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Perceived customer care and privacy protection behavior: The mediating role of trust in self-disclosure

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic has been a chance and a boost for those retailers that develop their online profile. This new context can raise privacy issues on the consumer side. For this reason, here we explore the determinants of online *self-disclosure*, and its relationship with *customer care*. We collected the data through an online survey (n = 426) and tested a variance-based structural equations model. The findings unriddle the role of perceived customer care as an antecedent of both perceived control and trust, the latter emerging as a key mediator of the impact of both perceived customer care and privacy concern on self-disclosure. Moreover, in line with previous studies, perceived control was found to be positively related with trust, and negatively with privacy concerns. According to the findings, we draw several managerial implications and suggest future research paths.

1. Introduction

Over the last two years, the socio-sanitary situation prompted has nudged companies to look for new ways to approach consumers. It has also changed how consumers behave (Donthu and Gustafsson, 2020; Pantano et al., 2020; Eger et al., 2021). In the first instance, the panic of contagion encouraged impulsive and obsessive consumption (Islam et al., 2021), which produced a “scarcity effect” of basic products, as defined by Hamilton et al. (2019). Regarding face-to-face sales, throughout the pandemic, it has been observed that many businesses decided to inform their customers about how to protect their health. This can signal the relevance of *customer care* which becomes even more necessary in a situation of uncertainty. It is common to see information panels on the mandatory use of hydroalcoholic gel before entering an establishment, as well as infographics on the correct use of face masks or proper hand washing, among others. As a result, we could expect that the firm’s concern for caring about the customer’s health would positively affect the customer’s perception about the seller.

In this context, fear of contagion and financial conditions have reshaped how consumers buy. These two fears have led them to consider shopping modes that reduce the risks (Truong and Truong, 2022). Consumers are looking for safer options of buying, such as home deliveries and card payments. Also, individuals who had never contemplated buying online find this choice less risky (Pantano et al., 2020). It means a substantial change and increase in e-commerce, due to the diverse effects of COVID-19 -it depends on the cases of coronavirus infection and deaths- (Abdelrhim and Elsayed, 2020). Some retailers used this challenge as an opportunity to strengthen their online profile, as many consumers preferred this means of purchase, especially during the lockdown. As a result, some of these businesses decided to give preference or even exclusivity in online sales to vulnerable people. In this sense, online consumption by certain sectors of the population has definitely increased, which implies a change towards this type of distribution channel.

However, this rise in e-commerce may also lead to higher surveillance than before from the side of online vendors which would, in turn, affect *privacy*. Sellers may expect to recruit more personal information from consumers that would help them target their customers in a personalized way. On the other hand, consumers might be prone to reveal sensitive information if they give more weight to the benefits of doing so in a time of emergency (Pantano et al., 2020).

Thus, *privacy concern* and other privacy-related constructs, as *self-*

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disclosure, might be affected due to the increase in online shopping. In addition, the use of sensitive personal data by companies may be more easily accepted by consumers if there are factors that enhance confidence in how the firms will make use of this information. Following this line, we find that the previous literature highlights *trust* and *privacy concern* as antecedents of *self-disclosure* (Taddei and Contena, 2013; Malhotra et al., 2004). Likewise, information *perceived control* has been found to exert an effect on both *trust* and *concern* (Sheehan and Hoy, 2000; Taddei and Contena, 2013; Mosteller and Poddar, 2017). On the other hand, literature on care management spotted the effect that favorable information about a firm may have on *perceived customer care* and *trust* (Sohn and Lariscy, 2012), but there is still a gap in the literature on whether both constructs might be interrelated. Thus, we have the purpose of contributing to the literature on *self-disclosure* and *customer care* by testing a research model that includes all these variables.

The manuscript presents, in section two, the theoretical background and hypotheses. Section three illustrates the methods, followed by the findings in the fourth section. Finally, section five is focused on the discussion of the results and conclusions, along with contribution to theory, limitations, implications, and further ideas for research.

