks– and lower in offline channels –where data disclosure and associated risks are more limited. By identifying these mechanisms, our research offers new insights into how personalized services and channel strategies can be optimized to build long-term consumer loyalty within the framework of social exchange.

Conceptual and theoretical background

Consumer sensitive data in the retailer-customer relationship

Consumer sensitive data are a special category of data that relate to an identifiable consumer and that go beyond mere demographic information, and the processing of which is deemed to pose a risk to the consumer's identity (GDPR, 2016). The risk may derive from the categories of information considered, such as financial and medical health records, and more particularly from a possible misuse of that information that can lead to identity theft (Krishnamurthy and Willis, 2009; Posey et al., 2010). In a retailer-customer relationship, sensitive data disclosure often occurs through a reciprocal process in which consumers gradually reveal more information about themselves over time (Derlega et al., 1993) in exchange for more personalized ad text with user-posted personal information, relative to generic text (Tucker, 2014), and unique experiences (Chen et al., 2021; Roggeveen and Sethuraman, 2020).

With regard to the nature of sensitive data, existing conceptualizations suggest that most specific individual consumer information used for marketing purposes falls into the following three collectively exhaustive categories: (1) demographic characteristics (e.g., age, gender) (Josiassen et al., 2011; Pearson et al., 1991; Slama and Tashchian, 1985), (2) lifestyle characteristics (e.g., media habits) (Barth and de Jong, 2017; Lai-yee and Leung, 2006), and (3) shopping/purchasing habits, location data, financial data, and personal identifiers (e.g., names, addresses, social security numbers, photographic images, fingerprints, and other biometric images) (Altman and Taylor, 1973; Foxman and Kilcoyne, 1993; Hughes, 1994; Nash, 1993; Nill and Aalberts, 2014; Nowak and Phelps, 1995; Prince, 2018). Essentially, consumers make decisions on whether to disclose their personal information to retailers based on the benefit they receive in terms of enhancing their shopping experience or convenience. More recently, data disclosure aims to provide real time positioning to achieve accurate offerings within a nearby retailer proximity. Such a proximity solution can provide nearby shoppers with additional information regarding the specific product they are looking for (Wang, 2021).

When examining self-disclosure, the literature looks at how firms collect and acquire consumers' data from multiple sources that include demographic data as well as sensitive information. It is an act manifesting authorization granted to firms to access consumers' data (Martin et al., 2017). This is usually acquired gradually, with retailers first requiring consumers to provide their personal information when they register for the first time online. During later interactions, companies will also periodically alert consumers to update their relevant information. In this sense, the decision regarding whether to disclose data and which data to capture is transferred from the firm to the consumers themselves (Moon, 2000; Utz, 2015; Zeng et al., 2021). No research to date has unified the definition of self-disclosure from the perspective of consumers when they consent to data collection (see Table 1 for a summary of prior literature on data disclosure).

[Insert Table 1 around here]

This research investigates what consumers perceive when they consent to data collection from retailers who can thus access socio-demographic information and acquire sensitive personal information during and after their interaction. We therefore define sensitive data disclosure as the overall amount of data disclosed about a consumer, whether acquired or given through explicit means (i.e., consumers have provided the sensitive data) or implicit means (i.e., retailers have obtained the sensitive data without consumers necessarily being aware). Nevertheless, there are two key distinctions worth noting: whether the data is given or acquired, and which will thus determine whether personal information gathered is courtesy data –such as demographic data –or sensitive data disclosure.

Extant data privacy research has investigated how and why consumers allow retailers to acquire sensitive data and what the consequences to consumer willingness to disclose such data are (see Martin and Murphy, 2017, for a review). When investigating the antecedents to data disclosure, attention has focused on how consumers feel about disclosing their sensitive data (Aquisti et al., 2012; Mothersbaugh et al., 2012; White, 2004) and on the handling of consumer data (Acquisti et al., 2013; Bleier and Eisenbeiss, 2015a,b; Tucker, 2014; White et al., 2008), with emphasis on privacy concerns (Aguirre et al., 2015; Malhotra et al., 2004; Norberg et al., 2007; Smith et al., 1996), consumer vulnerability (Acquisti et al., 2013; Awad and Krishnan, 2006; Dinev and Hart, 2004; Mothersbaugh et al., 2012), and organizational privacy communication (Martin et al., 2017).

Regarding the consequences of data disclosure, it has been acknowledged that sensitive data can provide benefits to the retailer through personalization, as consumers feel more connected (Lee et al., 2019) through trust or a belief that retailers are able to handle personal data correctly and with discretion. It has also been noted that consumer sensitive data available to retailers can provide consumers with tangible benefits, such as personalized financial offers (Acquisti and Varian, 2005; Bleier and Eisenbeiss, 2015a; Chellappa and Sin, 2005; Schumann et al., 2014), or intangible benefits, such as personalized products and services that can enhance satisfaction (Chellappa and Sin, 2005; Ko and Kuo, 2009; Mothersbaugh et al., 2012). By leveraging such data –particularly online– retailers can customize their offerings by adapting site content, offerings, layout, and communication (Alpert et al., 2003). Customization can be achieved passively, for example when websites automatically infer preferences based on browsing patterns, or actively when shoppers directly provide preference information (Alpert et al., 2003; Dinev and Hart, 2006; Krasnova et al., 2012; Li et al., 2010; Schumann et al., 2014; Wang et al., 2016).

There is, however, little research in the empirical literature investigating what role sensitive data may play in shaping the retailer-customer relationship, with no study to date having adopted a more comprehensive approach towards assessing sensitive data, taking into consideration its multiple facets (e.g., data related to demographics, lifestyle characteristics, shopping habits or financials). By conceptualizing the extent to which consumers believe their retailers have access to their personal data as an antecedent to consumer loyalty, this study aims to shed light on the role of perceived risk and benefits by explaining how perceived availability of consumer sensitive data affects consumer loyalty.

Consumer sensitive data and social exchange theory

Social exchange theorists conceptualize exchange relationships in terms of costs and rewards and relate these to relational outcomes such as loyalty (Awad and Krishnan, 2006; Bagozzi, 1975; Blau 1964). Drawing on the concept of reciprocity, the SET suggests a reciprocal exchange between two partners involved in a relationship, in which a benefit received from one partner results in an obligation to repay the benefit to the other partner.

We base our conceptualization of data disclosure on the SET, which considers direct social interactions between actors through four elements: trust, commitment, reciprocity, and power. By adapting the SET to develop the conceptual model of our study, we draw on prior data disclosure research to help model the attributes of data disclosure in a retailer-consumer relationship context (Cropanzano et al., 2017; Malhotra, et al., 2004; Urbonavicius, et al., 2021). To identify the benefits and costs of social exchange in a retail context, we consider the underlying attributes of the SET, with social exchange theorists classifying information as one of the exchanged resources (Foa and Foa, 1974). Cheshire (2007) argued that information can be a valuable resource of exchange as it is "much like any other good, since it can be transferred, and it has value." (p. 83). Disclosure of personal information in purchasing channels is thus one of the processes of social exchange. Exchange participants expect to gain benefits, and the exchange is typically repeated by nature and structured by the interdependence and power relations of the exchange partners. It is acknowledged that the perceived availability of consumer sensitive data related to decisions is mostly situational and strongly dependent on the purpose and context of the information disclosure (Bansal et al., 2016; Malhotra et al., 2004; Masur, 2019; Omrani and Souli'e, 2018). The context of perceived availability of consumer sensitive data is based on the mutual trust of the interacting partners, which encourages reciprocal exchange, with mutual trust being the fundamental underlying attribute of loyalty (Anderson and Srinivasa, 2003; Gummerus et al., 2004; Sirdeshmukh, et al., 2002). In the context of our study, the positive outcome is therefore loyalty, which lies within the scope of the SET.

Most personal information exchange situations in e-commerce, such as purchasing and browsing online, are examples of negotiated exchange (Szymczak et al., 2016; Yang, 2019). Marketers collect personal information in exchange for the offered benefits; in other words, access, convenience, inspiration or monetary compensation in the form of discounts or bonuses (Malgieri and Custers, 2018) and the process is formalized in terms of agreement or permission to use personal data. Perceived availability of consumer sensitive data thus largely depends on perceived trust to allow for the exchange of intangible resources –perceived convenience and perceived inspiration– which are received as positive outcomes of the exchange (Blau, 1964; Cropanzano et al., 2017). Risk is an inherent attribute of any exchange relation (Molm et al., 2000), since partners are never sure if the other side will reciprocate, or whether they themselves will obtain any benefit in exchange for the perceived availability of consumer sensitive data. Social media involvement is one example of a situation with a reciprocal exchange of personal information (Yang, 2019). People share personal information on social media in exchange for social support, recognition, and other benefits which they expect to gain from their exchange partners (Szymczak et al., 2016).

In line with Cook et al., (2013), in the retail context of our study we adapt the traditional elements as follows. First, we conceptualize loyalty as an adjunct to trust, acknowledging that digitalization and emerging technologies afford significant opportunities for developing robust loyalty programmes. Second, we introduce perceived availability of sensitive data as a proxy for commitment, implying that retailers are dedicated to delivering personalized experiences that sustain long-term consumer relationships. Third, we align the constructs of convenience and inspiration with the principle of reciprocity, suggesting that the continuity of the consumer-retailer relationship depends on the tangible benefits received by consumers. Finally, we reframe perceived risk in lieu of power, recognizing that retailers possess the capacity either to provide personalized experiences or to exploit consumer data. In summary, we replace the notion of ‘cost’ with perceived risk while framing ‘convenience’ and ‘inspiration’ as the primary benefits that constitute social exchange (Malgieri and Custers, 2018). This theoretical adaptation tailors the conceptual framework to the unique dynamics of the retail environment. To help conceptualize the relationship between sensitive data and relational outcomes in consumer-retailer relationships, the SET is useful in two ways. First, as regards the obligation to repay the benefits received, one can think of personal information as being given in exchange for a reward that can be influenced by social norms, self-interest, and the quality of the relationship with the retailer. Second, the SET suggests that consumers perform a risk-benefit analysis in assessing the outcomes they receive when providing personal data to retailers. In an effort to explain consumer willingness to disclose sensitive information, privacy literature has contextualized the SET to derive the privacy calculus model (Dinev and Hart, 2006).

The privacy calculus model suggests that the extent of data disclosure results from balancing the benefits against the risks which are assumed to occur due to disclosure (Chellappa and Sin, 2005; Martin et al., 2017; Pavlou, 2011). That is, each cumulative effect (e.g., benefit) can outweigh the other (e.g., risk) when determining a consumer’s final decision concerning the availability of their sensitive data. For example, if the cumulative effect of perceived risk is higher than the cumulative effect of perceived convenience and inspiration, consumers will more likely refrain from disclosing their sensitive data.

Privacy risk stems from the potential opportunistic behaviours of the receiver that can occur when an individual discloses personal information about how information is collected, recorded, stored, and used (Dekimpe, 2020; Dinev and Hart, 2006), which can lead to negative affective reactions (e.g., anger and anxiety). On the positive side, benefits can be seen as the favourable results of disclosure behaviour, and can encompass financial or monetary rewards, personalization, or social benefits such as shopping enjoyment (Smith et al., 2011). Awad and Krishnan (2006) suggest that when consumers have different perceptions about benefits they may perceive different outcomes for different contexts.

