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What Information Do Shoppers Share? The Effect of Personnel-, Retailer-, and Country-Trust on Willingness to Share Information

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Abstract

The relationship between consumers' privacy concerns and their willingness to disclose personal information to retailers is more complex than a simple negative one. The multi-faced context, within which privacy decisions take place, shapes and bounds this relationship. Drawing on privacy contextual integrity theory, we model the privacy decisions as influenced by individuals' multilevel trusting surroundings, which include trust in a retailer and in its personnel at the micro-level, and trust in a country at the macro-level. Based on 22,050 survey data across seven product categories in fourteen countries, our Bayesian multilevel modeling reveals that micro- and macro-level trust may promote consumers' disclosure intentions via three mechanisms: (1) micro-level trust positive effect on consumers' willingness to disclose their data; (2) micro-level trust effect by attenuating privacy concerns' negative influence on this willingness; and (3) the positive indirect effect of trust in the country on both the direct and indirect impacts of trust in a retailer and in its personnel. Interestingly, trust's direct effects are found in all the investigated types of information (i.e., identification, medical, financial, locational, demographic, lifestyle, and media usage data), whereas the indirect effects are found to vary across information types. Our post-hoc cluster analysis shows that different retail contexts can be classified into three clusters and help retailers understand whether they should invest in developing both trust in their retail company and in their personnel, or mainly on one of the two. By taking different types of trust and context effects into consideration, our findings help different retailers encourage customers to disclose their data with them.

Keywords: Privacy concerns; Trust in a retailer; Trust in retail personnel; Trust in a country; Willingness to provide information; Contextual integrity theory

Introduction

Retailers are at the forefront of leveraging digital technologies to create personalized customer experiences for their clients in order to increase sales and customer loyalty (Bleier and Eisenbeiss 2015; Inman and Nikolova 2017; Aguirre et al. 2015). This applies to physical and digital retailers, since we have entered a new retail era in which omnichannel strategies have reshaped the sector's competitive logic (Verhoef, Kannan, and Inman 2015), and in which customers buy as easily from a physical store as from an online e-commerce website (Gao and Su 2017). Given the various devices that multiply the number of touch points with clients and facilitate the collecting of their data (Bell, Gallino, and Moreno 2018), one could claim that creating a smooth, personalized shopping experience is rather straightforward. Nevertheless, retailers have never been so much in need of customer-specific data to reach their objective effectively than in this data era.

Two main elements complicate retailers' activities in the current landscape. First, technologies' effective utilization often requires collecting voluntarily disclosed customer data, such as identification and financial data that cannot be tracked. Second, in the wake of high-profile privacy scandals, customers have become increasingly worried about how organizations store and exploit their personal data. Consumers have therefore become more cautious about sharing such data with retail companies.

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In general, privacy concerns (PCs) are associated with negative consumer responses, the worst being refusal to provide personal information or to purchase. Researchers have, nevertheless, noted that consumers may be subjected to “the privacy paradox” (Dienlin and Trepte 2015; Norberg, Horne, and Horne 2007); that is, they “claim to value their data privacy while simultaneously acting in ways that compromise their privacy” (Palmatier and Martin, 2019, p. 9).

In various attempts to explain this discrepancy between PCs and behaviors, previous literature advanced numerous theoretical explanations (Kokolakis 2017) that share a common underlying element: the context. The aim of this paper is to take various context-specific elements into account and to investigate how they affect customers’ information disclosure decisions. In this way, we contribute to the retail privacy literature that has not yet integrated context-dependent variables, and help retailers boost customers’ data disclosure. We do so by relying on the emerging stream of research based on contextual integrity theory (Nissenbaum 2004, 2011).

According to this view, individuals’ data disclosure choice is based on their perception of whether the information flow is appropriate in a given context. Consequently, the type of organization (a retailer, a health organization, the government, etc.) with which customers share information may influence their willingness to do so, and is a first key contextual variable that could affect a study’s results. This implies that studies on privacy in other sectors may not be useful for retailers. Our literature review reveals that not many studies on privacy focus specifically on retail (see details in Web Appendix A). By specifically focusing on the context’s impact on privacy disclosure, we aim at helping retail companies gain further insights into what affects their customers’ willingness to disclose. To this end, we develop a multi-level contextual model that considers several intervening variables that could impact customers’ disclosure.

First, we analyze customers’ trust, which can simultaneously refer to several “objects,” namely the retailers from which they buy (hereafter labelled “retailer-trust”), the retailers’ personnel with whom they eventually interact (“personnel-trust”), and the broader institutional context at the country level within which the two above trusted relationships occur (“country-trust”). We classify these trust types into two main levels (Scott 2005), referring to them as micro-level trust (i.e., retailer- and personnel-trust) and macro-level trust (i.e., country-trust), and examine how trusts at different levels influence consumers’ willingness to share their personal information (WSPI) with retailers. To ensure variance in the country-trust, we collected data in fourteen countries: Argentina, Australia, Brazil, Canada, China, Colombia, France, Italy, Japan, Mexico, South Africa, Spain, the UK, and the US.

Second, the type of product that retailers sell may condition customers’ disclosure propensity; our study therefore considers seven different types of product categories that retailers sell: men and women apparel, children and teenager apparel, luxury goods, pharmaceuticals, grocery, home décor and DIY goods, and consumer electronics.

Finally, customers’ disclosure intentions are contingent upon the types of information retailers request their customers to provide. We therefore consider seven types of information: identification, medical, financial, location, demographic, lifestyle, and media usage data.

We test our model by using the multilevel Bayesian estimation method on 22,050 respondents; this method reflects the phenomenon’s hierarchical nested structure (i.e., the individual data nested within retailers’ product categories and within a specific country). In particular, we investigate a total of 686 contexts, comprising all possible combinations of the seven information types, seven product categories, and fourteen countries, and, in a post-hoc cluster analysis, explore how these contexts can be classified on the basis of the effect sizes of the trusts and PCs estimated in our multi-level model.

Our work contributes to prior retail privacy research by focusing 1) on the specific context in which the information sharing occurs and 2) on this context’s different levels by means of a cross-national multilevel modeling; it therefore provides a fine-grained contextual understanding of consumers’ WSPI, providing insights for retailers to develop privacy policies.

Privacy as Contextual Integrity

A growing body of theoretical scholarship is moving toward a contextual conceptualization of privacy. This literature stream was developed from Nissenbaum’s (2004, 2010 conceptualization of privacy as contextual integrity; that is, privacy is defined as the appropriate norms of information flow in a given context (Nissenbaum 2004, 2011). Unlike previous views, which usually conceptualized privacy as a static, generic concept cutting across different situations, the context-dependent view of privacy postulates that individuals have different privacy expectations in different contexts (Martin and Nissenbaum 2016; Martin 2016). This means that, when confronted with a specific disclosure request from retailers, customers assess this as either respecting or violating their privacy according to whether the request conforms to their expectations of the appropriate information flow within that particular context (Martin and Nissenbaum 2016). An important implication of defining privacy as contextual integrity is that it reveals the key difference between “giving up” privacy and giving up information (Martin and Nissenbaum 2016)—a central element which also explains the privacy paradox (Palmatier and Martin 2019). According to Martin and Nissenbaum (2016), when customers share their personal data, they do not relinquish their privacy, just certain personal information, because they perceive the information flow as appropriate for that specific context. This behavior is therefore compatible with privacy’s declared high value, which has often been found to be linked to high levels of PCs (e.g., Smith, Milberg, and Burke 1996; Baruh, Secinti, and Cemalcilar 2017).

PCs have long been considered a key factor that influences consumers’ decisions to disclose personal information negatively (Smith, Milberg, and Burke 1996; Li 2011). PCs are conceptualized as a general disposition that transcends a situation’s details and reflects an individual’s general tendency to worry about information privacy (Smith, Milberg, and Burke 1996; Bélanger and Crossler 2011). Many studies operationalize PCs as a multidimensional construct comprising four dimensions (Smith, Milberg, and Burke 1996): data collection, unauthorized secondary use, improper access, and errors. Extant empirical research on the relationship between PCs and information disclosure yields mixed findings (Baruh, Secinti, and Cemalcilar 2017; Gerber, Gerber, and Volkamer 2018). In keeping with contextual integrity theorization of privacy, we argue that much of the inconsistency is due to these studies' different contexts (Bansal, Zahedi, and Gefen 2016; Bansal, Zahedi, and Gefen 2010). While PCs are an individual variable remaining generally stable across contexts, decisions to disclose information are highly contextual—they are shaped by the informational norms deemed appropriate within the given context (Martin 2020). This suggests that the relationship between PCs and WSPI is more complex than a simple negative one, and that it can only be better understood by investigating the information flow's context in detail.

In this paper, we aim to contribute to the understanding of the relationship between PCs and WSPI by adopting the context-dependent view of privacy, which is based on the contextual integrity theory, and by applying it to the retail sector. This theory defines context as the social domain that comprises informational norms according to which customers develop context-specific expectations (Nissenbaum 2018).

Information disclosure decisions are, as mentioned, based on the evaluation of the information flow's appropriateness within a context (Nissenbaum 2004, 2011, 2018). That is to say, the context delimits the contours of the analysis within which the information flow's appropriateness is assessed. This appropriateness assessment depends on the discloser's perception of the informational norms (Martin and Nissenbaum 2016). These norms can be explicitly expressed in rules or laws, or they can be implicitly embodied in "conventional" behaviors (Nissenbaum 2004). Within their respective contexts, these norms emerge and develop over time as a result of the interactions between various actors and between the actors and the social settings (Nissenbaum 2018; Wright and Xie 2019) characterizing the context in which these actors interact. According to this theoretical framework, two key elements should therefore be investigated to better understand PCs' impact on WSPI: 1) the interactions between customers and retailers and 2) the context in which these interactions take place.

Is a Relationships Within Specific Contexts

Once privacy is viewed as mutually agreed-upon information flow norms built on and for the relationships within specific contexts, it primarily becomes attached to a relationship (Martin 2016; Martin 2018). Consequently, it is crucial to understand the relationship between customers and retailers within a specific context in order to unravel information disclosure's dynamics. Trust is a core construct for understanding relationships, particularly in a risky situation such as information disclosure. Trust, referred to as the intention or willingness to accept vulnerability based on one's positive expectations of another's intentions or behaviors (Rousseau et al. 1998), is essential for economic and social interactions (Mayer, Davis, and Schoorman 1995; Gefen, Karahanna, and Straub 2003). It arises from the need to curb risks in situations of uncertainty, interdependence, and fear of potential loss (Gefen and Pavlou 2012; Rousseau et al. 1998). Sharing personal information with retailers bears risks for consumers, making them vulnerable (Palmatier and Martin 2019). Trust built on confident, positive expectations of another's future behavior is an essential tool to lessen one's perceptions of risk and to encourage "a leap of faith" (Möllering 2006a) despite one's uncertainty and inability to monitor or control the other party's conduct. In keeping with the contextual integrity theory, trust can be seen as a kind of implicit social norms (Heide and John 1992) for the customer–retailer relationship.

Since this relationship is embedded in a specific context, its context's characteristics affect it. In retail settings, it is important that we take three contextual characteristics into account. First, the country-level institutional context in which the customer–retailer relationships occur, is a potential intervening variable. We therefore consider fourteen countries in this study to cover a variety of social institutional contexts, since these countries differ in the level of trust their citizens on average have in business in general.