2. Theoretical background and hypotheses

2.1. Perceived customer care, trust and privacy

Privacy protection has been extensively studied in the scientific literature (Rodríguez-Priego et al., 2022). Thus, the concept of privacy has been classified into different types, distinguishing between privacy referred to the social, to the psychological and to the physical spheres respectively, and information privacy, among others (Burgoon, 1982; Clarke, 1999; Smith et al., 2011; Hallam and Zanella, 2017).

Regarding online behavior, there is a need to mention previous studies where individuals express their concern regarding their privacy, but end up revealing personal information online. The literature on *privacy concern* has substantiated the inconsistency between consumers' concern and final behavior. This has been labelled as the *privacy paradox* and has been widely debated (Norberg et al., 2007; Krasnova et al., 2012; Kokolakis, 2017; Rodríguez-Priego and Porcu, 2022). Following this line, some authors describe privacy as a commodity that can be affected by the classic economic assumptions regarding cost-benefit and trade-off, which implies that individuals can negotiate with it, weighing the benefits they obtain from giving up their privacy (Bennett, 1995; Davies, 1997; Garfinkel, 2000; Campbell and Carlson, 2002; Xu et al., 2009). This infers that a subject may express concern about their privacy, but later engage in behaviors in which they provide sensitive information if they believe they are going to get something in return, so they do not protect their privacy as expected (Sayre and Horne, 2000; Brown, 2001; Spiekermann et al., 2001). More specifically, if we refer to an online purchase, the customer's willingness to reveal his or her sensitive information results from the balance between *trust beliefs* and *privacy concerns* (Dinev and Hart, 2006). On the other hand, Norberg et al. (2007) indicate that the amount of personal information that subjects reveal exceeds their intention to reveal information. Acquisti (2004) mentions the possibility of hyperbolic discounting leading to inconsistency in personal preferences over time. Thus, short-term events are valued differently than long-term events; this implies that the advantages of disclosing sensitive information are easily observable in the short term, but the risks of doing so may be invisible or perceived as occurring in the long term.

In addition, it emerges that users value the advantages of providing information more than the hazards of doing so (Beresford et al., 2012; Lee et al., 2013). More recently, Barth and De Jong (2017) differentiate between two factors that push subjects to make privacy decisions that contradict their concern: (1) when there is a risk-benefit evaluation, and the decision maker considers that the benefits exceed the risks; and (2) when the risk assessment is considered null or insignificant.

Since privacy is difficult to measure, various proxy variables are normally used for its measurement, among which we can highlight information *privacy concern* as one of the central constructs (Smith et al., 2011). This concept expresses the subjective perception of what is fair regarding the information that is recruited by firms (Campbell and Carlson, 2002), which usually differs depending on their opinion (Malhotra et al., 2004). It has been linked to a variety of privacy-protective and coping behaviors, such as the decline to reveal personal information or the distortion of this information (Son and Kim, 2008), and the application of privacy-protecting tools (Lwin and Williams, 2003). Regarding its measurement, Malhotra et al. (2004) revised the scale on concern for information privacy elaborated by Smith et al. (1996) for the e-commerce framework with a multidimensional approach.

Considering *privacy concern* as an explanatory construct and following the ideas introduced by Mayer et al. (1995) and McKnight et al. (1998) in the *trust* literature, Malhotra et al. (2004) present a behavioral model where information *privacy concern* negatively influences *trusting beliefs.* In this sense, more privacy concerned subjects are expected to have less confidence in the company effectively handling their data, keeping their major concerns in mind when handling the information, and being consistent and honest regarding the use of these private data.

In the context of information *disclosure*, previous studies define *trusting beliefs* toward a firm as the extent to which consumers believe that a company will protect their personal information (Grazioli and Jarvenpaa, 2000; Gefen et al., 2003). *Trust* also implies faith from consumers' side in the firm's or institution's reliability and integrity, and security when disclosing information to them (Gefen and Straub, 2004; Milne and Boza, 1999). Both *trust* and *privacy concern* were used indistinctively in past research, although both constructs are different and negatively correlated. This caused inconclusive results toward their response behaviors, such as *information disclosure* (Wirtz & Lwin, 2009).