Data disclosure across different channels

Data disclosure in retailing has changed dramatically over the last two decades due to the advent of the online channel and ongoing digitalization (Christensen and Raynor, 2003). In the past, data disclosure channels (e.g., grocery stores, both online and offline) were viewed as intermediaries that helped distribute and transfer products from manufacturers to their consumers. As a result, retailers employed a single channel that disclosed data on their consumers, such as a physical store, a call centre, or a catalogue. However, there were also instances where retailers employed multiple channels to enhance consumer convenience through multichannel marketing. The idea of multichannel marketing moved beyond product fulfilment to include a whole range of interactions between retailer and consumer (Neslin et al., 2006, p. 96). Although consumers may interact across multiple channels before a conversion occurs, in a multichannel context the retailers' focus is on managing and optimizing the performance of each channel separately.

With the continued growth in digitalization and AI systems, consumers today interact with retailers across multiple channels simultaneously –online, mobile, and offline channels– known as "omnichannel" marketing. Omnichannel marketing emphasizes more fluid data collection on consumer behaviour through a unified consumer experience rather than just facilitating transactions (Grewal and Roggeveen, 2020; Verhoef et al., 2015). Indeed, for retailers, omnichannel marketing entails managing a combination of different types of channels in a single unified experience so that they align well with the way their customers search, purchase, and consume their products and share those experiences (Ailawadi and Farris, 2017; Teixeira and Piechota, 2019). The advancement of AI also facilitates collaborative efforts with suppliers and end users for an integrated system of personalized marketing actions and marketing communications that offer tangible (e.g., discounts, vouchers, or gifts) or intangible (e.g., personalized service, status, or information) rewards (Bombaij and Dekimpe, 2020; Steinhoff and Palmatier, 2016). For example, Walmart and Google are collaborating on voice-controlled shopping capabilities to induce perceived value for their customers, who may become more willing to enrol and stay with retail loyalty programmes, thereby reinforcing their purchase behaviours and relationship with the firm.

Conceptual model and hypotheses

Our conceptual model draws on the SET and links the extent of the sensitive data that consumers perceive to be available to retailers with consumer loyalty through three mediating variables. One variable is *perceived risk*, which is consumers' "subjective evaluative assessment of potential losses to the privacy of confidential personally identifying information, including the assessment of potential misuse of that information that may result in identity theft." (Featherman et al., 2010, p. 220). Another variable is *perceived convenience*, which is consumers' evaluation of "control over the management, utilization and conversion of their time and effort in achieving their goals associated with access to and use of the service" (Farquhar and Rowley 2009, p. 434). The third variable is *perceived inspiration*, which is a consumer's "temporary motivational state that facilitates the transition from the reception of a marketing-induced idea to the intrinsic pursuit of a consumption-related goal" (Böttger et al., 2017, p. 117) (see Figure 1).

To help conceptualize the relationship between perceived availability of consumer sensitive data and relational outcomes in retailer-consumer relationships, the SET is useful in two ways. First, regarding the obligation to repay the received benefits, one can think of personal information as being given in exchange for a reward. Second, the SET suggests that consumers perform a risk-benefit analysis in assessing the outcomes they receive when providing personal data to retailers. In the next sections –and based on the SET– we explain why we expect consumer perception of sensitive data availability to affect their loyalty via perceived risk, convenience, and inspiration. For a more holistic picture of how perceived availability of sensitive data affects customer relationships, our conceptual model sums up and extends previous work on privacy literature by investigating multiple simultaneous mediation effects as well as several moderation effects on the provision of the extent of sensitive data disclosure (see Figure 1).

[Insert Figure 1 around here]

The mediating role of perceived risk

While consumers perceive risk in most purchasing decisions, consumers take particular risks when providing personally identifying data (Featherman and Pavlou, 2003; Suh and Han, 2003), as doing so raises concerns associated with unauthorized access or use of that personal data by the retailer or third parties. When consumers feel that a retailer knows too much about them, there is an expectation of high potential perceived risk for loss of well-being (Malhotra et al. 2004).

Regarding its potential outcomes, perceived risk can prompt a withdrawal of loyalty in search of a less risky transaction. According to the SET (Cropanzano and Marie, 2005), consumers are then likely to reduce their input into the retail relationship and will seek to restore the input-outcome ratio. We therefore hypothesize that:

H1a: Perceived availability of consumer sensitive data positively affects perceived risk.

H1b: Perceived risk negatively affects consumer loyalty.

H1c: Perceived risk mediates the effect of perceived availability of consumer sensitive data on consumer loyalty.

The mediating role of perceived convenience

Convenience in retailing occurs when the barriers to undertaking an activity are reduced or eliminated (Farquhar and Rowley, 2009). Seiders et al. (2007) identified five types of service convenience: decision convenience, which derives from situations that can help consumers make complex decisions (e.g., a consumer interested in purchasing a mobile phone service who is faced with a plethora of mobile phone providers and service plan configurations to choose from); access convenience, which derives from situations that can help consumers access and interact with a particular service provider (e.g., once the consumer has decided on a service provider, it may not be easy for them to access the service and interact with its provider); transaction convenience, regarding a situation that can help the consumer to complete the payment required to use the purchased service (e.g., it may not be easy for the consumer to make use of the service after payment); benefit convenience, regarding situations in which –once the service has been purchased– the consumer evaluates the consumption based on their expectation (e.g., the consumer evaluates whether they are satisfied with the benefits obtained from the service based on their expectation prior to consuming it); and post-benefit convenience, whereby the consumer requires additional assistance once the services have been consumed, such as after sales service (e.g., the consumer may initiate service complaints, request upgrades, or may request general service support and so they evaluate how easy it is to obtain the additional support required). According to this concept, service convenience can be seen as a non-monetary value obtained from the service that entails sacrificing time and effort during the purchase and use of a service (Berry et al., 2002).

Consumers who provide retailers with information about their own background, needs, and preferences should benefit from such retailers through more convenient shopping experiences in future purchase situations. For example, providing a retailer with information about one's address and financial details enables use of a quick check-out, as this information is already stored and does not need to be introduced to complete a purchase. Based on the SET (Blau, 1964), consumers who provide sensitive data will benefit from more convenient experiences, since retailers reciprocate this behaviour by offering a faster and easier shopping process. In turn, being offered a more convenient service should be seen as rewarding by consumers, as it facilitates a consumer's ability to fulfil their shopping intent. Again, drawing on the SET, consumers should reciprocate their retailers for the convenience benefit gained by increased levels of consumer loyalty. In light of this two-step reciprocation, we hypothesize that:

H2a: Perceived availability of consumer sensitive data positively affects perceived convenience.

H2b: Perceived convenience positively affects consumer loyalty.

H2c: Perceived convenience mediates the effect of perceived availability of consumer sensitive data on consumer loyalty.

The mediating role of perceived inspiration

Consumer inspiration represents an important positive emotional response to a retailer's offering. An increasing number of retailers attempt to position themselves as providers of inspirational shopping experiences by challenging consumers' imagination with new ideas, although this might prove difficult to achieve (Böttger et al., 2017). Specifically, when very little information is available concerning, for example, a consumer's preferences, it is very difficult for retailers to trigger elements of surprise and stimulation in consumers' minds. We therefore propose that inspiration can be viewed as a reward that motivates individuals to engage in self-disclosure that fosters loyalty in the relationship. This is because inspiration can provide a sense of meaning, purpose, and connection, which can enhance the quality of the relationship with a retailer (Böttger et al., 2017; Hart, 1998). For example, a retailer may inspire individuals by showcasing how their products or services have positively impacted their consumers' lives or by promoting social or environmental causes that align with consumers' values. We reason that the greater the amount of personal information disclosed by a consumer to the retailers, the greater the likelihood that the inspirational offering will be "wholesome" in terms of fitting the consumer's individual needs and wants.

Inspirational shopping experiences represent a benefit or reward. From a psychological perspective, bestowing a gratitude on the emotional sense –for example, by examining shop window displays and browsing websites, chatting with staff, or having fun finding bargains–

makes a shopping experience an adventure and encourages positive relational outcomes (MacInnis and Price, 1987). Following the SET, the reward a consumer receives from an inspirational retail experience should lead to feelings of obligation and the wish to reciprocate the retailer. In turn, this should enhance the consumer's desire to become more loyal (Böttger et al., 2017; Palmatier et al., 2009). In sum, the extent of the sensitive data available to retailers can help stimulate consumer inspiration which, in turn, increases consumer loyalty. We therefore hypothesize the following:

H3a: Perceived availability of consumer sensitive data positively affects perceived inspiration.

H3b: Perceived inspiration positively affects consumer loyalty.

H3c: Perceived inspiration mediates the effect of perceived availability of consumer sensitive data on consumer loyalty.

Moderating effect of purchase channel (online vs. offline) on perceived risk

Consistent with the SET and the underlying idea of reciprocity, retailers' benefits are contingent on rewarding consumers for disclosing their personal information (Blau, 1964). However, this form of reciprocity is based on the transaction, belief, and moral norms (Gouldner, 1960). This exchange is essentially supposed to curb risk and to support co-operation from the consumer (Molm, 1994), recognizing that the exchange is a continuous cycle (Cropanzano and Mitchell, 2005) wherein disclosing personal information to retailers is reciprocated by consumers being provided with more personalized offerings –whether convenience or inspiration. Social psychologists (Clark and Mills, 1979; Mursteinet et al., 1977) classify reciprocity in two forms: high exchange orientation reciprocity (consumers who readily reciprocate), or low exchange orientation reciprocity (those who reciprocate less). In the context of this research, reciprocity with high exchange orientation refers to a situation in which consumers interact with a retailer online and are more inclined to disclose personal information, for example through automated cookies –above and beyond basic demographic data– in return for tailored commercial offerings from retailers. In contrast, reciprocity with low exchange orientation refers to a situation in which consumers interact with a retailer face to face and are likely to disclose basic required demographic information in return for a purchase from the retailer, due to the rational thought process of seeking justification for the data collected.

Consumers show increasing levels of concern regarding disclosing information to companies, as retailers' access to their personal information heightens their feelings of vulnerability. Although consumers' personal information is crucial for targeting actual and potential consumers, the discussion regarding the determinants of consumer willingness to disclose personal information is limited. Ever-increasing digitalization has allowed retailers to collect more information about consumers than ever before and to use this information in multiple ways, thus resulting in a more personalized experience (Kim, Barasz, and John, 2018).

However, although consumers' personal information might help retailers to tailor their offerings –and thereby enhance loyalty– consumers may feel discomfort during data collection and use (e.g., due to a loss of privacy) (Aguirre et al., 2015; Thomaz et al., 2020). This is because the Internet and digital technologies have facilitated retailer collection of information for consumer profiling. This growing search for personal data –which often violates consumer privacy (Martin and Murphy, 2017)– makes consumers more reluctant to disclose personal information both online and offline (Phelps, Nowak, and Ferrell, 2000). This is especially true in the online context, where consumers are increasingly overwhelmed with personal data requests to complete their purchases (Kim, Barasz, and John, 2018; Olivero and Lunt, 2004). It is therefore important to take into account the source of data disclosure –whether it is online or offline. We shed light on which source of exchange, online or offline, can either reduce the risk or enhance the benefits when consumers disclose their personal information. This advances the SET by distinguishing the two types of reciprocity mentioned above (i.e., reciprocity with high vs. low exchange orientation). In line with said classification, we can distinguish two typical forms of disclosure: online data disclosure beyond demographic information (associated to reciprocity with high exchange orientation), or offline demographic information disclosure (associated to reciprocity with low exchange orientation).