Second, the type of retailer to which the information is given, can also influence customers' information disclosure decision making. In the marketing literature, previous studies on privacy in retail were sometimes experimental and referred to fictitious companies (e.g. Bleier and Eisenbeiss 2015; Aiken and Boush 2006), which clearly limits privacy's contextualization. Studies referring to actual retailers mainly focused on just one particular company, contextualizing it either online (e.g. McCole, Ramsey, and Williams 2010; Cho 2006) or offline (e.g. Inman and Nikolova 2017). This online/offline distinction is, we believe, not the best frame to consider, since the majority of retailers currently sell on both channels (Gao and Su 2017). We therefore consider actual companies and contextualize them by referring to seven product categories.

Finally, the type of information the retailer requests should also be taken into account. Previous research mainly referred to the information type's sensitivity (Malhotra, Sung, and Agarwal 2004; Bansal, Zahedi, and Gefen 2010; Rohm and Milne 2004), finding that, in general, consumers perceive medical and financial information as most sensitive; nonetheless, the information classifications were found to lack consistency (Milne et al. 2016; Markos, Labrecque, and Milne 2018). Contextual integrity theory actually calls for a more nuanced analysis, as general categorizations of context based on specific information classes might not be effective (Martin and Nissenbaum 2016). Our study therefore considers a broad range of personal information comprising seven types, and compares the nuanced analysis results with those based on the higher/lower sensitivity classification.

In the following pages, we develop a multilevel conceptual model (see Fig. 1) grounded in contextual integrity theory to investigate how trust-based interactions between customers and retailers impact the relationship between PC and WSPI in different contexts.

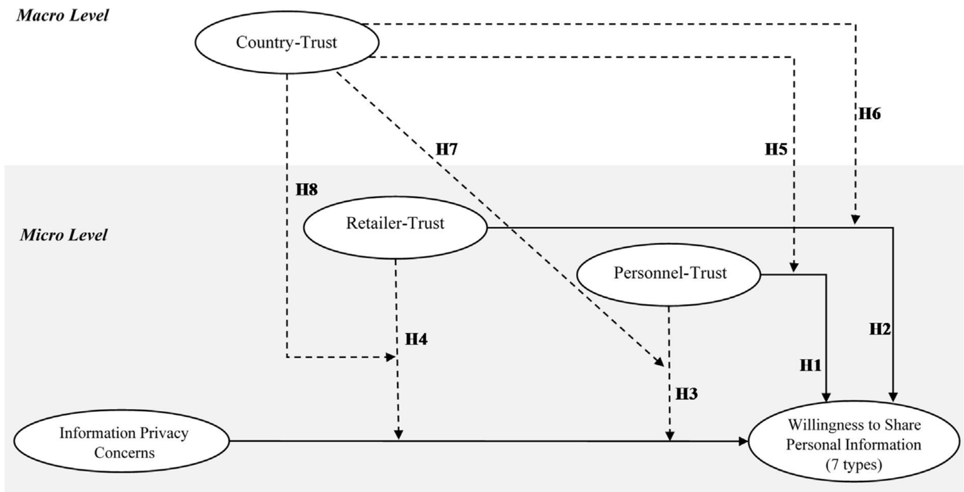

Fig. 1. Theoretical model.

Research Model and Hypotheses Development

In this paper, as mentioned, we adopt the contextual integrity view of privacy and consider trust as the key implicit social norm underlying the information flow from customers to retailers. We use customers' willingness to share seven types of personal information with retailers as the dependent variables (DVs). In this section, we will postulate our hypotheses referring generically to the WSPI; we do not formulate hypotheses pertaining to specific information types, since the lack of literature does not justify different results. To verify the contextual integrity theory's claim that the context needs to be investigated in a nuanced way (Martin and Nissenbaum 2016), we will report and compare the results of two models: 1) our model using willingness to share each type of information as the dependent variable (DV), resulting in a total of seven DVs and 2) an alternative model following traditional privacy research that classifies information types into higher vs. lower sensitivity types (e.g., Bansal, Zahedi, and Gefen 2010; Mothersbaugh et al. 2012), resulting in a total of two DVs.

We also focus on the central role of trust, which favors an information flow from customers to retailers. Previous literature distinguished between a first type of trust, which refers to customers' trust in individual firms and their representatives (thus only affecting the relationship in which it developed) and a second type, customers' trust in the broader social context in which a relationship might develop (Grayson, Johnson, and Chen 2008). Two main levels of trust can therefore be identified: the micro-level trusts (i.e., retailer- and personnel-trust) and the macro-level trust (i.e., country-trust), respectively embodying the micro- and macro-contexts in which privacy decisions are made (Scott 2005). Although trust is a multilevel phenomenon, our literature review (see Web Appendix A) revealed that previous empirical work on privacy and trust in the marketing literature had important limitations.[1] First, in marketing journals, only a few privacy studies focused specifically on retail (see the list and main findings in Table 1), which is why we also draw on other literature streams' findings to develop our hypotheses.

Second, previous studies were predominantly conducted at a single level of analysis, therefore largely ignoring trust and privacy's multilevel nature. Conceptually, single-level analysis confounds lower- and higher-level influences. Methodologically, single-level analysis does not account for data's nested structure (i.e., data's nonindependence), leading to biased standard errors of the estimates (Aguinis and Gottfredson 2010; Klein and Kozlowski 2000). Bliese and Hanges (2004) mentioned that the estimates based on single-level analysis can be "too liberal or too conservative," indicating that the bias can either inflate the significant level or reduce the power to detect a significant effect.

Third, previous studies on privacy and trust mainly referred to trust in the company (i.e., trust in the retailer in our study), thereby ignoring the macro-level trust, which Grayson, Johnson, and Chen (2008) identified. Consequently, although the traditional approach to information privacy research is valuable in terms of the richness and depth of the knowledge it has produced, focusing on just a single level of analysis at a time has prevented us from having a fully holistic and integrative view of our theorizing on information privacy. In fact, our observation of these limitations in marketing literature echoes what privacy scholars (e.g., Smith, Dinev, and Xu 2011; Bélanger and Crossler 2011; Baruh, Secinti, and Cemalcilar 2017) and trust scholars (Rousseau 2003; Fulmer and Gelfand 2012) have long pointed out. By considering the three trust types in the context of retail, and linking them with a multi-level approach, our study aims at overcoming these limitations. The multilevel trust conceptualization provides us with a framework to explore the contextual influences at multiple levels of analysis. In the next two sections, we present the micro- and macro-level hypothesized effects of trust on WSPI.

[1] Extensive literature reviews on privacy can be found in Baruh, Secinti, and Cemalcilar (2017), Yun, Lee, and Kim (2018), Smith, Dinev, and Xu (2011), Li (2011) and Martin and Murphy (2017).

Table 1
Findings of studies on trust and privacy in retail.

Study	Data collection context	Level of trust analyzed			Role of trust	Findings
		Macro-	Micro-level			
		Institutions/country	Company (in retailer)	Inter-personal (in personnel)		
Our study	RETAILER (offline and/or online)	X	X	X	MODERATOR & INDEPENDENT	We take a multilevel approach to examining how micro-level trust (i.e., personnel-trust, retailer-trust), macro-level trust (i.e., country-trust), and privacy concerns interact to influence customers' willingness to share personal information with the retailer. We also explore how the roles of trusts and privacy concerns differ across contexts as a function of the type of information to share, product category, and country.
Inman and Nikolova (2017)	RETAILER (physical)		X		MEDIATOR	Relationship trust and privacy concerns mediated the effect of the new retail technology on shopper behavioral reactions such as retail patronage intention and WOM communication.
Martin, Borah, and Palmatier (2017)	(experimental study) RETAILER (offline and/or online)		X		MEDIATOR	Trust in the retailer mediated the effect of customer data vulnerability on negative consumer reactions such as falsifying information, negative WOM, and switching behavior.
Bleier and Eisenbeiss (2015)	(experimental study) ONLINE RETAILER (targeted adv)		X		MODERATOR	Trust in the retailer moderated the impact of ad personalization on consumers' response (i.e. reactance, privacy concerns, click-through rate); personalized ads from less trusted retailers triggered increased privacy concerns.
Cases et al. (2010)	ONLINE WEBSITE (including retailers)		X		MEDIATOR	Low consumers' perceived privacy concerns facilitated the formation of trust in the website which, in turn, led to strong intention to return to the website.
McCole, Ramsey, and Williams (2010)	ONLINE RETAILER	X	X		INDEPENDENT	Trust in the internet, trust in the vendor, and trust in third parties were positively related to attitude towards online purchasing, and trust in the vendor became more important when consumers had high perceived privacy and security concerns.

Table 1 (*Continued*)

Study	Data collection context	Level of trust analyzed			Role of trust	Findings
		Macro-	Micro-level			
		Institutions/country	Company (in retailer)	Inter-personal (in personnel)		
Aiken and Bousch (2006)	(experimental study) ONLINE RETAILER	X			DEPENDENT	Internet retail firm could build trust via having third-party certificates (trustmark). Consumers' beliefs about privacy and security mediated the positive effect of trustmark on trust in the retailer.
Bart et al. (2005)	ONLINE WEBSITE (including retailers)		X		DEPENDENT	Different driving forces were behind the building of online trust across website categories and consumer segments. Privacy and order fulfillment were the dominant drivers of trust for sites in which both information risk and involvement were high.
Cho (2006)	ONLINE RETAILER		X		MEDIATOR	Consumers' judgements of an e-vendor's trustworthiness shaped trust and distrust which, in turn, influenced consumers' self-disclosure and willingness to commit.
Rifon et al. (2005)	(experimental study) ONLINE RETAILER		X		DEPENDENT	Privacy seal enhanced trust in the website. Privacy self-efficacy, confidence in ability to protect one's privacy, moderated seal effects.
White (2004)	(experimental) RETAILER		X		INDEPENDENT	Trust in the marketer enhanced consumers' willingness to disclose privacy-related personal information, but decreased their willingness to disclose embarrassing information in exchange for customized benefit offerings.
Wang et al. (2004)	(experimental) ONLINE RETAILER		X		MEDIATOR	Security disclosures and awards from neutral sources enhanced the building of initial trust in the online retailer which, in turn, positively influenced willingness to provide personal information.
Schoenbachler and Gordon (2002)	(mail order) RETAILER		X		MEDIATOR	The study examined the antecedents and outcomes of trust. Trust in the company was found to enhance customers' willingness to provide the information necessary to help build a strong relationship.

Micro-Level Context—Direct and Moderating Effects of Retailer- and Personnel-Trusts

Trust at the micro level can be defined as one party having confidence in its exchange partner's integrity and reliability (Morgan and Hunt 1994). In the context of customer–retailer relationships, customers' trust represents an overall belief that the retailer will take actions that will result in positive outcomes for them (Anderson and Narus 1990). The overall relationship a customer has with a company usually incorporates a set of different, but strictly interconnected, relationships (Guenzi, Johnson, and Castaldo 2009). In consumer markets, a distinction can be made between individual-to-individual and individual-to-firm relationships (Iacobucci and Ostrom 1996). The first type is particularly relevant in service environments, such as retailing (Guenzi, Johnson, and Castaldo 2009), where interpersonal interactions take place between customers and other individuals (e.g. salespeople and front line employees, but also by phone through call centers or online through chats). Customers' familiarity with the selling organization in general characterizes the second relationship type (Guenzi, Johnson, and Castaldo 2009). In this setting, customers develop trust in the retail company, but also in its personnel with whom they may eventually interact.