With these premises, we propose that *privacy concern* will negatively affect *trusting beliefs.* It means that if an individual is worried about the private information that a firm is recruiting from himself (*privacy concern*), it will negatively affect his beliefs regarding how the firm is protecting this information (*trusting beliefs*).

H1. Privacy concern will negatively affect trusting beliefs.

Regarding e-commerce, the trade-off between the customer and the seller is not limited only to the exchange of a product. In this case, the firm expects to obtain personal information about the consumer, allowing it to predict future purchases. Therefore, there is also an exchange of personal data that moves from the consumer's side to the company. In this transaction, the consumer's *trust* is related to the seller's subsequent use of his/her personal data. From his/her side, the consumer could expect the seller to use this personal information to offer him products that may be of interest to him, or to reduce the transaction length (for example, by sharing payment details, usual address, etc.). Thus, all the information revealed by the consumer will be under the *control* of the firm, and the secondary *control* of the customer. Here, firm's *control* is related to the gathering and usage of data, either for its own purposes or to be transferred to other organizations. At this point, we find that when consumers have a higher *perceived control*, this can positively affect *trust.* It means that if an individual has the perception that he can *control* what the firm shares and uses, he will increase the individual's *trust* on the firm (Krasnova et al., 2010; Mosteller and Poddar, 2017).

On the other hand, when considering information *privacy concern* as a dependent variable, the literature identifies *perceived control* as one of the greatest explanatory factors (Sheehan and Hoy, 2000). As opposed to *trusting beliefs*, it has been observed that *perceived control* negatively affects *privacy concerns* (Taddei and Contena, 2013; Mosteller and Poddar, 2017). This implies that if consumers perceive that they control the personal information that the company handles about them, their *privacy concerns* will be reduced. Consequently, we propose that *perceived* *control* will positively influence *trusting beliefs*, and it will negatively affect *privacy concern*. Hence, we propose that.

H2. Perceived control will positively affect trusting beliefs.

H3. Perceived control will positively affect privacy concern.

Similarly, as we have mentioned before, the pandemic has affected how consumers purchase, significantly boosting e-commerce, especially during the months of confinement. In fact, retail sales through this channel were 71.2% higher in June 2020, than in the same month of the previous year (INE, 2020). This can be a challenge for companies trying to maintain the levels of trust that customers may have in the firm when they buy offline. Difficulties arising may include the management of logistics after the online purchase, transport of the products, and perception of the whole process from the customer's side, coupled with the concern about the socio-sanitary situation caused by the COVID-19. To these aspects, we must add the usual concerns regarding the *perceived control* that the customer may have about how the firms handle their private data. In that matter, the literature has not paid sufficient attention to the relevance of *perceived customer care* on privacy related issues. However, previous studies testing the Theory of Planned Behavior have examined customer relationship management as a precedent of perceived control. In this regard, Intayos et al. (2021) focused on customer acquisition and retention through a positive relationship that is attained via customer knowledge, interaction and customization. Likewise, in the present study, we measure perceived customer care through retention, knowledge, interaction and customization regarding the demand. As Intayos et al. (2021) is the first study to explore the relationship between both constructs through a structural equations model, we expect that our results would feed into this research gap.

Here, we should note that the literature in retailing has paid little attention to care management so far. However, there is a parallelism with past studies in health management research, where there is a focus on patient's perspective of care management (Teng et al., 2010; O'Malley et al., 2017). Therefore, following this argument, our study will focus on the customers' perspective on care management, in the place of patients in health studies.