However, the reciprocal reward process might foster the continuous reciprocation of consumers disclosing their personal information even in the absence of social control (Chen et al., 2021; Schumann et al., 2014). As disclosure of personal information is a form of currency to reward providers with a personalized offering (Bagozzi ,1975), reciprocity can increase consumer willingness to disclose personal information both online and offline. However, whereas the physical environment in the offline context can nurture the release of personal information (Acquisti et al., 2015), data disclosure can be perceived as more risky in digital realms, where consumers do not interact directly with salespeople (Noble and Phillips, 2004, Vannucci and Pantano, 2019).

The lack of sensory information online can be a major disadvantage for some retail categories such as fresh meat, fruit, and vegetables that tend to be evaluated prior to purchase based on sensory information cues (Degeratu et al., 2000; Hoch, 2002; Laroche et al., 2005; Peck and Childers, 2003). Not being able to see or touch products can complicate the evaluation process and lead to greater uncertainty and a higher perceived risk of online purchases (Laroche et al., 2005; Pauwels et al., 2011; Weathers et al., 2007). This may increase the risk associated with disclosing personal information when buying products online (Gupta and Kim 2010) and result in relatively fewer online purchases compared to offline retail settings (Chintagunta et al., 2012). It is therefore hypothesized that:

H4: The purchase channel (online vs. offline) moderates the effect of perceived availability of consumer sensitive data on perceived risk, such that the effect of perceived availability of data on risk is stronger when the retailer has an online (vs. offline) platform to collect consumer data.

Moderation effect of purchase channel (online vs. offline) on perceived convenience

The relationship between willingness to disclose personal information and perceived convenience depends on the type of relationship between retailer and consumer (Schumann, von Wangenheim, and Groene, 2014). For example, the reciprocation involved in such a relationship may derive from a high (vs. low) exchange orientation between retailer and consumer. This means that the retailer could acquire information about the consumer through the provision of explicit sensitive data or implicitly derive sensitive data from online sources (or be given courtesy data from offline sources, i.e., face to face interaction) (Acquisti et al., 2015; John et al., 2010).

Information disclosure in an online context is seen as pivotal (Markos et al., 2018). However, companies can encourage consumers to disclose personal information by counterbalancing the risk with convenience by enhancing the reciprocity of disclosing personal information in exchange for enhanced convenience in consumers' shopping preferences. We therefore extend reciprocity, grounded in the SET, in which data disclosure online versus offline helps to offer free tailored services that save time and effort, which in turn elicits users' need to reciprocate by disclosing personal data to obtain even more convenience. Feelings of transparency through reciprocity (Mazurek and Małagocka, 2019) can enhance a positive company-consumer relationship by offering consumers an enhanced convenience service.

We therefore hypothesize that reciprocity is even more relevant in digital realms, where consumers do not interact directly with salespeople (Mazurek and Malagock, 2019; Noble and Phillips 2004; Vannucci and Pantano, 2019). This is because consumers' willingness to divulge sensitive information depends on their judgment of convenience (Acquisti et al., 2012, 2015) and the relevance of convenience to their needs (Moon, 2000). Most online grocery shoppers are multichannel shoppers who visit both the online and the offline channel, thereby combining convenience advantages of online shopping with the self-service advantages of offline stores (Alba et al., 1997; Chu et al., 2008, 2010; Konuş et al., 2008; Venkatesan et al., 2007). We therefore hypothesize that:

> **H5**: Purchase channel (online vs. offline) moderates the effect of perceived availability of consumer sensitive data on perceived convenience such that the effect of perceived availability of data on convenience is stronger when the retailer has an online (vs. offline) platform to collect consumer data.

Moderating effect of source of data disclosure (online vs. offline) on perceived inspiration

Marketing scholars have examined consumer inspiration (Böttger et al., 2017; Izogo and Mpinganjira, 2020; Winterich et al., 2019) and have noted that inspiration is an important component of the consumer experience (Liu et al., 2017). Some studies emphasize that consumer inspiration is closely linked to brand attachment (Park et al., 2013), to consumers' feelings of delight and satisfaction (Finn, 2005), and to the psychological flow of the consumer experience (Schouten et al., 2007).

In marketing, the notion of consumer inspiration has rarely been examined as a way to increase reciprocity (ideally from low to high exchange orientation reciprocity), thus motivating consumers to disclose personal data. Managing social exchange or consumer relationships is generally understood as a set of philosophies, strategies, systems, and technologies that help brands and companies to manage their transactions and relationships with consumers (Thakur and Workman, 2016). While the management of consumer relationships is widely accepted as an approach to develop and maintain long-term relationships with consumers (Li et al., 2019), it is necessary to examine the potential moderating role of online versus offline data disclosure in the relationship between perceived availability of consumer sensitive data and consumer inspiration. Such a moderating role of online versus offline data disclosure may help retailers to inspire consumers with new ideas (Böttger et al., 2017).

Prior literature suggests that consumers may derive benefits from enriching, inspirational shopping experiences (Lee and Bottger, 2017) and may experience transcendent moments during consumption (Arnould and Price, 1993; Celsi et al., 1993). For example, Amazon continues to capture sensitive data and responds quickly to a fast-moving trend which encourages consumers to feel inspired by their service offerings. This is because the company has sufficient means to extract relevant sensitive data to gratify consumers' emotional sense. By extension, in online (vs. offline) retail settings, consumers might be more inclined to perceive that a greater availability of personal data could increase the likelihood of their receiving inspirational offerings from retailers. We therefore hypothesize that:

H6: Purchase channel (online vs. offline) moderates the effect of perceived availability of consumer sensitive data on perceived inspiration such that the effect of perceived data availability on inspiration is stronger when the retailer has the online (vs. offline) platform to collect customer data.

Method

Sample and design

We collected 936 responses from randomly selected respondents from Cint UK online panel, a large sample exchange platform used in previous research (Ross and Kapitan, 2018; Toti et al., 2021) and involved in the survey in exchange for a monetary incentive. Cint was used because it ensures sample representativeness by leveraging a broad network of panel partners to ensure diverse and representative sampling across various demographics. Stratified sampling techniques were used to match the composition of the UK population. Specifically, demographic quotas were targeted based on age, gender, and geographic location in order to achieve representativeness. In this sense, the UK has proven to be an appropriate population to generalize results (e.g., Mariani et al., 2020; Mukherjee and Nath, 2007; Pizzi and Scarpi, 2020). To ensure the robustness of our findings, we employed advanced statistical methods to effectively identify and remove outliers. This involved using Mahalanobis, Cook's, and Leverage scores to detect significant deviations within our dataset, as recommended by Tabachnick and Fidell (2012). We removed 13 cases that significantly influenced the regression analysis. Our final sample thus comprised 923 UK grocery shoppers, on whom an online survey was conducted (see Table 2 for sample characteristics).

Respondents were asked to answer the survey questions based on their most frequently shopped retailer, which resulted in a broad perspective across the 13 UK grocery retailers from both online and offline channels (e.g., Tesco, Asda, Morrison's, Ocado, Aldi, Waitrose, and Lidl).

[Insert Table 2 around here]

Measures

To measure perceived availability of consumer sensitive data to the retailer, we first identified ten different data categories based on the literature (Nowak and Phelps, 1995) (see Table 3). We then asked respondents to report their perception of the extent to which data within each of the ten categories were available to the retailer by using a four-point ordinal scale, with higher values indicating greater availability of those data (1 = I assume [Retailer] does not have this type of data, and I am under no circumstances willing to provide it if asked, 2 = I assume [Retailer] does not have this type of data, but I could imagine providing it if asked, 3 = I assume [Retailer] has this type of data because they automatically collect it, 4 = I assume [Retailer] has this type of information because I actively provided it). As respondents could have different levels of sensitivity to each of the ten data categories, we pretested these categories to assess the level of perceived sensitivity so as to classify the ten data categories based on this characteristic. The pretest is detailed further in the Analytical approach section.

We also measured perceived risk using Keh and Pang's (2010) four-item scale, perceived convenience using a three-item scale adapted from Babin et al. (1994), and perceived inspiration using Bottger et al.'s (2017) three-item scale. We then assessed consumer loyalty using Morgan and Hunt's (1994) three-item scale. All these constructs were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

As control variables, we also included demographic characteristics such as age, gender, loyalty card ownership, and privacy concerns. Sociodemographic differences and privacy concerns may indeed influence consumer willingness to disclose information, with younger male consumers, for example, being less likely to have privacy concerns (Culnan, 1995). Familiarity through loyalty scheme membership can accumulate sensitive data from past consumption behaviour, potentially affecting customer loyalty for retailers who offer such schemes. Lastly, we control for the influence of privacy concerns, since this might affect customer loyalty, as demonstrated in prior research (Martin and Murphy, 2017) (see Table 3 for scale items)

Measurement model

As presented before, we applied structural equation modelling for our statistical analysis by using the PLS approach, as it does not suffer from the indeterminacy problems associated with other modelling techniques and does not require data normality (Wittmann et al., 2009). Moreover, PLS can handle both reflective and formative constructs (Chin and Newsted, 1999) and allows us to model first-order and second-order constructs. We modelled perceived risk, perceived convenience, perceived inspiration, consumer loyalty, and privacy concerns as reflective first-order constructs. In contrast, we modelled the two first-order constructs capturing the two subgroups of data categories with higher and lower perceived sensitivity as formative constructs. The second-order construct –capturing the broader concept of perceived availability of consumer sensitive data– was modelled as a formative, type IV hierarchical latent variable model, in accordance with Becker et al. (2012). Our model yielded an SRMR value of 0.10, which is considered a relatively good fit between the hypothesized model and the observed data, according to Hu and Bentler (1999).

We evaluated the measurement model of the reflective constructs by examining item reliability, internal consistency as well as convergent and discriminant validity (Roldán and Leal, 2003). All standardized item loadings were significant ($p < 0.01$). Cronbach's α values exceeded the minimum threshold of 0.60, and composite reliability values surpassed the threshold of 0.70, meeting the criteria for internal consistency and composite reliability (Bagozzi et al., 1991). The average variance extracted (AVE) for all constructs exceeded the recommended threshold of 0.5, confirming their convergent validity (see Table 3).

We evaluated the measurement quality of the formative, first-order constructs (perceived availability of consumer data with higher sensitivity and perceived availability of consumer data with lower sensitivity) by examining the weights of each item (Chin, 1998). The weights indicate how each item contributes to its respective construct. As shown in Table 3, the weights of perceived availability of consumer data with higher sensitivity items are statistically significant. The same is true for the weights of the lower sensitivity and perceived availability of consumer data with higher sensitivity items, except for the item "purchase behaviour (e.g., types, number and frequency of products bought)". We decided to keep this item, following Hair et al. (2017), as the loading factor for this item is above 0.5 (i.e., 0.642). We also checked the model for multicollinearity by calculating the variance inflation factor (VIF) for each item. The highest VIF was 2.792, which is below the threshold of 10 (Kleinbaum et al., 2013). Multicollinearity was not therefore a problem.

[Insert Table 3 around here]

Table 4 shows the different subgroups of the level of perceived sensitivity of consumer personal data that make up each sub-dimension. In order to validate the formative nature of the dimensions, we conducted a statistical analysis to assess the significance of each facet's contribution to the second-order construct. The satisfactory fit of the measurement models was confirmed by the outer weights of the two sub-dimensions. We also examined multicollinearity using the VIF and found that the values for both dimensions were below the threshold of 5, indicating no concerns regarding collinearity.