The privacy retail literature has not investigated personnel-trust's role, but broader studies on the customer–retailer relationship have done so. Sivadas and Baker-Prewitt (2000) demonstrated that sales personnel's characteristics and behaviors are a key component of customers' overall evaluation of the service quality, leading to higher customer satisfaction with the retailer. Although the specific linkages between interpersonal trust and WSPI have not been investigated, extant research on personnel-trust consistently supports the existence of a positive association between the quality of the personal relationship with the sales personnel and that of the overall relationship with the retailer (Beatty et al. 1996; Reynolds and Beatty 1999; Guenzi, Johnson, and Castaldo 2009), which could therefore translate into higher WSPI. We therefore hypothesize that:

H1. Personnel-trust is positively related to WSPI.

Prior research investigating the key factors shaping customers' WSPI focused mainly on trust in a company, and showed that trust promotes WSPI (Bansal, Zahedi, and Gefen 2016; Bansal, Zahedi, and Gefen 2015). Bowie and Jamal (2006) found that firms perceived as "safe" or "trustworthy" regarding consumers' information privacy have a competitive advantage. Similarly, trust building factors, such as familiarity and positive past experiences with a firm, have proven to ensure consumers that their personal information's collection and usage occur in terms of fair practices (Chellappa and Sin 2005). When consumers trust a retailer, they feel their collected personal data are safe with the firm and will be used ethically (Taylor, Davis, and Jillapalli 2009). Consumers are therefore increasingly inclined to disclose personal information in high-trust situations (Reichheld and Schefter 2000). We therefore hypothesize:

H2. Retailer-trust is positively related to WSPI.

As a key contextual factor for enhancing WSPI, we argue that trust could moderate PCs' impact on consumers' disclosure intentions. Trust has often been studied in tandem with PCs to explain privacy-related intentions/behaviors (Wirtz and Lwin 2009; Pavlou 2011; Bélanger and Crossler 2011; Gerber, Gerber, and Volkamer 2018). However, most researchers consider the two as independent factors exerting separate influences on intentions/behaviors to disclose personal information (Dinev and Hart 2006; Anderson and Agarwal 2011; Kehr et al. 2015). Their interacting effect has not been well studied (Martin 2018; Smith, Dinev, and Xu 2011; Pavlou 2011), although the studies by Alashoor, Han, and Joseph (2017) and Joinson et al. (2010) are exceptions. In an experimental study, Joinson et al. (2010) found that participants were willing to waive their PCs when faced with a trusted requestor. These findings suggest that personnel-trust could mitigate PCs' negative impact on WPSI. We therefore hypothesize:

H3. Personnel-trust moderates the negative relationship between PCs and WSPI, such that high trust in retail personnel mitigates this negative relationship.

Similarly, Alashoor, Han, and Joseph (2017) showed that concerned customers were more likely to provide falsified information about themselves in social networks, but that high levels of trust in a social network website could weaken the strength of the negative relationship between PCs and self-disclosure accuracy. Although previous literature found no direct evidence of retailer-trust's moderating role, these findings show that, in addition to its direct promoting effect on WSPI, trust in the retail company could exert an indirect effect by suppressing PCs' influence. We therefore hypothesize:

H4. Retailer-trust moderates the negative relationship between PCs and WSPI, such that high retailer-trust mitigates this negative relationship.

Macro-Level Context—How does Country-Trust Shape Micro-Level Privacy Decisions?

Nissenbaum (2010) defines contexts as "the structured social systems that have evolved to manage and accomplish aspects of social life recognized as fundamental in a given society" (p. 242–43). This definition implies two important points that need to be integrated into our contextual analysis of privacy in retail. First, contexts are social systems, or social domains as stated explicitly by Nissenbaum (2018) in one of her latest articles. By referring to social domains, contexts are understood as "abstract representation of social structures experienced in daily life" (Nissenbaum 2010, p. 134).

Second, contexts are structured. A social system comprises micro- and macro-level structures; consequently, context is multilevel by nature. Macro-level contextual factors, such as cultures, laws, technology, and regulations, bestow meanings, rules, tools, and structures to micro-level interactions (Möllering 2006); Hansen 2012; Grayson, Johnson, and Chen 2008). Customers' privacy decision making cannot therefore be fully understood without taking the macro-level context into account.

At this level, trust reflects customers' perceptions of the context with respect to their belief in the social system' ability and reliability to safeguard individuals' interests, including their privacy (Martin 2019). In this study, we capture the macro-level contextual influences relevant to the retail settings via the country-trust construct. Following the conceptualization of macro-level trust (e.g., Rousseau 2003; Fulmer and Gelfand 2012), country-trust refers to trust that the public of a country broadly hold in the overall business. This trust is collectively held and captures generalized attitudes that reflect the public's overall perception of the rules, norms, and regulations for businesses at the country level. Higher trust in the social system lessens customers' concerns about retailers' unfair collection, storage, and usage of their personal data, thereby promoting customers' information sharing (e.g., Martin and Murphy 2017).

Despite its conceptual emphasis on the multilevel and social aspects of the context, contextual integrity theory has not yet gone into the details of how contextual influences at different levels relate to one another and exert a joint influence on individual privacy attitudes/behaviors (Rule 2019). Previous research on multilevel trust (e.g., Grayson, Johnson, and Chen 2008) has, however, provided some directions to finding an answer to the above question. Möllering (2006b) argues that macro-level trust is a basis for micro-level trust. Similarly, Fuglsang and Jagd (2015) posit that a broader trusted environment is conducive to the emergence and reinforcement of micro-level trusts. Wang and Gordon (2011) demonstrated the macro-level context's enabling effect in a multilevel study by finding that a better performing national economy with a more robust legal system provides people with conditions favoring the development of trusting relationships.

Some trust researchers argue that not only does macro-level trust enable the creation of micro-level trust, it also enhances micro-level trust's effect on individual attitudes/behaviors (McEvily, Perrone, and Zaheer 2003; Fuglsang and Jagd 2015). In other words, high macro-level trust might amplify micro-level trust's impact on individual behaviors. Gefen and Pavlou (2012) examined how an institutional structure's perceived effectiveness influences online transactions. Focusing on online marketplaces, such as eBay and Amazon, they found that trust in the community of sellers facilitates online transactions and that this direct effect is enhanced when the institutional structures are perceived to be effective. These results provide preliminary support for macro-level trust's amplifying effect. In light of these findings, we postulate that macro-level trust facilitates the functioning of micro-level trust, thereby amplifying micro-level personnel- and retailer-trust's previously identified effects as follows:

H5. Country-trust moderates the positive relationship between personnel-trust and WSPI, such that high country-trust enhances this positive relationship.

H6. Country-trust moderates the positive relationship between retailer-trust and WSPI, such that high country-trust enhances this positive relationship.

H7. Country-trust moderates personnel-trust's moderating effect on the negative relationship between PCs and WSPI, such that high country-trust enhances this moderating effect.

H8. Country-trust moderates retailer-trust's moderating effect on the negative relationship between PCs and WSPI, such that high country-trust enhances this moderating effect.

Methodology

Measures

We undertook a comprehensive literature review of previous privacy studies to select the best scales to measure our variables. An expert panel of two retail professors (one each from the EU and the US) and four top retail managers (with different cross-cultural backgrounds – European, American, and Asian) evaluated the different scale options. The panel was responsible for checking the scales' content, scope, and purpose across the countries (content validity), ensuring their face validity. Based on the expert panel's inputs, we finalized the questionnaire in English (see details in Table 2). Professionals translated it into the seven languages required to cover all the countries, using the translation-independent back-translation procedure (Kim and Lim 1999).

Several scales have been developed to measure PCs,[2] of which Smith, Milberg, and Burke's (1996) scale is the one most adopted outside the information systems field, from which all these scales originated, probably because it was the first well-established scale that could be equally well applied to online and offline situations (Martin, Borah, and Palmatier 2017). The panel retained this scale to measure PCs at the individual level, but adapted it by deleting four items due to face validity issues (Table 2).

We used a context-specific measure of WSPI, asking the respondents about their willingness to share seven different types of information (Premazzi et al. 2010). The items were then split into information of higher sensitivity versus lower sensitivity based on a previous classification by Bansal, Zahedi, and Gefen (2010). By doing so, we could verify this classification's usefulness by means of our analysis.

We also used a context-specific conceptualization of trust at the micro level by asking the respondents to refer to a specific retailer when rating their level of retailer- and personnel-trust during the survey. At the beginning of the questionnaire, the respondents were asked to indicate, from a list of seven, the product categories with which they were familiar. Thereafter, the online survey system allocated them randomly to a product category from those the respondents had selected. In the next step of the data collection, the respondents were asked to focus on their buying experience in this assigned category, which was the first contextual control variable in our model (at level 2).

[2] The best -known scales include: the Concern for Information Privacy (CFIP) by Smith, Milberg, and Burke (1996), Internet Users' Information Privacy Concerns (IUIPCs) by Malhotra, Sung, and Agarwal (2004), and Internet Privacy Concerns (IPCs) by Dinev and Hart (2004).

Table 2
Measures details and validity.

Items	Factor loadings	Cronbach's Alpha	CR	AVE
PRIVACY CONCERN *Source: Adapted from* Smith, Milberg, and Burke (1996)[a]				
Data collection		0.890	0.890	0.737
When companies ask me for personal information, I sometimes think twice before providing it (PC_DCOL_1)	0.789			
It bothers me to give personal information to so many companies (PC_DCOLL_2)	0.902			
I am concerned that companies are collecting too much personal information about me (PC_DCOLL_3)	0.880			
Data access		0.868	0.872	0.773
Companies should devote more time and effort to preventing unauthorised access to personal information (PC_DACS_1)	0.869			
Companies should take more steps to ensure that unauthorised personnel cannot access personal information on their computers (PC_DACS_2)	0.889			
Data accuracy		0.887	0.892	0.773
Companies should take more steps to make sure that the personal information in their files is accurate (PC_DACR_1)	0.833			
Companies should have better procedures to correct errors in personal information (PC_DACR_2)	0.883			
Companies should devote more time and effort to verifying the accuracy of the personal information in their databases (PC_DACR_3)	0.852			
Data secondary usage		0.923	0.92	0.805
When people give personal information to a company for some reason, it should never use the information for any other purpose (PC_DUSE_1)	0.869			
Companies should never sell the personal information in their databases to other companies (PC_DUSE_2)	0.921			
Companies should never share personal information with other companies unless it has been authorised by the individuals who provided the information (PC_DUSE_3)	0.900			
RETAILER TRUST *Source:* Bart et al. (2005)		0.960	0.963	0.838
I have confidence in this retailer[b] (RT_1)	0.938			
Customers can trust this retailer[b] (RT_2)	0.954			
This retailer keeps its promises[b] (RT_3)	0.925			
This retailer[b] has my best interests at heart (RT_4)	0.823			
This retailer[b] is reliable (RT_5)	0.931			
PERSONNEL TRUST *Sources:* Guenzi, Johnson, and Castaldo (2009)/Swan, Bowers, and Richardson (1999)		0.913	0.915	0.782
This retailer's[b] personnel can be trusted	0.876			
This retailer's[b] s personnel have my interests in mind	0.875			
This retailer's[b] personnel keep their promises	0.902			
WILLINGNESS TO PROVIDE INFORMATION *Source:* Premazzi et al. (2010)				
Willingness to provide lower sensitive information		0.849	0.850	0.654
I am willing to share my demographic data with this retailer[b] (WINS_1)	0.804			
I am willing to share my lifestyle data with this retailer[b] (WINS_2)	0.821			
I am willing to share my media usage data with this retailer[b] (WINS_3)	0.800			
Willingness to provide sensitive information		0.745	0.800	0.434
I am willing to share my identification data with this retailer[b] (WIS_1)	0.514			
I am willing to share my medical data with this retailer[b] (WIS_2)	0.727			
I am willing to share my financial data with this retailer[b] (WIS_3)	0.623			
I am willing to share my location-based data with this retailer[b] (WIS_4)	0.745			

[a] Face validity issues emerged during the items' translation, as some items were too similar after translation into certain languages.
[b] The system specified the name of the retailer the respondent had selected in each question related to a retailer.