Furthermore, both offline and online, some companies have developed a series of messages related to how they take care of their customers, or how the customers themselves should take care to avoid being infected. In this respect, customers seem to also be influenced by how brands manage *customer care* regarding social distancing and the use of face masks, which would positively affect their *trust* on the brand (Edelman, 2021). Hence, regarding e-commerce, consumers trusting beliefs would be affected not only by concern about their privacy, but also by how the firm shows that they care about them. At the same, we would expect that *perceived customer care* would positively affect *perceived control* regarding the information that customers disclose to the firms when buying online.

Although the literature on *perceived customer care* is scarce, we have found that it is positively related to customer satisfaction (Webb and Jagun, 1997; Santouridis and Veraki, 2017). Also, recent research shows a positive correlation between the after-sale *customer care* and *trust* (Uthamaputhran et al., 2022). Thus, users' *trust* would increase when the firm provides better customer care service once the transaction is completed. Likewise, healthcare-related studies point to the relevance of enhancing the relationship with the customer in order to improve *trust*. In fact, they consider customer relationship management as a means to increase benefits (Yaghoubi et al., 2017). Following this argument, when focusing on social media, we also find that the bonds between the firm and the customer are predictors of *trus*t in the firm (Laroche et al., 2013). Hence, we posit.

H4. Perceived customer care will positively affect perceived control.

H5. Perceived customer care will positively affect trusting beliefs.

2.2. Self-disclosure

When considering privacy related behavioral responses that we may expect in the context of e-commerce, we find *self-disclosure* as a central construct in the literature. In a general context, *self-disclosure* describes personal information that is communicated to another (Wheeless and Grotz, 1976). Disclosure toward an organization may have the objective of authenticating, enabling the organization to recognize us in the future (Joinson and Paine, 2007). Krasnova et al. (2010) state that *self-disclosure* is rooted in Social Exchange Theory, which focuses on a trade-off between two parts based on the negative and positive aspects of sharing information. Among the benefits, past literature has mentioned relationship-building and the (usually) free use of services. On the other hand, the costs may include loss of control or information abuse (Hui et al., 2007; Choi et al., 2018; Kroll and Stieglitz, 2021).

More specifically, in the discipline of information systems, the role of self-disclosure has been examined from different perspectives (Chou et al., 2009; Zimmer et al., 2010; Li et al., 2011; Cheung et al., 2015; Rodríguez-Priego et al., 2016). Regarding e-commerce, online *self-disclosure* refers to customers' behavior of sharing sensitive information or personal data with others (i.e., other users or an e-commerce vendor). It includes disclosing information related to tastes, hobbies, and relationship status, apart from identifiable information (Gross and Acquisti, 2005), which might be used to target the consumer.

Increased use of e-commerce during the pandemic might have affected the personal data that customers share with the firms. We could expect that customers who are new to online shopping are less keen to share information compared with usual online buyers. However, their self-disclosure could also be affected by their confidence about the use that the firm will make of their data. On the other hand, firms will be interested in understanding the factors that determine customers' self-disclosure. If this is the case, firms could use this information from customers to offer products that might interest them.

In light of the literature review, *trusting beliefs* are a questionless determinant of *self-disclosure* (Malhotra et al., 2004; Bol et al., 2018). In that regard, Taddei and Contena (2013) compare different models to explain *self-disclosure* and highlight the central role of *trust*. They find that it is necessary to increase *trust* for attaining online *self-disclosure*. In addition, Bol et al. (2018) find that individuals who trust more in e-commerce firms, have a higher chance of self-disclosing. More recently, Nabity-Grover et al. (2023) also tested the effect that several types of trust (i.e., platform trust and community trust) may have on self-disclosure in social media. However, they did not find a significant effect. Thus, we propose.

H6. Trusting beliefs will positively affect self-disclosure.

Our overall model, which reflects the posited relationships and hypotheses, is presented in Fig. 1. We must highlight that one of the key contributions of the model we propose lies in the role of *trust* as a mediator regarding the effect of *perceived customer care* and *privacy concern* on *self-disclosure*, which is formulated via hypotheses H4, H5 and H6.