[Insert Table 4 around here]

In addition, we confirmed the discriminant validity of our constructs by adhering to the criteria established by Fornell and Larcker (1981). Specifically, we verified that (a) the square root of each construct's AVE was greater than its correlation with other constructs (see Table 5), and (b) that each item loaded more heavily on its associated construct than on any other construct. We also applied the criteria for establishing adequate discriminant validity recommended by Henseler et al., (2015) by examining the heterotrait-monotrait (HTMT) ratios of correlations. We confirmed that no single HTMT ratio exceeded the threshold of 0.85 (see Table 5), and that the corresponding confidence intervals did not include the value 1. In summary, all our constructs exhibited good psychometric properties.

[Insert Table 5 around here]

Common method bias

One potential limitation of our data is the use of a single key informant, which may introduce common method bias. To test our data for this bias, we employed the common method factor procedure recommended by Liang et al. (2007). This procedure involves adding a first-order factor to our theoretical model, with all measures serving as indicators. Using PLS, we converted each indicator into a single-indicator construct, transforming all major constructs of interest into second-order constructs. We then added a common method construct whose indicators included all principal construct indicators and were linked to all first-order constructs.

We calculated the variance of each indicator substantively explained by the principal construct and by the method (Williams et al., 2003). Our results showed that the average substantively explained variance of the indicators was 0.698, while the average method-based variance was 0.003. The ratio of substantive variance to method variance was 232/1, and most method factor loadings were not significant. These results are presented in Appendix A.

Additionally, we tested our theoretical model both with and without the common method factor to examine the significance of the structural parameters (Podsakoff et al., 2003). Our findings showed that the direction and p-value level of path coefficients remained consistent across both models.

Endogeneity

We first assessed the non-normality of perceived availability of consumer sensitive data, perceived risk, perceived convenience, and perceived inspiration using their standardized composite scores provided by Smart-PLS 4. This is a crucial identifying assumption for the copula method (Papies et al., 2017). The Kolmogorov-Smirnov test with Lilliefors correction (Sarstedt and Mooi, 2014) test rejects the null hypothesis of normality at $p < 0.01$ for all of them.

We also used the constructs' standardized composite scores to compute the Gaussian copula of the partial regressions in the structural model, as indicated by Hult et al., (2018). We used the REndo package of the R software (Gui et al., 2017). We also used Hult et al.'s (2018) R code and the boot package (Canty and Ripley, 2017) to compute bootstrap standard errors.

Results show that none of the Gaussian copulas are significant at a 0.1 level when accounting for endogenous variables, suggesting an absence of endogeneity issues (see Appendix B). Although copulas are included, causal inference is not asserted because the analysis is cross-sectional. The findings should therefore be viewed as an examination of theory-based associations.

Analytical approach

The proposed model is empirically tested using structural equation modelling (SEM), a methodology widely used in social sciences and marketing (e.g., Guenther et al., 2023; Hair et al., 2022). SEM's strengths include handling measurement issues of complex theoretical concepts and simultaneously estimating relationships between constructs, allowing for a holistic analysis while accounting for measurement errors (Bagozzi, 1994).

In the domain of advanced multivariate analysis techniques, there are two main approaches: covariance-based structural equation modelling (CBSEM) and partial least squares (PLS) (Davvetas et al., 2020; Sarstedt et al., 2016). CBSEM confirms theoretical models by reproducing the structure of variance-covariance. In contrast, PLS focuses on maximizing the explanatory power of endogenous variables and minimizing prediction error, making it suitable for predictive and exploratory research (Gefen et al., 2000; Schmueli et al., 2019). PLS does not require normal distribution, which adds flexibility in data handling through iterative least squares and regression analysis –known as “soft modelling” (Falk and Miller, 1992; Tenenhaus et al., 2005). This flexibility is a key advantage over CBSEM. In this sense, CBSEM requires reflective measurement scales for proper model identification, even when using formative indicators. PLS, however, accommodates both formative and reflective indicators, making it more adaptable to evolving theoretical models (Chin, 1998; Hair et al., 2019, 2023; Jarvis et al., 2003).

We employ PLS for model testing, since the inclusion of formative constructs in our model poses significant challenges for CBSEM. Use of PLS also aims to minimize prediction error and to maximize explained variance of the dependent variables (Chin and Newsted, 1999; Henseler and Schuberth, 2023; Tenenhaus et al., 2005), thus aligning with our research goal of identifying factors that contribute to self-assessed consumer loyalty in the context of all purchase channels. Additionally, PLS’s flexibility with variable metrics is advantageous, given our non-normally distributed data measured on a five-point Likert scale.

Our study builds on previous research exploring the relationship between perceived availability of sensitive consumer data and self-assessed consumer loyalty via perceived risk, convenience, and inspiration. As this research area still requires further development in measuring concepts and formulating hypotheses, PLS is particularly useful when compared to CBSEM for suggesting possible relationships between variables that need further refinement (Chin and Newsted, 1999; Magno et al., 2022).

We thus initiate the analysis by evaluating the fit of our measurement model using the PLS method with Smart PLS software version 4.0.9.5 (Ringle et al., 2022). To do so, we used the standardized root mean square residual (SRMR), a goodness-of-fit measure for PLS that can help prevent model misspecification (Becker et al., 2023; Henseler et al., 2016). Once the measurement model was validated, we evaluated the psychometric properties of the scales.

Perceived availability of consumer sensitive data scale

Prior to evaluating the psychometric properties of the scale assessing perceived availability of consumer sensitive data as described above, we conducted a pretest aimed at clarifying whether the ten categories of data could be reasonably classified into two macro-categories based on their different levels of perceived sensitivity. We gathered data from a sample of 70 UK consumers (34.1% male, 64.8% female, 1.1% non-binary/third gender), who were randomly recruited from Prolific Academic, a data collection platform widely used in social science research (Jeesha and Purani, 2021; Moon and VanEpps, 2023). We asked pretest participants to read each of the ten items reporting a particular category of data (e.g., personal identification data) and then to rate the degree of sensitivity they ascribed to each category of data using a five-point scale (1 = not sensitive at all, 5 = extremely sensitive). We then ordered the ten data categories based on the mean score received from the pretest respondents, and we split them into two subgroups: one comprising the least sensitive types of data and the other comprising the most sensitive types of data (see Table 6 for descriptive statistics).

[Insert Table 6 around here]

Consistent with prior research on perceived availability of sensitive data (Belen-Saglam et al., 2022; Nowak and Phelps, 1995), we used this classification to model the broader concept of perceived availability of consumer sensitive data as a multidimensional, second-order construct made up of two first-order constructs regarding the two macro-categories.

Based on the pretest results, we built a model in which the five items regarding the subgroup of data categories perceived as higher in sensitivity and the five items regarding the subgroup of data categories perceived as lower in sensitivity served as observed indicators of the two respective first-order constructs connected to a broader, second-order construct regarding perceived availability of consumer sensitive data. While this approach allowed us to consider respondents' higher versus lower sensitivity to the ten data categories (e.g., financial data, personal lifestyles, and interests), the presence of distinct groups of items in the perceived availability of consumer sensitive data does not imply any shortcomings in these sensitive data traits because a higher-order factor within a scale can include somewhat distinct or dissimilar lower-order factors. In other words, the first-order constructs refer to narrowly defined phenomena or fine-grained aspects of a broader construct, whereas the second-order construct captures a global or holistic phenomenon (Bagozzi and Edwards, 1998). Establishing a second-order construct can reduce the number of relations in complex structural models, making the estimation more parsimonious and easier to grasp (Hair et al., 2016).

Findings

Structural model

In PLS, the parameters of both the structural and the measurement models are estimated through an iterative process that combines simple and multiple regressions via traditional least squares, without making any assumptions about the distribution of the observed variables. To estimate the statistical significance of the parameters, we employed bootstrap resampling by generating 5,000 surrogate subsamples from the original dataset.

The results of our hypothesis testing for the mediating effects (H1abc, H2abc, and H3abc) are presented in Table 7. We found that perceived availability of consumer sensitive data has no significant direct effect on consumer loyalty (β = 0.03, $p = 0.142$). However, perceived availability of consumer sensitive data does exert a significant positive effect on perceived risk (β = 0.22, $p < 0.01$), perceived convenience (β = 0.40, $p < 0.01$), and perceived inspiration (β = 0.44, $p < 0.01$), thus providing support for H1a, H2a, and H3a, respectively. Furthermore, consistent with H2b and H3b, perceived convenience and perceived inspiration exert a positive effect on consumer loyalty (β = 0.20, $p < 0.01$; β = 0.51, $p < 0.01$, respectively). In contrast, perceived risk exerts a significant negative effect on perceived loyalty (β = -0.07, $p < 0.01$), thus providing support for H1b.

Interestingly, when we examined the indirect effects of perceived availability of consumer sensitive data on consumer loyalty via the three mediating variables (i.e., perceived risk, perceived convenience, and perceived inspiration), we found that all of them are significant (indirect effect via perceived risk: β = -0.02, $p < 0.05$; indirect effect via perceived convenience: β = 0.08, $p < 0.01$; indirect effect via perceived inspiration: β = 0.23, $p < 0.01$), thus supporting H1c, H2c, and H3c. This indicates that perceived risk, perceived convenience, and perceived inspiration fully mediate the relationship between the perceived availability of consumer sensitive data and consumer loyalty. In other words, as the perceived availability of consumer sensitive data increases, so do perceived convenience and perceived inspiration, leading to an increase in perceived loyalty. Conversely, as the perceived availability of consumer sensitive data increases, perceived risk also increases, leading to a decrease in perceived loyalty.

[Insert Table 7 around here]

The results of the hypothesis testing for the moderating effects (H4, H5, and H6) are shown in Table 8. Henserler's (2012) multi-group analysis was used to compare the effect of perceived availability of consumer sensitive data on perceived risk, perceived convenience, and perceived inspiration, respectively, across different subgroups of respondents regarding the type of channel they used (online vs. offline) on a pairwise basis. The original sample of 923 cases was reduced to 175 cases and 237 cases for the multi-group analysis by limiting the sample to those who purchased in a single channel (online vs. offline). This allowed us to isolate the effects of the different purchase channels and to compare their effects on the relationship between perceived availability of consumer sensitive data and perceived risk, perceived convenience, and perceived inspiration, respectively.

Henseler's nonparametric test is an approach to PLS-based multi-group analysis (PLS-MGA) that does not require any distributional assumptions (Henseler, 2012). The pairwise comparison of parameter estimates of multigroup analysis yields a non-significant difference between online purchase channel and offline purchase channel for the relationship between perceived availability of consumer sensitive data and perceived risk (difference between path coefficients = 0.00, p = 0.491), such that H4 is not supported. Conversely, we found significant differences between respondents who purchased online and those who purchased offline for the relationship between the perceived availability of sensitive data and perceived convenience (difference between path coefficients = -0.35, $p < 0.01$), thereby supporting H5. This means that the positive effect of perceived availability of consumer sensitive data on perceived convenience is stronger for the online purchase channel ($\beta = 0.64$, $p < 0.01$) than for the offline purchase channel ($\beta = 0.29$, $p < 0.01$). We also found that the pairwise comparison of parameter estimates of multigroup analysis yields marginally significant differences between the online purchase channel and the offline purchase channel for the relationship between perceived availability of sensitive data and perceived inspiration (difference between path coefficients = -0.12, $p < 0.10$), thereby partially supporting H6. In turn, the positive effect of the perceived availability of consumer sensitive data on perceived inspiration is stronger for the online purchase channel ($\beta = 0.53$, $p < 0.01$) than for the offline purchase channel ($\beta = 0.41$, $p < 0.01$).