Imposing the same retailer on the whole sample would have meant that some respondents might not have known this company. Respondents were therefore asked to indicate a known retailer from a proposed set within the assigned product category and to refer to this company throughout the questionnaire. The panel of experts structured the list to be as exhaustive as possible, using the country's main players in each product category. As previous studies had done (e.g. Martin, Borah, and Palmatier 2017), our focus was on retailers in general, not specifically on online versus offline retailers; the list therefore comprised different company profiles, such as international, mainly online players (such as Amazon.com), international brick-and-mortars companies (such as Walmart), but also local (at the country level) players. Respondents were also given the opportunity to specify a retail company not on our list and to refer to it during the questionnaire. Allowing the respondents to choose a company reduced the response bias (Podsakoff, MacKenzie, and Podsakoff 2012).

The scales measuring the retailer- and personnel-trust at the micro level were taken from existing literature (Table 2).

We screened the main sources of trust measured at the country level, selecting the Edelman Trust Barometer[3] as the most suitable measure of trust at the macro level in a country. This barometer measures and tracks the public's trust in their NGOs, government, business, and media across the globe. An overall score of trust in each institution is provided for each country. Since retail is part of the business world, we use the Edelman Trust Barometer's score of trust in business to measure country-trust at our model level 3 (i.e., the country level). The barometer measures this trust by asking the survey participants to indicate how much in general they trust businesses to do what is right on a nine-point scale. One means that they "do not trust them at all" and nine that they "trust them a great deal."

Finally, we considered several controls. At our model level 1 (i.e., the individual level), we considered: the respondents' demographic characteristics (age and gender), past privacy violations (yes/no), the length of their relationship with the retailer (in years), and the frequency of their visits. We used the product category on which the respondents were asked to focus at our model level 2. Finally, we used two controls at our model level 3 (i.e., the country level). First, we included the Hofstede classification of countries to take the national culture into account. Second, we considered the French Committee of IT and Liberty's (CNIL) world privacy protection level.[4] This body classifies all countries according to their level of protection by analyzing their laws in this respect. Countries are allocated a score ranging from 0 (maximum level of protection, which applies to European countries since the introduction of the new GDPR law on the topic), to 5 (minimum level of protection, applying to countries with no specific law on privacy protection). We reversed this score to facilitate its interpretation.

Since several of our study's variables were collected from the same questionnaire, we needed to establish whether common method bias (CMB) was an issue. We addressed this by following a number of recommendations during the research design and during the analysis phases (Podsakoff et al. 2003; Podsakoff, MacKenzie, and Podsakoff 2012). The data collection could not be temporally separated, owing to the risk of a lower response rate during the second round of collection, and the impossibility of controlling for any intervening variable that could determine the responses between the two rounds. In the research design phase, we therefore guaranteed the survey respondents' anonymity and their data's confidentiality. We also structured the questionnaire to maximize the psychological and methodological separation of the questions referring to our model's variables. We added a few differently structured questions to map the overall shopping decision process, mentioning that this was a market research survey to mask the study's real objective and to avoid desirability bias (Nederhof 1985). Finally, CMB was assessed in our data by means of Harman's single-factor test (Podsakoff et al. 2003) and the marker variable technique (Lindell and Whitney 2001), whose results are reported in web appendix C and show that CMB is not an issue in our database. The same web appendix reports on our multicollinearity tests, which were once again not an issue. Prior to distribution, the data provider tested the questionnaire on a small sample of 30 subjects, slightly revised the IT interface for data collection, and retested the survey to avoid issues during the actual collection.

Sample

Over a four-month period, we collected data in 14 countries via a web survey, and using the online panel members of MarketTools, an independent third party used in previous multi-country studies (Migliore 2011). Using this company ensured that our final sample would represent the various countries' populations as far as possible, avoided cross-national studies' traditional use of students as a convenient sample, and allowed us to control for data collection equivalence (Hult et al. 2008). Using the same online administrative process without a time lapse, we also controlled for the data collection's coverage comparability (Hult et al. 2008). Randomly selecting a representative sample of each country from the MarketTools panel – a minimum of whom reflected the key demographic characteristics (i.e., gender, age, income, study degree, etc.) – ensured comparability across the countries and guaranteed that uncontrolled, systematic errors would not bias our results (Hult et al. 2008). The final sample comprised 22,050 usable questionnaires, referring to 368 retail brands. The participants' ages ranged from 13 (parental approval was required for minors) to 99 years old.

Model Development

This section presents our multi-level model. We begin by modelling the relationships between PCs, personnel- and retailer-trust and customers' WSPI at the individual relationship level (level 1), the product category level (level 2), and the country level (level 3). Thereafter, we detail the random coefficient analysis and its drivers at the product category level (level 2) and the country level (level 3). This is followed by a description of the estimation method.

Testing the Link between PCs, Personnel-Trust, Retailer-Trust, and WSPI

To assess PCs' impact on customers' WSPI with a retailer at the individual relationship, product category, and country levels, we used a three-level (based on Choi and Seltzer 2010), hierarchical Bayes model (Rossi and Allenby 2003). In this study, customers' willingness to share different types of personal information were estimated jointly (Asparouhov and Muthén 2010) in the following structure:

[3] https://www.edelman.com/trust-barometer.

[4] https://www.cnil.fr/en/data-protection-around-the-world.

At the first level,

$$\begin{aligned} \mathrm{WSPI}_{ibct} = {} & \beta_{1bct} + \beta_{2bct}\mathrm{PCs}_{ibc} + \beta_{3bct}\mathrm{Personnel\_Trust}_{ibc} \\ & + \beta_{4bct}\mathrm{Retailer\_Trust}_{ibc} + \beta_{5bct}\mathrm{PCs} \times \mathrm{Personnel\_Trust}_{ibc} \\ & + \beta_{6bct}\mathrm{PCs} \times \mathrm{Retailer\_Trust}_{ibc} + \beta_{7jt}X_{[j]ibc} + \varepsilon_{ibct}, \end{aligned} \tag{1}$$

At the second level,

$$\beta_{1bct} = \gamma_{1ct} + u_{1cjt}Z_{[j]bc} + \varepsilon_{1bct}, \tag{2}$$

$$\beta_{2bct} = \gamma_{2ct} + u_{2cjt}Z_{[j]bc} + \varepsilon_{2bct}, \tag{3}$$

$$\beta_{3bct} = \gamma_{3ct} + u_{3cjt}Z_{[j]bc} + \varepsilon_{3bct}, \tag{4}$$

$$\beta_{4bct} = \gamma_{4ct} + u_{4cjt}Z_{[j]bc} + \varepsilon_{4bct}, \tag{5}$$

$$\beta_{5bct} = \gamma_{5ct} + u_{5cjt}Z_{[j]bc} + \varepsilon_{5bct}, \tag{6}$$

$$\beta_{6bct} = \gamma_{6ct} + u_{6cjt}Z_{[j]bc} + \varepsilon_{6bct}, \tag{7}$$

at the third level,

$$\gamma_{1ct} = \gamma_{1t} + u_{1t}\mathrm{Country\_Trust}_c + u_{2jt}C_{[j]c} + \varepsilon_{1ct}, \tag{8}$$

$$\gamma_{2ct} = \gamma_{2t} + u_{2t}\mathrm{Country\_Trust}_c + \varepsilon_{2ct}, \tag{9}$$

$$\gamma_{3ct} = \gamma_{3t} + u_{3t}\mathrm{Country\_Trust}_c + \varepsilon_{3ct}, \tag{10}$$

$$\gamma_{4ct} = \gamma_{4t} + u_{4t}\mathrm{Country\_Trust}_c + \varepsilon_{4ct}, \tag{11}$$

$$\gamma_{5ct} = \gamma_{5t} + u_{5t}\mathrm{Country\_Trust}_c + \varepsilon_{5ct}, \tag{12}$$

$$\gamma_{6ct} = \gamma_{6t} + u_{6t}\mathrm{Country\_Trust}_c + \varepsilon_{6ct}, \tag{13}$$

WSPI_{ibct} denotes customer i's willingness to share a specific type (t) of personal information with a retailer. Specifically, in the first set of analyses, we examined two categories of personal information: WSPI of both higher and lower sensitivity with a retailer (hence, t ranges from 1 to 2 in which t = 1 denotes "higher sensitive data" and t = 2 denotes "lower sensitive data"). In a subsequent analysis, the different information types were explored further (hence, t ranges from 1 to 7 in which t = 1 denotes "identification data," t = 2 denotes "medical data," t = 3 denotes "financial data," t = 4 denotes "locational data," t = 5 denotes "demographic data," t = 6 denotes "lifestyle data," and t = 7 denotes "media usage data"). $X_{[j]ibc}$ is a vector of five (j = 5) control variables at the individual customer level (age, gender, past privacy violations, length of relationship, and visit frequency), while $Z_{[j]bc}$ is a vector of six (j = 6) product categories. These categories include men and women apparel, children and teenager apparel, luxury goods, pharmaceuticals, grocery, home décor and DIY goods, and consumer electronics. Note that the product category home décor and DIY goods serves as a reference category. $C_{[j]c}$ is a vector of four (j = 4) control variables taken into account at the country level and includes Hofstede's cultural values and data-protection level classification.

PCs_{ibc} denotes the customer's PCs; $\mathrm{Personnel\_Trust}_{ibc}$ and $\mathrm{PCs} \times \mathrm{Personnel\_Trust}_{ibc}$ reflect personnel-trust's direct and indirect effect on WSPI; $\mathrm{Retailer\_Trust}_{ibc}$ and $\mathrm{PCs} \times \mathrm{Retailer\_Trust}_{ibc}$ reflect the direct and indirect effect of retailer-trust on WSPI; ε_{ibct} are the error terms with the intercorrelation ρ.

Testing the Impact of Country-Trust and Product Category: Random Coefficients Analysis

The parameter β_{1bct} is the random intercept (hereafter referred to as "link a"). The specification of a random intercept (β_{1bct}) allows different retail brands (at level 2) and countries (at level 3) to have different regression intercepts, thereby accounting for unobserved heterogeneity and decreasing the potential endogeneity problems that omitted variables usually cause (Germann, Ebbes, and Grewal 2015). The parameters β_{2bct}, β_{3bct}, β_{4bct}, β_{5bct}, and β_{6bct} are the random slopes. In a similar vein, the random slopes allow PCs to influence WSPI (β_{2bct}; hereafter referred to as "link b"), personnel-trust's influence on WSPI (β_{3bct}; hereafter referred to as "link c"), the influence of retailer-trust on WSPI (β_{4bct}; hereafter referred to as "link d"), the influence of PCs × personnel-trust on WSPI (β_{5bct}; hereafter referred to as "link e"), and the influence of PCs × retailer-trust on WSPI (β_{6bct}; hereafter referred to as "link f") to diverge from the population average at both the retail brand (b, or level 2) and country (c, or level 3) levels. In other words, each retail brand within a specific country (i.e., level 2) and each country (i.e., level 3) are allowed to have their own effects on the WSPI, which could deviate from the population-averaged parameter estimates. Specifically, the impact of product categories and country-trust on the estimated random effects are respectively explored at the second (Eqs. (2)–(7)) and third levels (Eqs. (8)–(13)).