3. Methodology

3.1. Data collection

We obtained the dataset through an online survey with Spanish Amazon customers as target respondents. Amazon was selected for the field study due to its leading position as an e-commerce seller in Spain in 2020, with over 8.3 billion euros invoiced, according to the *Spanish E-commerce Guide 2021* elaborated by *Marketing 4 E-commerce* (Statista, 2022a). In addition, Amazon was in the first position of the top online stores in Spain in 2021, by e-commerce net sales (Statista, 2022b). The sample was recruited by a market research company that invited respondents via e-mail. The composition of the sample was provided to

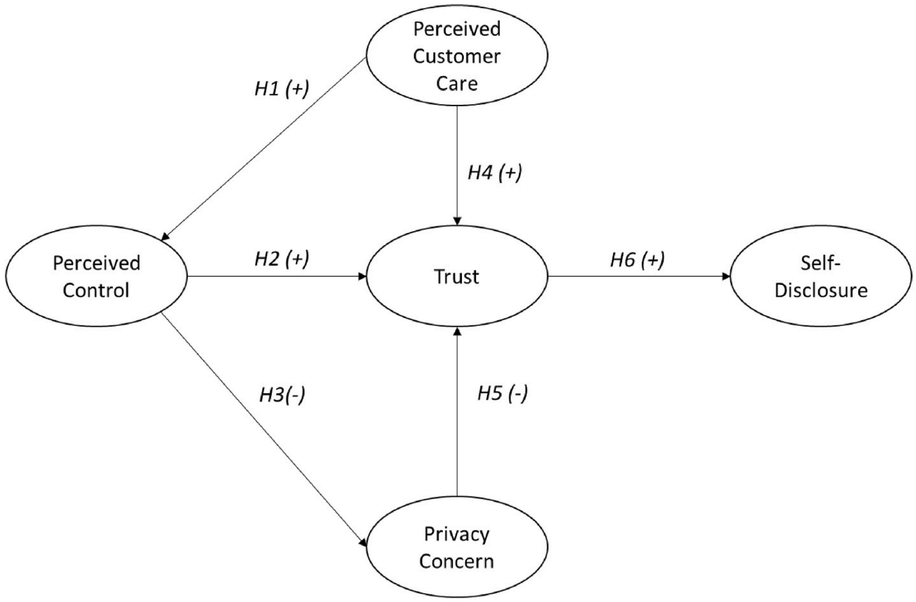

Fig. 1. Conceptual model.

ensure that it was according to the most recent data from the "*Instituto Nacional de Estadística*" (INE, in English "National Institute of Statistics"), following the distribution of Spanish internet users that made an online purchase in 2021, in terms of age range (Statista, 2022c). A total of 426 valid responses have been gathered, equally distributed in terms of gender representation (214 female and 212 male respondents). In addition, the sample meets the following representation of age ranges: 18–24 (n = 43); 25–34 (n = 92); 35–44 (n = 106); 45–54 (n = 93); 55–64 (n = 66); 65 and over (n = 26). Table 1 shows the results of the descriptive analysis of the sample.

3.2. Measures

To measure the variables included in this research, a set of scales were selected from previous studies and slightly adapted to the field of study. To assess "perceived customer care", the 5-item Likert type scale proposed by Sohn and Lariscy (2012) was applied. Three items were drawn from Zhao, Lu, and Gupta (2012) and Mosteller and Poddar (2017) to assess "perceived control", while the constructs "privacy concern" and "trust" were assessed by means of six items (three per each construct) that were drawn and slightly adapted from Malhotra et al. (2004), Pantano et al. (2020), Wirtz and Lwin (2009), and Gabisch and Milne (2013). Finally, a scale proposed by Malhotra et al. (2004) and Gabisch and Milne (2013) was adapted and served to assess the "self-disclosure".

Table 1
Descriptive statistics.