[Insert Table 8 around here]

Discussion

The results show that perceived availability of consumer sensitive data impacts consumer loyalty towards the retailer through the mediating mechanisms of perceived risk, perceived convenience, and perceived inspiration, which help shape consumer relationships with retailers. Specifically, the online channel has the potential to improve the retail shopping experience and thus contribute to consumer acceptance of data disclosure.

While several prior studies have investigated types of data disclosure (Aquisti et al., 2012; Tucker, 2014; Zeng et al., 2021), analysis of self-disclosure from the consumer perspective has remained a neglected topic, especially in the retail context. We therefore adapt the SET to this underdeveloped research context by assessing the impact of perceived availability of consumer data on loyalty in retail channels. We identify the benefits and costs of social exchange in a retail context by considering the underlying attributes of the SET. In doing so, we build on previous research exploring the relationship between perceived availability of sensitive consumer data and consumer loyalty via perceived risk, convenience, and inspiration. This is because the SET relies on social exchanges that are open-ended and require long-term commitment (Blau 1964) –an attribute of loyalty (Anderson and Srinivasa, 2003; Gummerus, et al., 2004; Sirdeshmukh, et al., 2002). Given our research context, we measure loyalty as a long-term commitment to social exchange. Recognizing that the SET emphasizes that the resources which facilitate these exchanges (such as reciprocity, convenience, and inspiration) are often intangible in contrast to the tangible financial benefits and costs in purely economic transactions, we tailor our measures accordingly. Specifically, we replace the notion of 'cost' with perceived risk while framing 'convenience' and 'inspiration' as the primary benefits that constitute social exchange (Malgieri and Custers, 2018). This is because (1) the relationship between perceived availability of consumer sensitive data and perceived 'convenience' and 'inspiration' within retail contexts typically extends over time beyond the single exchange transaction; (2) the exchange also entails reciprocity and obligation. Both 'convenience' and 'inspiration within our research context are components of the SET (Molm et al., 2000).

Theoretical contributions

Our research makes two main contributions to the literature. First, we contribute to consumer experience and privacy literature by investigating the impact of perceived availability of consumer sensitive data to help shape consumer loyalty through the mediating role of perceived risk, perceived convenience, and perceived inspiration. This finding suggests that new technologies offer important opportunities for developing loyalty programmes that increase the acceptance of data disclosure to retailers. Virtual accounts through online and mobile applications can help reduce the risk associated with sensitive data disclosure by providing an enhanced service (e.g., by integrating and consolidating large data to form connected services across digital platforms such as wearables that can help detect heart rate, blood pressure or dietetic information in order to prompt inspirational and convenient purchases). In turn, this can stimulate customer engagement with loyalty programmes that can increase perceived value and strengthen customer lifetime value and relationships with retailers.

Indeed, our data show that risks are linked to the consequences of privacy concerns, loss of control, and risks from hackers, which can create doubt and stress and in turn inhibit retail loyalty programme adoption and use (Cloarec, 2020; Martin et al., 2020). Striking the right balance between benefit versus risk is thus crucial, as it takes time to build customer loyalty, whereas it can be destroyed very quickly if customer data are "exploited" without permission, or are inadequately protected (Dekimpe, 2020). These findings are in line with the SET (Bagozzi, 1975; Blau 1964), and privacy calculus theory (Culnan and Armstrong, 1999), which suggest that consumers perform a risk-benefit analysis when assessing the outcomes they receive as a result of providing retailers with personal data.

Second, by advancing on the SET, we demonstrate the moderating effect of online and offline channels on the relationship between perceived availability of consumer sensitive data and the three mediators regarding perceived risk, perceived convenience, and perceived inspiration. Our contribution in this regard is evidenced through the reciprocated exchange orientation, in which consumers perceive that the availability of sensitive data is either high (online data disclosure beyond demographic information) or low (offline interaction associated with exchanging demographic information) to offset perceived risk and gain perceived convenient and perceived inspirational experiences. Consumers see a retailer's ability to handle their sensitive data as a sign that the retailer is concerned with the interest and well-being of shoppers. When consumers assume that their sensitive data are being leveraged beyond the individual transaction, they feel a loss of control (Dinev and Hart, 2006), which is evident when a retailer has obtained high levels of exchange orientation knowledge through sensitive data. We therefore propose that retailers should involve their consumers in an information privacy dialogue concerning how, why, and where sensitive data are being used. Transparent procedures –coupled with a high level of consumer control about which data are collected and stored– are preconditions if any data privacy strategy is to be successful in the long term.

Our findings also demonstrate that online and offline channels not only provide firms with a further channel of distribution, communication, and service delivery but also a means of developing consumer loyalty programmes, which in turn benefits from repeat purchase intentions, lower cost acquisition, and word-of-mouth (Evanschitzky et al., 2012; Gandomi and Zolfaghari, 2013; Gurau, 2003). More specifically, our findings suggest that the online channel can improve the retail shopping experience and thus contribute to consumer acceptance of data disclosure. Convenience and inspirational experiences not only play an important role in achieving customer loyalty but also have a greater impact on accepting sensitive data disclosure across online channels than offline channels. Drawing attention to personalization is thus pivotal to the adoption of more advanced digital services such as AI (Kumar et al., 2020; Gao and Liu, 2022). This suggests that customers value the ability of advanced online personalized services to satisfy inspirational experiences, which reinforces the importance of hedonic value across the retail platform. This finding can help retailers identify the impact of specific sensorial properties to inspire consumers (e.g., medical history to help with retail purchases). Similarly, inspiring consumers with new ideas to gratify their emotional senses can offset the psychological risk and encourage consumers to reciprocate in exchanging sensitive data.

Practical implications

Our findings suggest that retailers should only follow a data-intensive strategy if they can ensure that the increased level of risk is more than compensated by the positive effects of data use in terms of convenience and inspiration. Through the availability of consumer sensitive data, retailers could improve consumers' perceived convenience with the retailer via one or more types of service convenience (i.e., decision convenience, access convenience, transaction convenience, benefit convenience, and post-benefit convenience). Similarly, retailers should focus on their strategies that provide experiences which inspire each individual by showcasing their products or services with a sense of meaning, purpose, and connection to the retailer. This is because enhancing inspirational and convenient benefits that consumers can derive from data disclosure are mechanisms that create value in loyalty programmes, while ensuring that consumer privacy is maintained throughout data usage. Indeed, sensitive data disclosure can provide retailers with a positive differentiator. Similar to Martin et al.'s (2020) findings, our results suggest that consumers value retailers who protect their personal data and that, in turn, consumers reward the retailer for providing the transparency of sensitive data protection. Transparency can therefore be key to offsetting psychological risk.

As inspiration is a stronger determinant of loyalty, when consumers voluntarily disclose sensitive data, retailers can adopt AI systems in a more innovative and inspiring way to help consumers who are browsing items and making purchases. For example, Amazon is experimenting with how to link payment information to people's physical hands; technologyenabled shoppers would simply wave their hand at a checkout terminal, have it read their palm, and complete the payment. Retailers can develop more inspiring ways to engage consumers' hedonic senses with relevant experiential configurations to expedite easy, seamless shopping processes. For example, we may consider virtual try-on menus, which enable customers to tilt, shake, and tap the intended product on personalized apps in order to gain more information (e.g., visualization of how to cook meals) (McLean et al., 2020). These features would not only provide customers with clarity vis-à-vis the disclosure of sensitive data but also provide sensory customization and interaction during their shopping activities that can offset the associated psychological risk of sensitive data disclosure. In doing so, this can increase two-way communications, responsiveness, synchronicity, and omnipresence (Yang and Lee, 2017), which could enhance the adoption of customized loyalty programmes.

Retailers can implement strategies that inspire consumers through AI digital humans to play short games with shoppers (noughts and crosses, I spy, etc.), or even a guessing game where *"the digital human"* attempts to guess which type of product the customer wants to buy based on clues provided by the consumer. This can generate a genuinely pleasing social situation –both in-store and online. Given the rise in data disclosure through both online shopping and hybrid shopping formats, involving online ordering and curbside pickup (Guha et al. 2021) can provide new avenues for predictive models powered by AI to examine customer data and store data simultaneously, and to provide new types of data relating to factors such as weather, traffic, and the quickest online pick-up routes from local drop off points for a more convenient experience.

Moreover, our findings suggest that consumers may be inclined to accept perceived sensitive data disclosure online when compared to offline. Retailers should therefore leverage the online channel to enhance consumer loyalty programmes by using the online platform for collecting and using sensitive data to build customized loyalty programmes. However, retailers need to be transparent about data collection, usage, and sharing if they are to enhance the reciprocation of sensitive data disclosure with retailers' convenient and inspirational offers, which will ultimately increase consumer loyalty. In this line, retailers should customize privacy policies for different channels and align them with their unique characteristics. By doing so, they would maintain transparency and so establish trust and credibility.

Additionally, retailers should also empower consumers with control over their personal data and its use, enabling them to manage their data preferences effectively. They should be aware of the varying levels of sensitivity in personal data and should tailor data collection strategies accordingly. In addition, trust can be further built if retailers continuously monitor consumer feedback on privacy concerns and adapt policies accordingly.

Overall, our findings suggest that the benefits of a sensitive data-exchange related strategy are more effective in the short term when retailers offer gratifying experiences with high utility and quality. The exchange argument may be less effective in the long term, as privacy in marketing will become less a question of where data are stored and more a question of whether a consumer feels that the predictions made by data are intrusive. Firms can therefore use sensitive data disclosure in a way that focuses on using aggregated, anonymized, and depersonalized data to provide consumers with convenience benefits and inspirational experiences that will encourage personalized retail loyalty adoption programmes. Overall, the findings are not only applicable to the retail industry but also across finance and healthcare industries.

Limitations and future research

We acknowledge that our work has some limitations. First, perceptual data from consumers were used to operationalize all the constructs in our model. Objective measures of consumer loyalty are not available or reliable. We therefore used perceptual data from consumers, who are more likely to be able to accurately assess their loyalty to a retailer. Nevertheless, perceptual data were collected using a survey instrument that has been shown to be reliable and valid. Second, the research is cross-sectional, such that we cannot guarantee causality. However, we theoretically set out the sense of the relationships included in our model based on arguments found in prior literature. A longitudinal study into this topic might capture the effect of perceived availability of consumer sensitive data in perceived risk, perceived convenience, and perceived inspiration, in online and offline purchase channels, as well as in performance.

However, beyond the limitations, this study does provide opportunities for future research. One key avenue for future inquiry concerns investigating the moderating role of other online services such as mobile apps and the mediating roles of perceived risk, convenience, and inspiration. This is important, given the continuing growth in digitalization. Today's consumer interacts with retailers across multiple channels simultaneously –online, mobile, and offline– a concept that has come to be known as "omnichannel" marketing. Expanding the range of channels considered in future studies could prove relevant, considering that omnichannel marketing emphasizes more fluid data collection on consumer behaviour through a unified consumer experience rather than just facilitating transactions (Verhoef et al., 2015).

Second, our findings show that firms need to adopt convenient and inspiring strategies to create and maintain loyalty with consumers so as to develop long-term mutually beneficial relationships (Pan et al., 2012). Through qualitative interviews, it would be worth exploring how consumers would like to be inspired, both in store and online, in order to help provide a deeper understanding of the inspirational and convenient constructs that will encourage sensitive data disclosure and ultimately enhance consumer relationships with retailers. This will help to enhance overall marketing effectiveness, as consumers demand a more personalized shopping experience, making marketing offers based on consumers' inspirational experiences to conveniently benefit and inspire consumers purchasing decisions.