Estimation

We estimated the Bayesian multilevel moderation models using the Markov chain Monte Carlo (MCMC) techniques. Yuan and MacKinnon (2009) mention that, unlike conventional frequentist analysis, the Bayesian approach does not impose restrictive normality assumptions on estimates' sampling distributions, which makes statistical inference straightforward and exact. In addition, Gelman and Hill (2006) maintain that the Bayesian estimation provides a more natural and simpler analysis in multilevel models. Furthermore, modelling the multilevel data in our research required Bayesian estimation, since models with ML estimation do not converge well (see the Robustness Checks section below). In line with Yuan and MacKinnon (2009, p. 302), we used Bayesian inference as an ideal approach to the complex multilevel analyses outlined in the aforementioned equations.

We ran three independent MCMC chains with different starting points (as suggested by Gelman and Rubin 1992) for our analyses and 60,000 iterations each, of which the first half is considered the "burn-in" phase and the remaining half is used to estimate the parameters' posterior distribution, resulting in a distribution based on 90,000 points. As recommended in the literature (Asparouhov and Muthén 2010), and following the approach of Keiningham Timothy et al. (2018) and Larivière et al. (2016), we used the Inverse-Wishart for the error covariance matrix IW(0, -p-1) and the normal distribution for the remaining priors N(0, infinity). Next, we assessed the Gelman-Rubin convergence statistic R and examined the autocorrelation plots and the trace plots of the parameter estimates' residual variance. This investigation provided evidence of the MCMC algorithm's convergence. Specifically, given the last 30,000 iterations (used to estimate the parameters), the largest value of the Gelman-Rubin convergence statistic R ranged between 1.013 and 1.089 (note that Yuan and MacKinnon (2009) have suggested that a value of R close to 1 [the highest cut-off being 1.2] is an indication of reasonable convergence).

Finally, we ran several robustness checks, whose results are reported in Web Appendix C. Specifically, we ran different models, starting with a simple model based on Eq. (1) only and fixed effects, followed by adding more complexity by including moderators and random effects at levels 2 and 3. Across the models, the results showed that we obtain similar findings regarding the focal effects (expressed in the hypotheses) and that the Bayesian estimation was preferred for model convergence and for performance.

Findings

Measurement Model

In order to assess the scales' psychometric measurement properties, we undertook a confirmatory factor analysis (CFA) that, in line with prior literature, modeled PCs as a second-order latent variable (Smith, Milberg, and Burke 1996). Similar factor loadings were obtained for all the level 1 latent variables when comparing the single level factor loadings with the multilevel CFA. The CFA indicated a good model fit (GFI = 0.917, TLI = 0.949, CFI = 0.955, and the RMSEA = 0.055, sRMR = 0.055).

All the standardized factor loadings (Table 2) were larger than the cut-off value (>0.514) and significant ($p < .000$). We checked the measurement model several times. We first assessed the internal consistency by using Cronbach's alpha. As shown in Table 2, Cronbach's alpha scores exceed the minimum suggested level of 0.7 for internal consistency (Lin and Huang 2008), with the exception of willingness to provide higher sensitive data. Second, we checked for convergent validity by using the composite reliability (CR) and the average variance extracted (AVE) values. The CR values were no less than 0.7 and the AVE above 0.5 (Table 2), suggesting that the study's convergent validity is acceptable (Zhang, Cheung, and Lee 2014). The only issue is the AVE of the willingness to share higher sensitive information, which does not reach the cut off value.

A key issue was to test that the instruments used to measure our model's relevant constructs are a cross-national invariant in each of the countries, because conclusions based on this scale could be erroneous if a measure lacks invariance (Steenkamp and Baumgartner 1998). Web Appendix B shows the details of the measurement invariance check.

The Direct Impact of Personnel-Trust on the WSPI (Testing H_1)

The first hypothesis postulates that personnel-trust is positively related to WSPI. Table 3 provides strong evidence that personnel-trust enhances customers' WSPI with a retailer, since all types of data have significant and positive parameter estimates (link c, β_{3bct}), thereby supporting H_1.

In addition, we observe that the impact of personnel-trust is significantly (see Web Appendix D for the p-values of different data dependents) higher regarding higher sensitive data ($\beta_{3bc\_all\_higher\_sensitive\_data} = 0.103$) than for lower sensitive data ($\beta_{3bc\_all\_lower\_sensitive\_data} = 0.050$). The personnel-trust effect size differs as a function of the information type (see Web Appendix C).

The Direct Impact of Retailer-Trust on WSPI with a Retailer (Testing H_2)

The second hypothesis postulates that retailer-trust is positively related to WSPI. Table 3 reveals that retailer-trust has a positive effect on customers' WSPI, since all types of data have significant and positive parameter estimates (link d, β_{4bct}), thereby supporting H_2.

Interestingly, we also observe that the impact of retailer-trust is significantly (p-value <.01; see Web Appendix D) less in respect of higher sensitive data ($\beta_{4bc\_all\_higher\_sensitive\_data} = 0.136$) than lower sensitive information ($\beta_{4bc\_all\_lower\_sensitive\_data} = 0.189$). The retailer-trust effect size differs as a function of the information type (see Web Appendix D).

The Moderating Impact of Personnel-Trust (H_3)

The third hypothesis postulates that personnel-trust moderates the negative relationship between PCs and WSPI, such that high personnel-trust mitigates this relationship. Table 3 reveals that identification data only have a significant moderating effect ($\beta_{5bc\_identification\_data} = 0.025$), whereas no significant moderating effects are found for all other types of data sharing. As depicted in Fig. 2, low levels of PCs (in contrast to high levels of PCs) are associated with a higher willingness to share identification data, while higher levels of personnel-trust (dashed line) are also associated with a higher willingness to share identification data with a retailer, such that the highest levels of willingness to share identification data are observed when PCs are low and trust in retail personnel is high. A similar, but slightly stronger, moderating influence is found in situations in which PCs are high. Consequently, H_3 is supported in respect of identification data, whereas no such influence was observed in respect of all other data types.

The Moderating Impact of Retailer-Trust (Testing H_4)

The fourth hypothesis postulates that retailer-trust moderates the negative relationship between PCs and WSPI, such that high retailer-trust mitigates this relationship. Table 3 reveals that all of the lower sensitive dependents' moderating effects are significant ($\beta_{6bc\_demographic\_data} = -0.053$; $\beta_{6bc\_lifestyle\_data} = -0.042$; $\beta_{6bc\_media\_usage\_data} = -0.045$), whereas the higher sensitive dependents' only significant effects are observed in respect of

Table 3
Model findings.

Panel 1 (fixed effects)		Willingness to share information of higher sensitivity to the retailer					Willingness to share information of lower sensitivity to the retailer			
		All (Higher Sensitive Data[1])	Identification Data[2]	Medical Data[2]	Financial Data[2]	Locational Data[2]	All (Lower Sensitive Data[1])	Demographic Data[2]	Lifestyle Data[2]	Media Usage Data[2]
Intercept (link a)		1.220**	5.646**	4.621**	4.563**	5.683**	0.720**	5.855**	5.270**	5.941**
Level 1 (individual relationship level)										
Key drivers										
	Privacy Concerns[1] (PC) (link b)	−0.204**	−0.169**	−0.297**	−0.410**	−0.280**	−0.018**	0.017*	−0.177**	0.062**
	Trust in Retail Personnel[1] (link c) (Testing H_1)	0.103**	0.125**	0.175**	0.176**	0.120**	0.050**	0.076**	0.105**	0.064**
	Retailer Trust[1] (link d) (Testing H_2)	0.136**	0.300**	0.212**	0.084**	0.233**	0.189**	0.316**	0.257**	0.333**
	Privacy Concerns × Trust in Retail Personnel (link e) (Testing H_3)	0.009	0.025*	0.010	0.011	0.006	0.005	0.010	0.020	−0.009
	Privacy Concerns × Retailer Trust (link f) (Testing H_4)	0.003	−0.036**	0.001	0.057**	−0.019	−0.029**	−0.053**	−0.042**	−0.045**
Control variables										
	Gender_female (1 = female, 0 = male)	−0.142**	−0.173**	−0.023	−0.359**	−0.246**	−0.025**	−0.084**	−0.168**	0.122**
	Age	−0.004**	−0.002**	−0.004**	−0.011**	−0.008**	−0.004**	−0.006**	−0.006**	−0.006**
	Previous_privacy_violation (1 = yes, no = 0)	−0.142**	−0.275**	−0.224**	−0.149**	−0.189**	−0.122**	−0.167**	−0.258**	−0.150**
	Length_of_relationship	0.002 *	0.003	0.001	0.003*	0.004*	0.002**	0.003*	0.006**	0.001
	Visit_frequency	0.033**	0.022**	0.065**	0.052**	0.053**	0.025**	0.029**	0.051**	0.039**
Level 2 (retail category level)										
Control variables										
	Product_category _MenWomenApparel	−0.013	−0.012	0.007	0.008	−0.078*	−0.020	0.035	−0.081*	−0.056
	Product_category _YouthKidsTeenApparel	−0.012	0.032	0.039	−0.066	−0.054	−0.011	0.011	−0.055	−0.012
	Product_category_Luxury	0.251**	0.168**	0.326**	0.556**	0.372**	0.107**	0.168**	0.270**	0.086*
	Product_category _Pharmaceuticals	0.002	−0.205**	0.259**	−0.086*	0.036	0.031	0.049	0.088*	0.025
	Product_category_Grocery	−0.117**	−0.230**	−0.101*	−0.191**	−0.167**	−0.073**	−0.087*	−0.135**	−0.128**

Table 3 (*Continued*)

Panel 1 (fixed effects)	Willingness to share information of higher sensitivity to the retailer					Willingness to share information of lower sensitivity to the retailer			
	All (Higher Sensitive Data[1])	Identification Data[2]	Medical Data[2]	Financial Data[2]	Locational Data[2]	All (Lower Sensitive Data[1])	Demographic Data[2]	Lifestyle Data[2]	Media Usage Data[2]
Product_category_ConsumerElectronics	0.020	0.022	−0.004	0.106**	−0.017	−0.027	−0.041	−0.025	−0.067*
Level 3 (country level)									
Control variables									
Individualism (Hofstede)	−0.003	0.011**	−0.011**	−0.004	−0.009*	0.002	0.004	0.005	−0.001
Masculine (Hofstede)	−0.004	−0.017**	0.004	−0.003	−0.008	−0.003	−0.006	−0.004	−0.003
Uncertainty Avoidance (Hofstede)	−0.007**	−0.007*	−0.002	−0.012**	−0.016**	−0.004	−0.005	−0.011*	−0.005
Data Protection Level (reversed)	−0.002	−0.088*	−0.077	−0.010	0.149*	−0.023	−0.067	0.002	−0.041
R-squared	0.097**	0.050**	0.055**	0.096**	0.054**	0.060**	0.050**	0.045**	0.061**