Item	N	Mean	Min	Max	S.D.
PCONTROL_1	426	4.65	1	7	1.69
PCONTROL_2	426	4.70	1	7	1.67
PCONTROL_3	426	4.68	1	7	1.72
PCARE_1	426	4.94	1	7	1.54
PCARE_2	426	5.27	1	7	1.46
PCARE_3	426	5.06	1	7	1.52
PCARE_4	426	5.02	1	7	1.51
PCARE_5	426	5.05	1	7	1.48
PRIVCON_1	426	3.51	1	7	1.41
PRIVCON_2	426	3.67	1	7	1.65
PRIVCON_3	426	3.72	1	7	1.69
SDISC_1	426	4.96	1	7	1.49
SDISC_2	426	4.86	1	7	1.57
SDISC_3	426	4.76	1	7	1.61
TRUST_1	426	5.28	1	7	1.48
TRUST_2	426	5.57	1	7	1.41
TRUST_3	426	5.26	1	7	1.49

Source: The authors

3.3. Data analysis

The collected dataset has been analyzed via means of Structural Equation Modeling (SEM), which is considered a valuable approach to assess the relationships included in the conceptual model and test the hypotheses formulated in this study. More specifically, in this research, we opted for a variance-based SEM approach via Partial Least Squares (PLS; Hair et al., 2022). For many years, covariance-based structural equation modeling (CB-SEM) was the method preferred by researchers to analyze the complexity and interrelationship that characterize the relationships between observed and latent variables. However, in the last decade, the *corpus* of research published using PLS-SEM has been strengthen and the number of publications using this approach is *in crescendo* compared to CB-SEM, being it broadly implemented in social sciences, such as marketing. The PLS-SEM method is a causal-predictive approach to SEM that emphasizes prediction in estimating statistical models, whose structures are designed to provide causal explanations (Hair et al., 2022). Thus, it is very appealing to researchers aiming to assess complex models.

Moreover, consistent PLS (PLSc, Dijkstra and Henseler, 2015 was introduced to address the lack of consistency and, currently, several leading authors of the field support the use of PLS as a silver bullet (Hair et al., 2011) and a full-fledged SEM approach (Henseler et al., 2016). More recently, Benítez et al. (2020) suggest that, thanks to the introduction of PLSc and a test, which is based on the bootstrapping procedures, that enables to calculate the overall model fit, this path modelling approach can be taken when researchers seek to identify causal relationships between the constructs included in a model. However, when it comes to the advantages of applying PLSc, it is to be acknowledged that this approach true values asymptotically, while non-recursive models can be estimated, and a global assessment of goodness-of-fit is obtained (Benítez et al., 2020). With these premises, the PLSc approach was implemented to assess the proposed theoretical model using *SmartPLS 4* (Ringle et al., 2022), and all the constructs analyzed in the conceptual model were first-order and reflective. To estimate the significance level of weights, loadings and path coefficients, the consistent bootstrap technique was performed using 5000 sub-samples, while the blindfolding and the *PLS predict* procedures were applied to assess the predictive relevance of the estimated model.

The procedures for the analysis of the dataset were performed in three steps: (1) the measurement ("outer") model was evaluated to validate the scales adopted; (2) the explanatory power and predictive relevance of the model were assessed; (3) hypotheses testing by evaluating the structural ("inner") model. The findings obtained in each of the above-mentioned steps are reported in detail in the next section.

4. Results

4.1. Estimation of the measurement model

The first stage of the data analysis is focused on estimating the measurement model examining the loadings and significance of each indicator used for the first-order reflective constructs included in the model. Table 2 shows that all indicator loadings are statistically significant ($p < .01$) and above the recommended 0.707 cutoff (Hair et al., 2022). In the second step, the internal consistency reliability was assessed through the calculation of Cronbach's α scores and Composite Reliability (CR), which exceeded the .7 threshold in all cases, this allowed to confirm the reliability of the measurement scales. The third step is measuring the convergent validity of each construct by calculating the Average Variance Extracted (AVE) for all items on each construct, all the values obtained being above the recommended threshold of .5, thus confirming an adequate convergence validity of the measures.