Third, our findings show that online acceptance of sensitive data disclosure is more significant than offline. Future studies could experimentally test the acceptance of sensitive data disclosure by the same consumers across two channels (i.e., online and offline). This will be insightful, given that the boundaries between online and offline channels are becoming increasingly blurred and that customers expect to be able to switch between channels seamlessly. Will the same customer in the offline store have a problem with disclosing their data while accepting all terms and conditions online? Through which channel (online or offline) should retailers obtain the sensitive data in order to enhance the adoption and use of customer loyalty programmes?

Fourth, further studies could test our conceptual model using retailers' actual purchase data or a longitudinal approach to clarify the dynamic processes of 'give and take' in retailer-customer relationships. Future studies might also define the relationships between hedonic shopping orientation and the intention to reuse multiple or combined channels. In doing so, firms will have the benefit of identifying which channel provides diminishing returns to data collection and which can be removed from acquiring data disclosure. For instance, some consumers may hesitate to disclose their sensitive data because they believe that firms may not appropriately compensate them for data disclosure, thereby increasing psychological risk. Future studies might thus prove useful in identifying which platform design can inspire consumers to disclose their data vis-à-vis acquiring a more enhanced experience.

Fifth, future studies might test our conceptual model in other settings that rely on providing sensitive data (e.g., fashion retailing, DIY retailing, banking or financial services) with their loyalty programmes. This is essential, given the shift in numerous financial developments ranging from smartphone apps and online banking systems to artificial intelligence and sophisticated analytics. Maintaining data privacy while implementing new technologies can help foster trust and confidence in customers, which can improve the overall experience. The financial sector perceives robust data privacy as critical for competitive advantage in a constantly changing market, by mitigating emerging risks and maintaining customer confidence.

Further research could thus determine whether our results hold in other industries. The findings can be corroborated with qualitative data in order to gain a more in-depth understanding of consumer opinion towards loyalty programmes across different industries, since not all industries' loyalty programmes prove to be successful.

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Figure 1. Conceptual Model

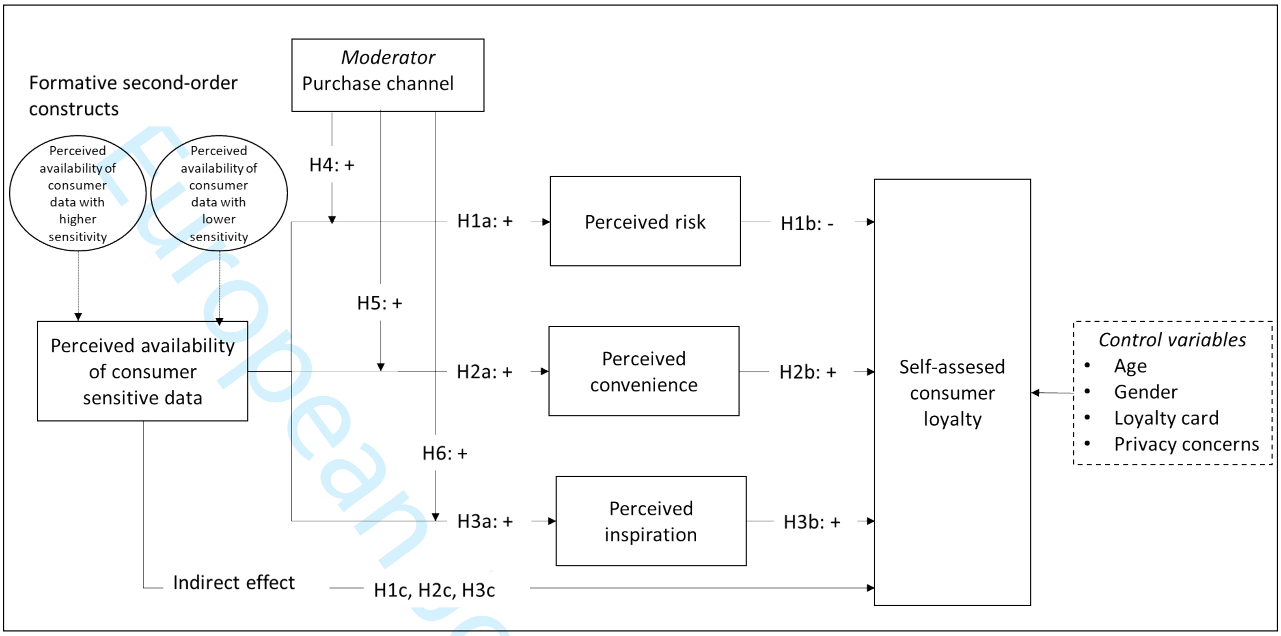

Table 1. Summary of key literature in data disclosure

Author	Type of data disclosure	Definition of Data disclosure	Data collection	Theory	Antecedents	Moderators /mediators	Outcome(s)
Cheah et al., 2022	Privacy concern	Not defined	Survey	Stimulus-Organism-Response and Psychological Reactance Theory	Consumer perception of channel integration	**Moderator:** Privacy concern **Mediators:** Consumer empowerment, Trust	Patronage intention in omnichannel retailing
Scarpi et al., 2022	Review privacy related to digital technologies in marketing	Integrity and safety of personal information across platforms/channels/contexts, the right to decide how personal data are used at various stages, and the ability to trade personal information for customized value offerings from marketers	NA	NA	NA	NA	Review to deepen the understanding of digital technologies and privacy across four domains – communication, retailing, pricing, and product personalization
Guha et al., 2021	Adoption of AI in retail and ethical concern	Define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." (p. 29)	Interviews with senior manager	NA	**Propositions**: AI application type (customer facing vs. non-customer facing)	**Proposed Moderators:** Application value, online vs. in-store, ethical concerns	AI adoption
Zeng et al., 2021	Intensive self-disclosure	Not defined	Field experiment	Foot-in-the-door effect	Privacy assurance, personalization declaration	**Mediators:** act of self-disclosure, intensity of self-disclosure	Purchase
Martin et al., 2020	Data privacy in retail contexts	Perspectives related to information privacy…germane to organizations' access, use, dissemination, and protection of consumer personal data for marketing purposes". (See Table 1, page 136	In-depth expert interviews, a large-scale consumer survey and global case study	NA	Convergence among three key stakeholders – consumer, retailer, and regulatory	NA	Three stakeholders underscore the complex interrelations among consumers, retailers, and regulatory forces
Martin and Murphy, 2017*	NA	"Perspectives related to information privacy…germane to organizations' access, use, dissemination, and protection of consumer personal data for marketing purposes". (See Table 1, page 136, Martin and Murphy, 2017*)*	NA	NA	Privacy concerns, consumer vulnerability, individual differences, organizational privacy communication	**Moderators**: *Privacy enhancing factors:* Organizational trust, personalization value, consumer control, data transparency *Privacy failure:* Data breach, identity theft, hyper-competitive actions	Purchase intent, disclosure willingness, click-through, falsifying information, negative word of mouth, switching. *Organizational Outcomes*: firm performance, brand equity, customer relationships, privacy self-regulation, privacy as strategy
Martin et al., 2017	*Data breach*: Misuse of given data disclosure	Perspectives related to information privacy…germane to organizations' access, use, dissemination, and protection of consumer personal data for marketing purposes	Experiment and field data	Gossip theory	*Customer vulnerability*: data manifest vulnerability, data breach vulnerability, spill over vulnerability, data access vulnerability	**Moderators**: Transparency, control	Falsifying information, negative word of mouth, switching behaviour

Wang et al., 2016	Personal information via mobile applications	Not defined	Survey	Calculus theory	Self-presentation, personalized services, perceived severity, perceived control	**Mediators:** Perceived benefits, perceived risk	Disclosure of personal information
Aguirre et al., 2015	Personalized service offers	Not defined	Exploratory field study on Facebook and secondary data about a personalized advertising campaign	Personalization paradox - psychological ownership theory	Information collection (overt vs. covert), website credibility (e.g., Facebook, CNN), personalization (less vs. more), information icon (present vs. absent)	**Mediator:** Perceived vulnerability	Click-through intentions
Bleier and Eisenbeiss, 2015a	Personalization of online ad communication	Not defined	Field and lab experiments	Consumer choice theory	Degree of content personalization (high vs. medium vs. low)	None	Click through in purchase decision process
Bleier and Eisenbeiss, 2015b	Personalization breadth (name of retailer)/depth (products from the category that a consumer primarily viewed/ previously placed in their virtual wish list or shopping cart in the retailer's online store).	Not defined	Quasi-experimental field study and a lab experiment	Choice theory	Depth and breadth of personalization	**Moderator:** Trust in the retailer **Mediators:** Usefulness, reactance, privacy concerns	Click through
Utz, 2015	Intimate information	Not defined	Online survey on social media (Facebook)	Social network sites and social penetration theory	*Contents of message*: Intimate, positive entertaining *Type of message:* Own update, private conversation, friends updates	None	*Motives*: Sharing, relationship maintenance, entertainment, self-presentation
Schumann et al., 2014	High information sensitivity	Disclosure of intimate personal behavioural or attitudinal data	Scenario-based experiment and survey	Reciprocity theory and social exchange theory	Reciprocity, relevance	**Moderators:** Advertising clutters, advertising informativeness, website quality, utility of the website **Mediators**: Need for distinctive justice, Procedural justice	Acceptance of behavioural targeting, acceptance of targeted advertising, level of user-generated content
Tucker, 2014	Personal information	Personalizing ad text with user-posted personal information relative to generic text	Field experiment	Psychological reactance theory	Privacy policy change	None	Click through on online advertising on a social networking website
Acquisti et al., 2013	Personal data	Not defined	Field experiment	Privacy trade-off	Willingness to protect public information, willingness to accept the disclosure of private information	None	Gift card endowment
Acquisti et al., 2012	Personal data	Potentially embarrassing and even sensitive information	Experiment, survey	Foot in the door, door in the face	Admission rates of engagement in sensitive behaviours, order of intrusiveness	None	*Herding effect*: Perception of intrusiveness and willingness to engage in disclosing sensitive information
Krasnova et al., 2012	Privacy concern	Concerns about possible loss of privacy as a result of information disclosure	Survey	Social exchange theory	Enjoyment, privacy concern,	**Moderators**: Individualism, uncertainty avoidance	Self-disclosure