Panel 2 (random effects)	Willingness to share information of higher sensitivity to the retailer					Willingness to share information of lower sensitivity to the retailer			
	All (Higher Sensitive Data[1])	Identification Data[2]	Medical Data[2]	Financial Data[2]	Locational Data[2]	All (Lower Sensitive Data[1])	Demographic Data[2]	Lifestyle Data[2]	Media Usage Data[2]
Drivers of Random Effects at Level 2 (retail category level)									
Moderating influence of retail category on the random intercept (link a)									
Product_category_MenWomenApparel	−0.004	0.001	0.009	0.015	−0.071	0.015	0.040	−0.067	−0.055
Product_category_YouthKidsTeenApparel	−0.007	0.025	0.041	−0.059	−0.063	0.013	0.003	−0.046	−0.034
Product_category_Luxury	0.214**	0.108*	0.277**	0.478**	0.320**	0.073**	0.127**	0.230**	0.008
Product_category_Pharmaceuticals	0.005	−0.219**	0.258**	−0.091*	0.033	0.034	0.046	0.082*	0.018
Product_category_Grocery	−0.112**	−0.229**	−0.104*	−0.176**	−0.183**	−0.074**	−0.100**	.138**	−0.142**
Product_category_ConsumerElectronics	0.024	0.024	−0.014	0.114**	−0.024	−0.031	−0.047	−0.036	−0.083**
Moderating influence of retail category on the PC – WTSPI relationship (link b)									
Product_category_MenWomenApparel	0.020	0.025	0.099**	−0.026	0.034	0.050**	0.099**	0.066	0.080*
Product_category_YouthKidsTeenApparel	0.033	0.085**	0.059	0.029	0.039	0.018	0.025	0.033	0.039
Product_category_Luxury	0.047*	0.062	0.148**	0.005	0.086*	0.079**	0.101**	0.188**	0.097*
Product_category_Pharmaceuticals	0.000	−0.013	0.071*	−0.043	−0.002	0.035	0.020	0.082*	0.060

Table 3 (*Continued*)

Panel 1 (fixed effects)	Willingness to share information of higher sensitivity to the retailer					Willingness to share information of lower sensitivity to the retailer			
	All (Higher Sensitive Data[1])	Identification Data[2]	Medical Data[2]	Financial Data[2]	Locational Data[2]	All (Lower Sensitive Data[1])	Demographic Data[2]	Lifestyle Data[2]	Media Usage Data[2]
Product_category_Grocery	0.024	−0.014	0.060	0.035	0.038	0.035	−0.002	0.111**	0.043
Product_category_ConsumerElectronics	0.025	0.104**	0.032	−0.007	0.044	0.010	−0.030	0.079*	0.015
Moderating influence of retail category on the Trust in Retail Personnel – WTSPI relationship (link c)									
Product_category_MenWomenApparel	0.049*	0.163**	0.084*	−0.003	0.089*	0.044*	0.037	0.100**	0.092*
Product_category_YouthKidsTeenApparel	0.033	0.115**	0.015	0.022	0.074	0.014	0.001	0.069	0.019
Product_category_Luxury	0.071**	0.125 *	0.093	0.074	0.150**	0.008	−0.032	0.021	0.060
Product_category_Pharmaceuticals	−0.001	0.086	−0.022	−0.082*	0.065	0.001	0.005	0.016	0.007
Product_category_Grocery	0.000	0.091*	−0.055	−0.033	0.026	0.003	0.001	−0.011	0.031
Product_category_ConsumerElectronics	−0.017	0.023	−0.083*	−0.037	0.020	−0.039	−0.096**	−0.067	−0.017
Moderating influence of retail category on the Retailer Trust - WTSPI relationship (link d)									
Product_category_MenWomenApparel	−0.030	−0.136**	−0.041	0.013	−0.046	−0.033	−0.022	−0.081*	−0.063
Product_category_YouthKidsTeenApparel	0.002	−0.115**	0.048	0.008	0.033	0.005	0.027	−0.062	0.042
Product_category_Luxury	0.008	−0.037	0.003	0.093	−0.034	0.063*	0.129**	0.061	0.111*
Product_category_Pharmaceuticals	−0.012	−0.176**	0.129**	0.010	−0.067	−0.007	−0.001	−0.033	−0.007
Product_category_Grocery	−0.009	−0.116**	0.053	0.009	−0.008	−0.022	−0.023	−0.008	−0.050
Product_category_ConsumerElectronics	0.046*	−0.043	0.161**	0.116**	0.005	0.065**	0.141**	0.090*	0.065
Moderating influence of retail category on the impact that Trust in Retail Personnel has on the PC – WTSPI relationship (link e)									
Product_category_MenWomenApparel	0.101**	0.132**	0.178**	0.105**	0.137**	0.089**	0.159**	0.137**	0.109**
Product_category_YouthKidsTeenApparel	0.052*	0.009	0.166**	0.030	0.039	0.042	0.063	0.038	0.076*
Product_category_Luxury	0.082**	0.077	0.119**	0.136**	0.067	0.020	−0.005	0.006	0.042
Product_category_Pharmaceuticals	0.094**	0.154**	0125**	0.140**	0.083*	0.062**	0.118**	0.047	0.085*
Product_category_Grocery	0.037	0.069	0.041	0.024	0.047	0.010	0.023	−0.028	0.018
Product_category_ConsumerElectronics	0.039	0.074	0.083*	0.024	0.014	0.078**	0.138**	0.082*	0.136**
Drivers of Random Effects at Level 2 (retail category level)									
Moderating influence of retail category on the impact that Retailer Trust has on the PCs - WSPI relationship (link f)									
Product_category_MenWomenApparel	−0.060**	−0.083*	−0.099*	−0.058	−0.088*	−0.073**	−0.115**	0.126**	−0.073*
Product_category_YouthKidsTeenApparel	−0.019	0.029	−0.102*	−0.005	0.017	−0.012	−0.004	−0.059	0.031
Product_category_Luxury	0.004	0.046	0.031	−0.005	0.026	0.037	0.074	0.068	0.097**
Product_category_Pharmaceuticals	−0.030	−0.053	−0.030	−0.014	−0.041	−0.034	−0.059	−0.033	−0.025

Table 3 (*Continued*)

Panel 1 (fixed effects)		Willingness to share information of higher sensitivity to the retailer					Willingness to share information of lower sensitivity to the retailer		
	All (Higher Sensitive Data[1])	Identification Data[2]	Medical Data[2]	Financial Data[2]	Locational Data[2]	All (Lower Sensitive Data[1])	Demographic Data[2]	Lifestyle Data[2]	Media Usage Data[2]
Product_category_Grocery	−0.008	−0.026	−0.004	−0.004	0.030	0.005	0.018	0.033	0.020
Product_category_ConsumerElectronics	−0.006	−0.017	0.010	−0.013	0.007	−0.024	−0.052	−0.012	−0.018
Drivers of Randeom Effects at Level 3 (country level)									
Moderating influence of country trust on the random intercept (link a)									
Country-Trust (Edelman Barometer)	0.065	−0.047	0.204*	0132*	0.056	0.007	0.008	−0.064	0.070
Moderating influence of Country Trust on the PCs - WSPI relationship (link b)									
Country-Trust (Edelman Barometer)	0.011	−0.017	0.040	0.002	0.019	0.016	0.023	−0.015	0.034*
Moderating influence of Country Trust on the Trust in Retail Personnel - WSPI relationship (link c)									
Country-Trust (Edelman Barometer) (Testing H5)	0.031**	0.013	0.017	0.039	0.026*	0.027**	0.018*	0.005	0.014
Moderating influence of Country Trust on the Retailer Trust - WSPI relationship (link d)									
Country-Trust (Edelman Barometer) (Testing H6)	0.018	0.061**	0.017	0.037*	−0.011	−0.014	0.004	−0.017	−0.021
Moderating influence of Country Trust on the impact that Trust in Retail Personnel has on the PC - WTSPI relationship (link e)									
Country-Trust (Edelman Barometer) (Testing H7)	−0.004	−0.003	0.006	0.006	−0.001	−0.011	0.015	−0.011	−0.021*
Moderating influence of Country Trust on the impact that Retailer Trust has on the PCs - WSPI relationship (link f)									
Country-Trust (Edelman Barometer) (Testing H8)	0.014	0.033**	−0.003	0.006	0.003	0.008‘	−0.012	0.003	0.005
Intercepts at Level 3									
Link a	−0.038	4.581**	2.657**	2.528**	3.948**	0.190	5.044**	4.984**	4.884**
Link b	−0.299**	−0.129	0.589**	−0.439**	−0.420**	−0.140*	−0.144	−0.176	−0.175
Link c	−0.082	−0.022	0.090	−0.021	−0.080	−0.106*	−0.014	0.067	à.039
Link d	0.045	0.063	0.064	−0.142	0.312**	0.262**	0.267**	0.361**	0.441**
Link e	−0.026	−0.030	−0.123	−0.080	−0.040	0.019	−0.150*	0.042	0.040
Link f	−0.047	−0.207**	0.057	0.045	−0.016	−0.052	0.043	−0.036	−0.073

Notes: [1] Factor scores are used, based on the results of the multilevel confirmatory factor analysis (CFA); [2] Single items are used, as measured in the questionnaire; ** p ≦ .05 * p ≦ .10; PC = privacy concerns; WTSPI = willingness to share personal information to the retailer; L1 = level 1 (i.e., individual relationship level), L2 = level 2 (i.e., retail category level); L3 = level 3 (i.e., country level).
To facilitate the interpretation of the moderating influence of trust on the impact of privacy concerns on the willingness the share personal information to the retailer, Panel 1 of this Table reports the fixed slopes of these variables, which are obtained from a model in which the parameter estimates for the antecedent variables are not allowed to be retail category/country specific (i.e., fixed effects). In Panel 2, the results of the random models are reported (i.e., random coefficients analysis).

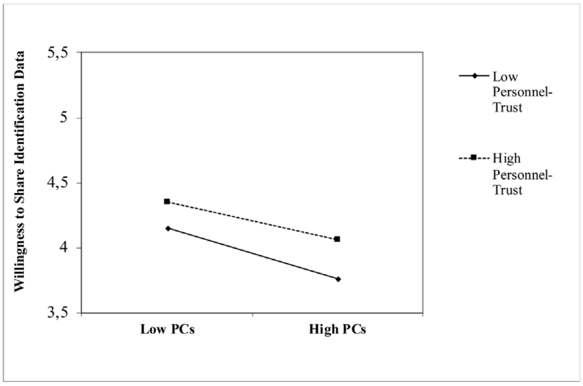

Fig. 2. The moderating impact of personnel trust.

identification ($\beta_{6bc\_identification\_data} = -0.036$) and financial ($\beta_{6bc\_financial\_data} = 0.057$) data. As depicted in panel A of Fig. 3, low levels of PCs (in contrast with high levels of PCs) are associated with a higher willingness to share identification data, while higher levels of retailer-trust (dashed line) are associated with a higher willingness to share identification data with a retailer. A similar, but slightly weaker moderating influence, is found in situations in which consumers' PCs are high. With respect to sharing financial data, Panel B of Fig. 3 reveals that customers are most likely to share financial data with a retailer if their PCs are low, regardless of their level of retailer-trust. In contrast, when PCs are high, higher levels of retailer-trust are likely to mitigate PCs' negative impact on consumers' willingness to share financial data. With respect to both demographic and media usage data, Panels C and E reveal that higher levels of retailer-trust are associated with a higher willingness to share both demographic (Panel C) and media usage (Panel E) data, irrespective of consumers' PCs' level (i.e., a flat dashed line). In contrast, when retailer-trust is low (solid line), individuals with high PCs tend to be more likely to share their demographic and media usage data than in situations in which their PCs are low. This effect is small, but nevertheless significant, and in line with PCs' positive parameter estimate ($\beta_{2bct\_demographic\_data} = 0.017$; $\beta_{2bct\_media\_usage\_data} = 0.062$) regarding willingness to share demographic and media usage data. Finally, Panel D of Fig. 3 reveals that high levels of retailer-trust are associated with greater willingness to disclose lifestyle data with a retailer, especially when consumers' PCs are low. Consequently, H_4 is only supported for consumers' identification, financial, and lifestyle data, since we found no effects regarding medical and locational data or contrary ones (we observed PCs' positive impact) on demographic and media usage.

The Moderating Impact of Country-Trust (Testing H_5, H_6, H_7, and H_8) and of Product Categories

The results presented in Table 3 also provide the parameter estimates of the random slopes analysis. Specifically, the impact of country-trust combined with that of different product categories on the estimated random effects (cf. *link a, link b, link c, link d, link e* and *link f)* is presented in Panel 2 of Table 3. These findings allow us to test the hypotheses linked to country-trust's moderating impact on WSPI with a retailer.

The fifth hypothesis postulates that country-trust moderates the positive relationship between personnel-trust and WSPI (i.e., link c), such that high country-trust enhances this relationship. With respect to H_5, we see a positive, significant influence of country-trust on both the willingness to share information of higher ($u3_{\_all\_higher\_sensitive\_data} = 0.031$) and lower ($u3_{\_all\_lower\_sensitive\_data} = 0.027$) sensitivity with a retailer. Interestingly, we observe that these significant effects only apply to locational ($u3_{\_locational\_data} = 0.026$) and demographic ($u3_{\_all\_higher\_sensitive\_data} = 0.018$) data. Consequently, H_5 is supported in respect of locational and demographic data.

With respect to the remaining hypotheses linked to the moderating influence of country-trust on *link d* (H_6), *link e* (H_7), and *link f* (H_8), and in line with the aforementioned reasoning, Panel B in Table 3 reveals that H_6 is only supported in respect of identification and financial data. This is due to country-trust's positive, significant effect on the relationship between retailer-trust and willingness to disclose identification ($u_{4\_identification\_data} = 0.061$), as well as on financial data ($u_{4\_financial\_data} = 0.037$). H_7 is not supported, since country-trust has no positive, significant effects on any of the data-sharing dependents; H_8 is only supported in respect of identification data, since country-trust has a positive, significant effect on the moderating influence of retailer-trust on the relationship between PCs and willingness to disclose identification data ($u_{6\_identification\_data} = 0.033$).

The Impact of Control Variables

Our findings reveal that past privacy violations exert a strong negative influence, since they lessen customers' willingness to share all types of data with a retailer. Higher visit frequencies are associated with higher tendencies to share all types of data with a retailer, while the length of the customer relationship is found to have a positive effect on customers' willingness to share financial, locational, demographic, and lifestyle data. In addition, older customers are less inclined to share data with a retailer, since the impact of age has been found to have a significant, negative influence on all types of data under investigation in this study, with the exception of medical data, in respect of which we could not find that age has a significant effect. With respect to gender, the findings reveal that men are more likely to share identification, financial, locational, demographic, and lifestyle data than women, but that women are more likely to share media usage data. With respect to product categories, the findings indicate that customers are more inclined to share data with retailers of luxury brands, and less likely to share their data with grocery stores. Our results also take the impact of country differences on willingness to share data with a retailer into account. The findings reveal that higher levels of Hofstede's uncertainty avoidance are associated with a lower willingness to share identification, financial, locational, and lifestyle data with a retailer. Finally, a country's higher data protection level is also associated with a higher willingness to share locational data with a retailer.

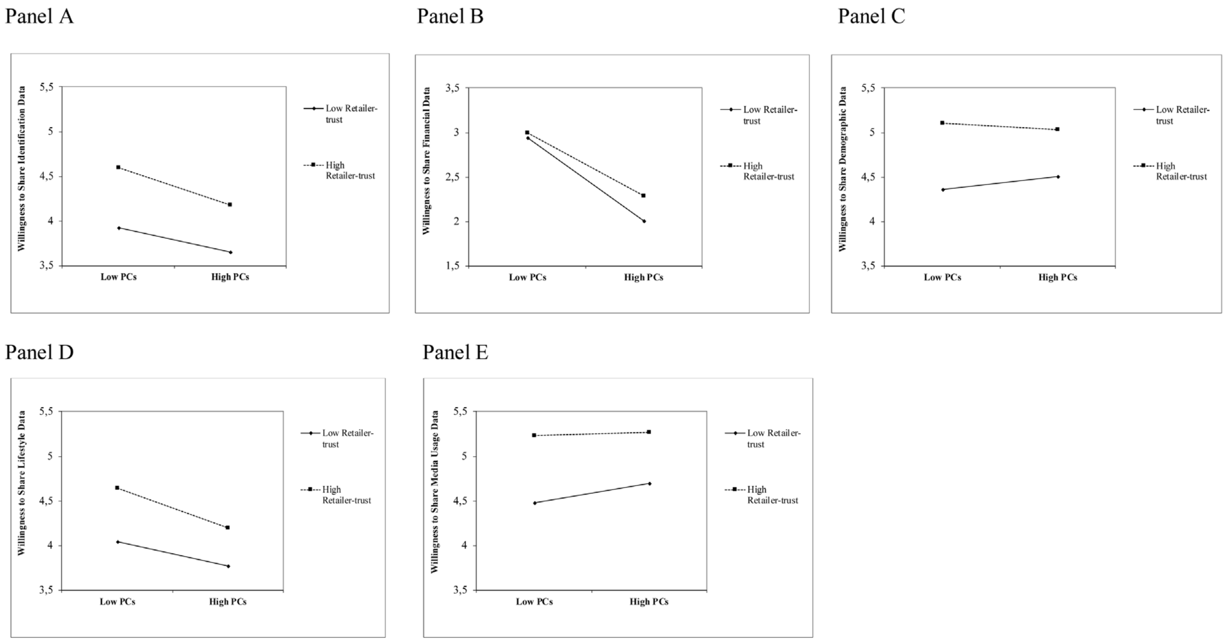

Fig. 3. The moderating impact of retail trust.

Post-hoc analysis on trust effect size across contexts

The last aim of our analysis was to see if a taxonomy of retail contexts, based on trust's different effect sizes, could be identified (Wang et al. 2017). To this end, we ran the level 1 model on each context in our database (Eq. (1)). A context was identified by combining countries, product categories, and information types in our sample. This resulted in the analysis of 686 contexts in our study.

The next step consisted of employing k-means cluster analysis (Hair et al. 1998; Milligan 1980). Table 5 illustrates the effect sizes' cluster means, which was the final assignment of cases into clusters, resulting in three clusters of $n_1 = 248$ (36% of the sample), $n_2 = 235$ (34% of the sample), and $n_3 = 203$ (30% of the sample). The ANOVA indicates significant mean differences across the three clusters in respect of all the effect sizes, with the exception of the interaction between PCs and retailer-trust. This finding implies that the moderating effect of retailer-trust does not change in terms of magnitude in the three clusters. Further, Tukey's HSD post hoc tests shows differences between specific cluster means in respect of the direct effect sizes of the PCs, personnel- and retailer-trust, as well as the interaction between PCs and personnel-trust.

PCs' strong negative effect on WSPI characterizes Cluster 1, while personnel- and retailer-trust have a similar direct and indirect effect (see Table 5); we therefore labelled this cluster "PCs relevant contexts." Retailer-trust's strong direct impact on WSPI, as well as PCs' and personnel-trust's very low direct effect characterize Cluster 2, while trust's indirect effect is similar in the two types of trust; we labelled this "retailer-trust relevant contexts." Finally, personnel-trust's strong direct and indirect impact on WSPI, PC's medium negative impact, and retailers' low direct impact characterize Cluster 3; the interaction of the latter in this cluster is the same as in the other two clusters, as the ANOVA is not significant; we labelled this "personnel-trust relevant contexts."

The difference between the clusters regarding personnel- and retailer-trusts' effect on WSPI is confirmed in respect of all the types of information considered in our study, (see Fig. 4).

We tried to identify which contexts correspond to each cluster by means of (1) the type of data sharing, (2) country differences, and (3) product category differences. Cluster 1 (PCs' relevant contexts) is linked to financial and location information types, mainly in France, Argentina, South Africa, and Mexico and to the man and women apparel and to the home décor and DIY goods categories. Cluster 2 (retailer-trust relevant contexts) is mainly linked to identification and media usage data in the US, the UK, Japan, and China and to consumer electronics as a product category. Finally, Cluster 3 (personnel-trust relevant contexts) is mainly linked to lifestyle data in Brazil, Colombia, and Italy, and to the luxury goods category.

These cluster descriptions seem to contradict well-established classifications in the literature. For example, countries considered traditionally "similar," mainly appear in the different clusters. This becomes more evident if we consider that neither the Hofstede dimensions, nor the country-trust explain why a context belongs to a cluster. The same applies to the information types, as no meaningful patterns can be discerned when trying to profile the clusters based on the classification of higher/lower sensitivity information types. Furthermore, some countries' (Canada, Spain, and Australia) product categories (children and teenager apparel, grocery, and pharmaceuticals) and information types (medical and demographic) cannot be clearly attributed to a cluster. This indicates that the context' variety is so complex that none of the established classifications related to privacy can parameterize a context simply. Our cluster results are therefore helpful for managers in that retailers

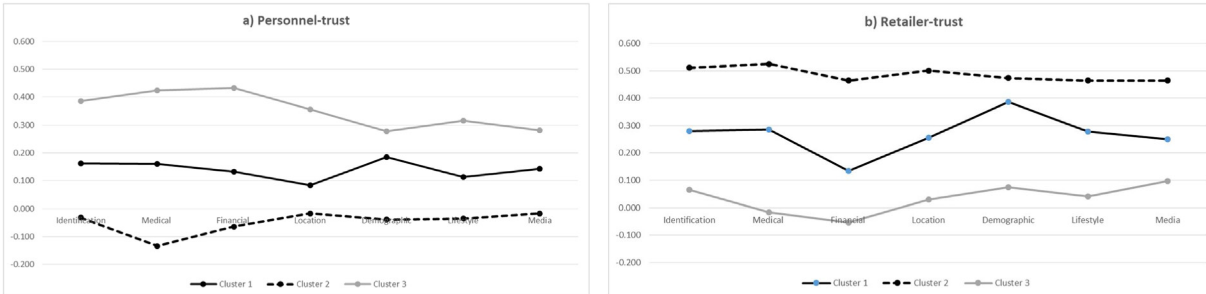

Fig. 4. Direct effects of personnel-and retailer-trust on willingness to disclose different types of information within clusters.

can refer their specific context to identify in which type of trust (personnel- or retailer-trust, or both) they should invest more to improve their relationships with their customers. This confirms the need for a contextual view of privacy in retail. How these results could benefit retailers will be discussed in the next section.