					Trust in the social network site provider, trust in the social network site members		
Mothersbaugh et al., 2012	Self-disclosure	Name, preferences, and demographics, sensitive information	Online experiment in a fictitious online service context	Prospect theory	Perceived level of customization, perceived frequency of website usage, perceived customization value	**Mediators:** Consumer privacy online concern, firm specific information control, perceived customized benefits	Willingness to disclose online
Li et al., 2010	Individual's decision-making on information disclosure	Not defined	Experiment	Cost-benefit trade-offs	Perceived usefulness, monetary rewards, privacy protection belief, privacy risk belief	**Moderator:** perceived relevance	Behavioural intention to disclose personal information
Ko and Kuo, 2009	Self-disclosure	How individuals communicate with others using their own information, including personal thoughts, feelings, and experiences, for the purpose of sharing (Derlega et al., 1993)	Survey	Self-disclosure theory	Self-disclosure	**Mediators:** social integration, social bonding, social bridging	Subjective well-being
White et al., 2008	Personalized email message	Not defined	Factorial experiment	Psychological reactance theory	*Distinctiveness*: Email personalization	**Mediator:** Reactance	Click-through intentions, perceived utility/benefits
Norberg et al., 2007	Personal information disclosure	Not defined	Repeated experimental measures design	Privacy paradox	Risk, trust	**Mediator:** behavioural intention to disclose	Disclosure behaviour
Awad and Krishnan, 2006	Location privacy by articulating the rich impact of geosurveillance on the consumer.	Not defined	Construct and stimuli development	Social penetration theory	Location privacy, familiar service providers, georeferencing style	None	Personalization value and personalization receptivity
Chellappa and Sin, 2005	Personalized data	The ability to proactively tailor products and product purchasing experiences to tastes of individual consumers based upon their personal and preference information	Survey	Customer relationship theory	Value for personalization, concern for personalization, trust building factors	None	Likelihood of using personalization services
Dinev and Hart, 2004*	Privacy concerns	Not defined	Survey	Privacy calculus	Perceived vulnerability, perceived ability to control	None	Perceived privacy concern
Malhotra et al., 2004	Personal information	"Personal information defined as the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others" (Westin 1967, page 7)	Two separate field surveys and interviews	Social contract theory	Collection, control, awareness, types of information	None	Trust belief, risk belief, behavioural intention
White, 2004	*Self-disclosure*: Private information and embarrassing information	Not defined	Survey experiment	Social exchange theory	Relationship type, information type manipulation, marketer benefit offerings	None	Willingness to reveal private information, willingness to reveal embarrassing information
Alpert et al., 2003	Personalized website	Described as a system that "adapts the content structure, and/or presentation of the networked hypermedia objects to each individual user's characteristics, usage behaviour, and/or usage environment"	Lab experiments	Customer relationship theory	Personalized feature clusters	None	Commerce web site for computing machinery sales and support

Moon, 2000	Intimate information from consumers via computers	Not defined	Laboratory experiment	The principle of reciprocity: social response theory	Depth of intimate self-disclosure, breadth of intimate self-disclosure, number of intimate self-disclosures, attraction	None	Likelihood of revealing intimate information via computer
Our study	Sensitive data disclosure	Overall amount of data disclosed about a consumer whether acquired or given through explicit (i.e., consumers have provided the sensitive data) or implicit (i.e., retailers have obtained the sensitive data without consumers being necessarily aware)	Field survey	Social exchange theory Beyond purchase decisions, consumer behaviour encompasses constant interaction between the consumers and their environment, influenced by personal preferences, social influences, channel, and past experiences.	Perceived availability of consumer sensitive data	**Moderator:** purchase channel **Mediators:** Perceived risk, perceived convenience, perceived inspiration	Consumer loyalty (attitudinal and behavioural) with online and offline channels to enhance consumer lifetime value; through the adoption and use of loyalty programmes.

Note: *Systematic review. NA = Not applicable.

Table 2. Sample characteristics

Variable	% of total
Age	
18-25	7.2
26-32	16.5
33-39	21.2
40-46	16
47-53	15.9
54-60	15.3
61-67	7.6
68-74	0
Older than 74	0.3
Total	100
Gender	
Male	44.1
Female	55.9
Total	100
Loyalty card	
Yes	67
No	33
Total	100

Note: $N = 923$.

Table 3. Reliability and convergent validity

Construct	Indicator	*M*	*SD*	Factor loading	Factor weight
Consumer loyalty[a] (α = 0.897; AVE = 0.830; CR = 0.936)					
I have a strong commitment to continue my relationship with [Retailer]	PL_1	2.07	0.999	0.882**	
I believe that my relationship with [Retailer] deserves my maximum effort to maintain it	PL_2	2.51	1.168	0.917**	
My effort to maintain my relationship with [Retailer] indefinitely	PL_3	2.41	1.095	0.933**	
Perceived availability of consumer data with higher sensitivity[b] (α = N.A.; AVE = N.A.; CR = N.A.)					
Personal identification data (e.g., name, address, telephone number, email-address)	PAS_2	1.66	0.934		0.232**
Financial data (e.g., bank information, income level)	PAS_4	2.94	1.130		0.117**
Location data (i.e., information from the network or service about the location of a phone or other device)	PAS_8	2.47	0.994		0.343**
Social network (i.e., information about friends and/or family members from Facebook, Instagram, Twitter)	PAS_9	3.22	0.960		0.369**
Medical data (e.g., blood group, DNA)	PAS_10	3.50	0.871		0.237**
Perceived availability of consumer data with lower sensitivity[b] (α = N.A.; AVE = N.A.; CR = N.A.)					
Demographic data (e.g., gender, age, marital status, postcode, occupation)	PAS_1	1.95	1.014		0.232**
Personal lifestyle and interests (e.g., hobbies, leisure activities, travel interests)	PAS_3	2.80	0.932		0.424**
Visiting behaviour (e.g., number, frequency and duration of visits, time of visits)	PAS_5	2.07	0.793		0.469**
Purchase behaviour (e.g., types, number and frequency of products bought)	PAS_6	1.99	0.767		-0.006
Browsing behaviour (e.g., movement through store or online shop)	PAS_7	2.22	0.875		0.172**
Perceived risk[a] (α = 0.961; AVE = 0.895; CR = 0.971)					
Because [Retailer] has collected my personal data...					
...shopping at [Retailer] makes me feel psychologically uncomfortable	PR_1	4.23	1.108	0.933**	
...shopping at [Retailer] gives me a feeling of unwanted anxiety	PR_2	4.29	1.062	0.960**	
...shopping at [Retailer] makes me experience unnecessary tension	PR_3	4.27	1.084	0.950**	
…I worry a lot when buying at [Retailer]	PR_4	4.38	0.991	0.940**	
Perceived convenience[a] (α = 0.898; AVE = 0.831; CR = 0.936)					
Because [Retailer] has collected my personal data...					
... it is overall very convenient to shop at [Retailer].	PC_1	1.81	0.940	0.883**	
… I overall save a lot of time as I do not have to provide data each time I shop.	PC_2	2.03	1.017	0.914**	
… I save a lot of effort	PC_3	2.09	1.013	0.937**	
Perceived inspiration[a] (α = 0.927; AVE = 0.873; CR = 0.954)					
Because [Retailer] has collected my personal data...					
...shopping at [Retailer] stimulates my imagination.	PI_1	2.94	1.240	0.928**	
…when shopping at [Retailer], I am often intrigued by new ideas.	PI_2	2.75	1.197	0.951**	
…when shopping at [Retailer], I always discover something new.	PI_3	2.72	1.207	0.924**	
Control variable	**Indicator**	***M***	***SD***	**Factor loading**	**Factor weight**
Purchase channel (0 = Offline, 1 = Online)	N.A.	0.42	0.495	N.A.	
Age (Ordinal scale)[c]	N.A.	3.95	1.746	N.A.	
Gender (1 = Male, 0 = Female)	N.A	0.44	0.497	N.A	
Loyalty card (1 = Yes, 0 = No)	N.A	0.67	0.471	N.A	
Privacy concerns[a] (α = 0.857; AVE = 0.773; CR = 0.911)					
I am generally sensitive to the way companies handle my personal information.	N.A.	2.32	0.985	0.883**	
Personal privacy is very important for me, compared to other subjects.	N.A	2.07	0.927	0.915**	
Generally, I am concerned about threats to my personal privacy	N.A	2.25	1.025	0.838**	

Note: $N = 923$. [a] 5-point Likert scales (1 = Strongly disagree, 5 = Strongly agree); [b] 4-point ordinal scales (1 = I assume [Retailer] does not have this type of data, and I am under no circumstances willing to provide if asked, 2 = I assume [Retailer] does not have this type of data, but I could imagine providing it if asked, 3 = I assume [Retailer] has this type of data because they automatically collect it, 4 = I assume [Retailer] has this type of information because I actively provided it); [c] Ordinal scale (1 = 18-25, 2 = 26-32, 3 = 33-39, 4 = 40-46, 5 = 47-53, 6 = 54-60, 7 = 61-67, 8 = 68-74, 9 = Older than 74). α = Cronbach's alpha; AVE =Average Variance Extracted. CR = Composite Reliability. N.A. = Not Applicable. * $p < 0.05$, ** $p < 0.01$.

Table 4. Quality criteria of second-order measurement

Formative second-order construct facets/components	Outer weights (path)	VIF
Higher level of perceived availability of consumer sensitive data	0.544^{**}	2.467
Lower level of perceived availability of consumer sensitive data	0.517^{**}	2.467

Note: $N = 923$. VIF = Variance Inflation Factor. Bias-corrected bootstrap significance levels: * $p < 0.05$, ** $p < 0.01$ (one-tailed test).

Table 5. Zero-order correlations and discriminant validity

	1	2	3	4	5	6	7	8	9	10
1. Consumer loyalty	**.911**	.353	.072	.568	700	.022	.018	.069	.147	249
2. Perceived availability of sensitive data	.312**	N.A.	.234	.462	476	.225	.132	.152	.426	.194
3. Perceived risk	-.043	.185**	**.946**	.109	.060	.066	.163	.223	.046	.162
4. Perceived convenience	.510**	.405**	-.103**	**.911**	.620	.172	.036	025	.326	.287
5. Perceived inspiration	.640**	.428**.	.053	.566**	**.934**	.048	.131	.061	.187	.282
6. Purchase channel	-.031	-.294**	.111*	-.221**	-.070	N.A.	.118	.049	.452	.059
7. Age	.016	.074*	.160**	.035	.126**	-.171**	N.A.	.001	.133	.039
8. Gender	-.066*	-.117**	-.218**	-.012	-.059	-.074	-.001	N.A.	.026	.090
9. Loyalty card	-.076*	-.277**	-.001	-.125**	-.141**	.008	.052	.044	N.A.	.080
10. Privacy concerns	.217**	.160**	.148**	.249**	.250**	.076	-.027	-.084*	-.103**	**.879**

Note: $N = 923$. The diagonal elements (in bold) are the values of the square root of the AVE. The values below the diagonal are the zero-order correlation coefficients. The elements above the diagonal are the values of the HTMT ratio. N.A.: Not Applicable. * $p < 0.05$, ** $p < 0.01$.

Table 6. Descriptive statistics regarding the degree of consumer sensitivity to each of the pretested categories of data

Construct	*M*	*SD*
Categories of data with higher level of perceived sensitivity		
Financial data (e.g., bank information, income level)	4.84	0.500
Social network (i.e., information about friends and/or family members from Facebook, Instagram, Twitter)	4.60	0.806
Personal identification data (e.g., name, address, telephone number, email-address)	4.47	0.829
Medical data (e.g., blood group, DNA)	4.28	0.922
Location data (i.e., information from the network or service about the location of a phone or other device.)	4.10	0.871
Categories of data with lower level of perceived sensitivity		
Demographic data (e.g., gender, age, marital status, postcode, occupation)	3.31	1.186
Browsing behaviour (e.g., movement through store or online shop)	3.27	1.089
Visiting behaviour (e.g., number, frequency and duration of visits, time of visits)	3.07	1.243
Purchase behaviour (e.g., types, number and frequency of products bought)	3.09	1.139
Personal lifestyle and interests (e.g., hobbies, leisure activities, travel interests)	2.66	1.075

Note: $N = 70$.