Discussion

Our research drew on contextual integrity theory of privacy as the overarching theoretical framework to develop the multilevel conceptual model with which we examined the context-specific role of micro- and macro-level trusts in shaping consumers' WSPI with retailers. In general, our findings supported context integrity theory's suggestion that consumers' privacy intentions are context-dependent, and confirmed the importance of taking a multilevel approach to examining privacy intentions. As summarized in Table 4, our study confirmed that trust plays an important role in influencing WSPI. At the micro-level, trust (e.g., retailer- and personnel-trust) is directly and indirectly positively related to WSPI by attenuating PCs' negative impact on it. While the direct effects of retailer- and personnel-trust hold for all types of information, trust's indirect effect at the micro- and macro-levels was found to be context-dependent and to vary across information types.

Interestingly, PCs' effect on WSPI was highly unstable across different contexts, which might be why we couldn't find full support for our H_3, H_4, H_7, and H_8 – the hypotheses related to the PCs-WSPI link. In particular, PCs were found to be positively rather than negatively related to willingness to share demographic and media usage data; which is in line with the privacy paradox previously observed in the literature (Dienlin and Trepte 2015; Norberg, Horne, and Horne 2007). Moreover, our model showed that the sum of the regression coefficients[5] of retailer- and personnel-trust's direct effects exceeded the regression coefficient of PCs' direct effect for all types of information, with the exception of financial data. This finding suggests that trust might directly overwrite PCs' negative impact—if any—on consumers' intentions to disclose almost all types of information. In respect of financial data, retailer-trust was reported to have both a significant direct and an indirect effect on WSPI. This suggests that trust promotes sharing financial data directly with retailers, while simultaneously alleviating the negative impact of customers' PCs. In a similar vein, our cluster results showed that clusters 2 (retailer-trust relevant contexts) and 3 (personnel-trust relevant contexts) were contexts in which PCs only had a small effect on WSPI and the two clusters combined represented 64% of the 686 analyzed contexts. In cluster 1 (PCs relevant contexts), in which PCs' effect is strong, PCs' and trust's relative effect sizes (see Table 5) suggest that the combined effect of personnel- and retailer-trust (including their direct and moderating effects) outweighs PCs' negative impact on WSPI. All these results corroborate the contextual integrity theory's argument that the reliance on general PCs—an individual disposition variable—to understand privacy behaviors is flawed.

Our results also reveal that the conventional categorization of information types into higher versus lower sensitivity information does not help explain how different contextual forces interact to shape consumers' privacy intentions within specific contexts. We concur with previous privacy research that consumers' perceptions of information sensitivity are highly contextual—a type of information could be perceived as highly sensitive in one context, but not sensitive in another (Milne et al. 2016; Markos, Milne, and Peltier 2017; Markos, Labrecque, and Milne 2018). This confirms the contextual integrity theory argument that a general one-size-fits-all categorization of information types according to degrees of sensitivity is of little use to researchers and practitioners, since they fail to capture the privacy decision context's nuances, and could potentially lead to ill-informed privacy policies and practices (Martin and Nissenbaum 2016).

Theoretical implications

Our study drew on contextual integrity theory to examine how the multilevel context conditions privacy disclosure intentions in retailing. This research makes several theoretical contributions.

First, our study contributes to the retail privacy research by introducing the contextual view that has to date been neglected, and by considering the context's different levels. In this way, we provide a context-dependent and nuanced understanding of consumers' WSPI, thus supporting retailers' privacy policies.

Second, our study adds to the contextual integrity theory by providing empirical support for its development. In particular,

[5] Note that PCs, retailer-trust and personnel-trust were all measured with the same seven-point scale anchored by "1 = strongly disagree" and "7 = completely agree", such that the regression coefficients can be compared.

Table 4
Summary of the findings.

Hypothesis	Result
H_1: positive impact of personnel trust on WSPI	Supported for all types of data
H_{2a}: positive impact of retailer trust on WSPI	Supported for all types of data
H_3: moderation of trust in retail personnel on PC → WSPI	Supported for identification data
H_4: moderation of retailer trust on PC effect on WSPI	Supported for identification data; for identification and lifestyle data, the moderating effect of retailer trust is significant but in opposite direction; for demographic and media usage data, there is significant moderating effect of retailer trust on the positive relationship between PCs and WSPI.
H_5: moderation country trust on trust in retail personnel → WSPI	Supported for location and demographic data
H_6: moderation country on retailer trust → WSPI	Supported for identification and financial data
H_7: moderation of country trust on trust in retail personnel → WSPI	Not supported (for media usage data, the moderation effect is significant but negative).
H_8: moderation of country trust retailer trust → WSPI	Supported for identification data

Controls	Result
Privacy violations	Reduces willingness to share all types of data
Visit frequency	Increases willingness to share all types of data
Length of relationship	Increases willingness to share financial, location, demographic and lifestyle data
Age	Reduces willingness to share all types of data except medical data
Gender:	
MALE	Greater willingness to share identification, location, demographic and lifestyle data
FEMALE	Greater willingness to share media usage data
Retail category:	
LUXURY	Increases willingness to share all types of data
GROCERY	Reduces willingness to share all types of data
Uncertainty avoidance	Reduces willingness to share identification, financial, location and lifestyle data
Data protection level	Increases willingness to share location data

Table 5
Results of non-hierarchical cluster analysis.

	Mean values[a]			F.	Sign.
	Cluster 1: PCs relevant contexts	Cluster 2: retailer-trust relevant contexts	Cluster 3: personnel-trust relevant contexts		
PCs' effect size	**−0.437**	−0.029	−0.122	304.726	0.000
Personnel trust's effect size	0.129	−0.035	**0.351**	284.796	0.000
Retailer trust's effect size	0.238	**0.482**	0.035	344.992	0.000
PCs X trust in retail personnel effect size	0.163	0.157	**0.205**	8.162	0.000
PCs X retailer trust effect size	0.150	0.160	0.170	0.878	0.416

[a] Parameter estimates marked in **bold**, emphasize what characterizes this cluster compared to the other clusters.

by exploring a multitude of retail contexts (all together 686), our work is one of the first to provide large scale empirical support for contextual integrity theory's suggestions that privacy can only be understood properly within its specific contexts (Martin and Nissenbaum 2016; Nissenbaum 2011).

Third, we extend literature on trust and privacy by focusing on the roles that different types of trust (i.e., personnel-, retailer-, and country-trust) play in privacy decisions, and by pointing out the under-investigated interaction between trust and PCs. In particular, our work answers the call by Smith, Dinev, and Xu (2011) and Bélanger and Crossler (2011) for more multilevel empirical research on privacy. Our multilevel modelling reflects the multilevel nature of trust and sheds light on the dynamic mechanism through which trusts at the micro- and macro-levels work in tandem to influence individuals' privacy decisions. As such, our study also adds to the growing body of research on multilevel trust (Rousseau 2003; Fulmer and Gelfand 2012; Wang and Gordon 2011) within the retailing context.

Finally, our results corroborate recent criticisms of the overreliance on PCs to understand privacy (Martin 2016; Nissenbaum 2011; Martin 2020) by demonstrating that PCs' influence is highly conditioned by the contextual elements of a privacy decision, such as the type of information to share, with whom, and the relationships between the parties involved in the information sharing.

Managerial Implications

Our results show that trust's relevance at different levels is important for information disclosure to retailers. The first managerial implication of our study is that a trust strategy should be considered a good alternative to (or in combination with) more traditional PCs' containing/reducing strategy to obtain customers' data. Our model showed both retailer- and personnel-trust's key role in mitigating PCs' direct effect on WSPI by indicating that retailers aiming to collect customers' data need to have a stronger trust strategy.

The second relevant implication is that there is no unique recipe for managing trust. We investigated micro- and macro-contexts to demonstrate the different trustee interfaces' variable roles. The same retail chain, operating in different contexts, might need a privacy strategy based on the required information type, country, and product category. To properly outline their strategy, retailers should first of all define the information type they need, and then define each context in which they operate in terms of the country and product category. These data allow retailers to position the specific company context in one of the three identified clusters, providing them with a better understanding of retailer- and/or personnel-trust's role. This will subsequently allow them to define their managerial priorities. The results of our post-hoc cluster analysis therefore provide retailers with a useful instrument to understand which type of micro-level trust (personnel- or retailer-trust or both) they should prioritize when managing their relationship with consumers. For a practical example of how to apply it, see our Web Appendix E.

Furthermore, our research underlines personnel-trust's key role in many contexts (in clusters 1 and 3, and covering 66% of the context we examined). This implies that retailers should include their personnel in their privacy strategies. For instance, employees could be trained to understand customers' PCs, and to alleviate their effect by building customers' trust. In such situations, it is essential to design appropriate incentive mechanisms to support sales staff's role in increasing WSPI. According to this logic, online retailers specifically should invest in developing a "human touch" in respect of their customers, which some are already doing, for example, by means of their "personal shopper" or "home delivery by the concierge" services. These investments should be carefully evaluated according to the different contexts in which the retailers operate and be developed as prioritized local strategies in the contexts (indicated in our cluster 3), in which personnel-trust is the most relevant.

Our data also reveal that the frequency with which customers visit retailers is associated with higher willingness to disclose all types of information. Retailers should therefore invest in promoting activities that can increase customers' visit frequency. The retail personnel can also play a key role in this regard by building trustworthy relationships with customers.

Finally, retail managers should be aware that in some retail settings it is more difficult and challenging to promote customers' information sharing. Our results point out that customers are more inclined to share data with luxury retailers than with grocery ones. This implies that grocery retail managers should put extra emphasis on and effort in fostering trust with their customers to increase willingly information sharing.

Limitations and Future Research

This research has limitations that future research could address. First, our conceptualization of context is not exhaustive, since we based it on the country, information type, and product categories. Future studies could investigate other variables that might provide additional insights into the multi-faceted privacy-related context, such as retailers' pricing and promotion policies, retail concentration, and competitive intensity.

Second, risk is a key variable linked to PCs (Dinev and Hart 2006; Kehr et al. 2015; Wang, Duong, and Chen 2016). Although we considered it implicitly within the definition of trust (based on vulnerability), we did not measure it explicitly. Future studies could focus on the perceived risk of data disclosure to examine how this variable interacts with the others.

Third, this study is cross-sectional. Future research could consider a longitudinal analysis that might reveal how the observed relationships evolve in keeping with the customers' lifecycle evolution, changes in retailers' privacy policies, and regulatory evolutions.

Finally, we focused on retailing in general, without distinguishing between online and offline ones, since this differentiation makes less sense in the omnichannel era in which retailers are investing in increasing the convergence of the shopping experience in these two channels. This convergence is in progress, so there might be differences in retailers' omnichannel strategy's advancement, which could impact customer disclosure choices. Future studies should include retail companies' omnichannel advancement as another intervening variable.

Conclusions

The nexus between privacy concerns and information disclosure behaviors is more complex than a mere negative relationship. Drawing on the contextual integrity theory of privacy, we modelled privacy decisions in retailing's complex context as the multilevel, trusting surroundings of an individual, ranging from trust in retail personnel and in the retailer at the micro-level of analysis to country-trust at the macro-level. Our Bayesian multilevel analysis reveals that the interplay between trusts, privacy concerns, and information type shapes consumers' information disclosure intentions and that the context plays a central role in influencing this interplay.

Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jretai.2020.08.002.

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