Table 7. Standardized parameter estimates of the mediation model

Path	Direct effect	Indirect effect
Perceived availability sensitive data → Perceived loyalty	0.03	
Perceived availability sensitive data → Perceived risk (H1a supported)	0.22**	
Perceived risk → Perceived loyalty (H1b supported)	-0.07**	
Mediator: Perceived risk (H1c supported)		-0.02*
Perceived availability sensitive data → Perceived convenience (H2a supported)	0.40**	
Perceived convenience → Perceived loyalty (H2b supported)	0.20**	
Mediator: Perceived convenience (H2c supported)		0.08**
Perceived availability sensitive data → Perceived inspiration (H3a supported)	0.44**	
Perceived inspiration → Perceived loyalty (H3b supported)	0.51**	
Mediator: Perceived inspiration (H3c supported)		0.23**
Control relationships		
Age → Perceived loyalty	-0.04*	
Gender → Perceived loyalty	-0.06*	
Privacy concerns → Perceived loyalty	0.05*	
Loyalty card ownership → Perceived loyalty	-0.07	
R^2 of Perceived loyalty		0.45
R^2 of Perceived convenience		0.16
R^2 of Perceived inspiration		0.20
R^2 of Psychological risk		0.05

Note: $N = 923$. * $p < 0.05$, ** $p < 0.01$. Two-tailed test for the control relationships and one-tailed test for the hypothesized relationships.

Table 8. Standardized parameter estimates of multigroup analysis for online purchase channel vs. offline purchase channel and path coefficient differences

	Group 1 Online purchase channel (175 cases)	Group 2 Offline purchase channel (237 cases)	Path coefficients difference (offline vs. online)
Perceived availability sensitive data → Perceived loyalty	0.18*	0.01	-0.17†
Perceived availability of consumer sensitive data → Perceived risk (H4 not supported)	0.11	0.11	0.00
Perceived availability of consumer sensitive data → Perceived convenience (H5 supported)	0.64**	0.29**	-0.35**
Perceived availability of consumer sensitive data → Perceived inspiration (H6 partially supported)	0.53**	0.41**	-0.12†
Perceived risk → Perceived loyalty	-0.04	-0.06	-0.02
Perceived convenience → Perceived loyalty	0.34**	0.14*	-0.20*
Perceived inspiration → Perceived loyalty	0.37**	0.48**	0.11
Control relationships			
Age → Perceived loyalty	-0.03	-0.11	-0.08
Gender → Perceived loyalty	-0.07	0.06	0.13
Privacy concerns → Perceived loyalty	0.06	-0.14	-0.20
Loyalty card ownership → Perceived loyalty	-0.12	-0.05	0.07

Note: † = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$ (one-tailed test). Significance levels based on bias-corrected bootstrap confidence intervals.

Appendix A– Common method factor procedure results.

Construct	Indicator	Substantive factor loading (R_S)	R_S^2	Method factor loading (R_M)	R_M^2
Perceived loyalty	PL_1	0.914**	0.835	-0.045*	0.002
	PL_2	0.895**	0.801	0.031	0.001
	PL_3	0.924**	0.854	0.013	0.000
Perceived convenience	PC_1	0.899**	0.808	-0.017	0.000
	PC_2	0.930**	0.865	-0.022	0.000
	PC_3	0.907**	0.823	0.037*	0.001
Perceived inspiration	PI_1	0.888**	0.789	0.047*	0.002
	PI_2	0.974**	0.949	-0.028	0.001
	PI_3	0.941**	0.885	-0.019	0.000
Perceived risk	PR_1	0.939**	0.882	-0.018	0.000
	PR_2	0.962**	0.925	-0.007	0.000
	PR_3	0.955**	0.912	-0.018	0.000
	PR_4	0.928**	0.861	0.043**	0.002
Perceived availability of consumer sensitive data	PAS_1	0.699**	0.489	-0.034	0.001
	PAS_2	0.651**	0.424	-0.097	0.009
	PAS_3	0.687**	0.472	0.032	0.001
	PAS_4	0.677**	0.458	-0.069	0.005
	PAS_5	0.808**	0.653	-0.060	0.004
	PAS_6	0.785**	0.616	-0.083	0.007
	PAS_7	0.715**	0.511	0.044	0.002
	PAS_8	0.696**	0.484	0.006	0.000
	PAS_9	0.572**	0.327	0.110	0.012
	PAS_10	0.446**	0.199	0.156*	0.024
Privacy concerns	PC_1	0.865**	0.748	0.041*	0.002
	PC_2	0.881**	0.776	0.017	0.000
	PC_3	0.900**	0.810	-0.058**	0.003
Average			**0.698**		**0.003**

Note: $N = 923$. * $p < 0.05$, ** $p < 0.01$.

Appendix B

In the absence of suitable instruments, Gaussian copulas (Park and Gupta, 2012) are employed to address endogeneity concerns. Before initiating the Gaussian copula approach to test for endogeneity in our model, we verified whether the variables that might exhibit endogeneity are non-normally distributed. We did so by running the Kolmogorov-Smirnov test with Lilliefors correction (Sarstedt and Mooi 2014) on the standardized composite scores of Perceived availability of consumer sensitive data (PACSD), Perceived risk (RISK), Perceived convenience (CONV), and Perceived inspiration (INSP), which Smart-PLS 4 provides. As shown in Table B1, the observed D-values for these variables –together with their corresponding p-values strongly– suggest that the data for these variables do not follow a normal distribution, as the p-values are significantly below 0.05. This allows us to use Gaussian copula analysis to test for endogeneity.

Table B1. Results of the Kolmogorov-Smirnov test

Variables	Observed D	*p-value*
PACSD	0.0405	0.0014
RISK	0.2648	0.0002
CONV	0.1523	0.0002
INSP	0.0886	0.0002

Note: PACSD: Perceived availability of consumer sensitive data; RISK: Perceived risk; CONV: Perceived convenience; INSP: Perceived inspiration.

To conduct the Gaussian copula analysis, we created four regression models in which we considered the independent constructs PACSD (model 1), RISK (model 2), CONV (model 3), and INSP (model 4) as possibly exhibiting endogeneity. In addition, in order to simultaneously account for multiple endogenous variables when applying the Gaussian copula approach, we created 11 regression models that included all possible combinations of multiple endogenous variables in our PLS path model: PACSD and RISK (model 5), PACSD and CONV (model 6), PACSD and INSP (model 7), RISK and CONV (model 8), RISK and INSP (model 9), CONV and INSP (model 10), PACSD, RISK and CONV (model 11), PACSD, RISK and INSP (model 12), PACSD, CONV and INSP (model 13), RISK, CONV and INSP (model 14), and PACSD, RISK, CONV and INSP (model 15). We used the constructs' standardized composite scores to compute the Gaussian copula of the partial regressions in the structural model, as indicated by Hult et al. (2018). We also used the REndo package of the R software (Gui et al. 2017) and Hult et al.'s. (2018) R code, together with the boot package (Canty and Ripley 2017) to compute bootstrap standard errors.

The results in Table B2. indicate that none of the Gaussian copulas were significant at a 0.1 level when accounting for endogenous variables, suggesting an absence of endogeneity issues. Despite including copulas, causal inference is not claimed due to the cross-sectional nature of the analysis. Instead, the findings should be interpreted as a test of theory-based associations.

Table B2. Results of the Gaussian Copula Approach.

Variables	**Original model**		**Gaussian Copula Model 1 (Endogenous variable: PACSD)**		**Gaussian Copula Model 2 (Endogenous variable: RISK)**		**Gaussian Copula Model 3 (Endogenous variable: CONV)**		**Gaussian Copula Model 4 (Endogenous variable: INSP)**		**Gaussian Copula Model 5 (Endogenous variables: PACSD, RISK)**	
	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*
PACSD	0.0241	0.4214	0.0202	0.7884	0.0239	0.4285	0.0245	0.4057	0.0240	0.4200	0.0164	0.8357
RISK	-0.0572	0.0146	-0.0571	0.0159	-0.0531	0.0669	-0.0568	0.0144	-0.0574	0.0154	-0.0522	0.0810
CONV	0.2024	0.3117	0.2022	0.3589	0.2022	0.2894	0.2186	00089	0.2038	0.0182	0.2018	0.3074
INSP	0.5177	0.0000	0.5178	0.0000	0.5173	0.0000	0.5177	0.0000	0.5423	0.0000	0.5174	0.0000
GC (PACSD)			0.0031	0.9598							0.0061	0.9254
GC (RISK)					-0.0017	0.8493					-0.0020	0.8277
GC (CONV)							-0.0159	0.8456				
GC (INSP)									-0.0180	0.6237		

Variables	**Original model**		**Gaussian Copula Model 6 (Endogenous variables: PACSD, CONV)**		**Gaussian Copula Model 7 (Endogenous variables: PACSD, INSP)**		**Gaussian Copula Model 8 (Endogenous variables: RISK, CONV)**		**Gaussian Copula Model 9 (Endogenous variables: RISK, INSP)**		**Gaussian Copula Model 10 (Endogenous variables: CONV, INSP)**	
	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*
PACSD	0.0241	0.4214	0.0153	0.8482	0.0097	0.9010	0.0243	0.4108	0.0241	0.4186	0.0240	0.4131
RISK	-0.0572	0.0146	-0.0564	0.0158	-0.0570	0.0157	-0.0553	0.0936	-0.0588	0.0583	-0.0574	0.0126
CONV	0.2024	0.3117	0.2212	0.0110	0.2034	0.3583	0.2160	0.0341	0.2039	0.3931	0.2011	0.0343
INSP	0.5177	0.0000	0.5180	0.0000	0.5455	0.0000	0.5175	0.0000	0.5437	0.0000	0.5432	0.0000
GC (PACSD)			0.0076	0.9078	0.0117	0.8540						
GC (RISK)							-0.0006	0.9565	0.0006	0.9514		
GC (CONV)			-0.0189	0.8242			-0.0134	0.8948			0.0027	0.9776
GC (INSP)					-0.0200	0.5917			-0.0188	0.6425	-0.0186	0.6631

Variables	**Original model**		**Gaussian Copula Model 11 (Endogenous variables: PACSD, RISK, CONV)**		**Gaussian Copula Model 12 (Endogenous variables: PACSD, RISK, INSP)**		**Gaussian Copula Model 13 (Endogenous variables: PACSD, CONV, INSP)**		**Gaussian Copula Model 14 (Endogenous variables: RISK, CONV, INSP)**		**Gaussian Copula Model 15 (Endogenous variables: PACSD, RISK, CONV, INSP)**	
	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*	value	*p-value*
PACSD	0.0241	0.4214	0.0145	0.8557	0.0100	0.9009	0.0096	0.9036	0.0241	0.4159	0.0098	0.9023
RISK	-0.0572	0.0146	-0.0546	0.1047	-0.0576	0.0718	-0.0570	0.0155	-0.0587	0.0742	-0.0578	0.0856
CONV	0.2024	0.3117	0.2179	0.0351	0.2034	0.2896	0.2041	0.0348	0.2031	0.0616	0.2052	0.0585
INSP	0.5177	0.0000	0.5178	0.0000	0.5460	0.0000	0.5453	0.0000	0.5438	0.0000	0.5456	0.0000
GC (PACSD)			0.0080	0.9013	0.0115	0.8600	0.0118	0.8551			0.0117	0.8576
GC (RISK)			-0.0008	0.9433	0.0002	0.9826			0.0005	0.9608	0.0003	0.9769
GC (CONV)			-0.0157	0.8784			-0.0007	0.9943	0.0008	0.9942	-0.0018	0.9870
GC (INSP)					-0.0202	0.6131	-0.0198	0.6445	-0.0190	0.6657	-0.0200	0.6423

The Impact of Perceived Availability of Consumer Data on Loyalty in Retail Channels: A Relational Exchange Perspective

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