To assess discriminant validity, we applied the procedures developed by Fornell and Larker (1981), based on the fact that the shared variance for all model constructs should not be greater than their AVEs. Thus, the square root of the AVE was calculated (see Table 3) and resulted in being greater than the correlations between each pair of constructs, meeting the criterion posed to confirm the discriminant validity.

However, Henseler et al. (2015) suggested that this metric is not adequate to measure discriminant validity in the case of slight differences in the indicator loadings on a construct, proposing the heterotrait-monotrait (HTMT) ratio as the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct (Hair et al., 2022). Therefore, the HTMT ratio was computed (see Table 4), the resulting values ranging from 0.259 to 0.786, meeting the most conservative criterion of HTMT <0.85 and providing evidence for the

Table 3
Assessment of discriminant validity via the criterion proposed by Fornell and Larker (1981)

	pcontrol	pcare	privcon	sdisc	trust
pcontrol	**.92**				
pcare	.66	**.86**			
privcon	−.27	−.26	**.87**		
sdisc	.64	.58	−.34	**.85**	
trust	.74	.79	−.37	.74	**.86**

Note: The diagonal entries (in **bold**) represent the square root of AVE estimates; the off-diagonal entries represent the correlations between constructs.
Source: The authors

Table 4
Assessment of discriminant validity via Heterotrait-Monotrait (HTMT) ratios.

	pcontrol	pcare	privcon	sdisc	trust
pcontrol					
pcare	.658				
privcon	.267	.259			
sdisc	.645	.584	.336		
trust	.737	.786	.376	.735	

Source: The authors

Table 5
PLSpredict assessment of manifest variables.

Items	PLS-SEM		LM-RMSE	PLS-SEM -LM RMSE
	$Q^2_{predict}$	RMSE		
PCONTROL_1	.345	1.360	1.365	**−.005**
PCONTROL_2	.347	1.337	1.348	**−.011**
PCONTROL_3	.324	1.405	1.410	**−.005**
PRIVCON_1	.032	1.692	1.698	**−.006**
PRIVCON_2	.040	1.764	1.754	.010
PRIVCON_3	.047	1.771	1.743	.028
SDISC_1	.272	1.273	1.271	.002
SDISC_2	.227	1.383	1.391	**−.008**
SDISC_3	.179	1.464	1.480	**−.016**
TRUST_1	.425	1.123	1.125	**−.002**
TRUST_2	.428	1.066	1.067	**−.001**
TRUST_3	.417	1.146	1.128	.018

Source: The authors

Table 2
Results of the measurement (outer) model.

Items	Constructs	Indicator Loadings	*t*	Cronbach's α	AVE	CR
PCONTROL_1	Perceived Control (pcontrol)	.94 ***	45.047	.943	.846	.943
PCONTROL_2		.91 ***	40.059			
PCONTROL_3		.90 ***	40.694			
PCARE_1	Perceived Customer Care (pcare)	.94 ***	34.025	.934	.740	.934
PCARE_2		.82 ***	23.203			
PCARE_3		.86 ***	31.856			
PCARE_4		.89 ***	35.664			
PCARE_5		.79 ***	20.380			
PRIVCON_1	Privacy Concern (privcon)	.81 ***	10.882	.903	.760	.905
PRIVCON_2		.87 ***	18.806			
PRIVCON_3		.93 ***	15.541			
SDISC_1	Self-disclosure (sdisc)	.94 ***	41.475	.886	.726	.887
SDISC_2		.83 ***	24.198			
SDISC_3		.77 ***	15.092			
TRUST_1	Trust (trust)	.86 ***	44.868	.894	.737	.894
TRUST_2		.85 ***	39.936			
TRUST_3		.87 ***	42.248			

Notes: *** = $p < .01$.
Source: The authors

discriminant validity of the measurement constructs.

Finally, following Hair et al. (2022), as a preliminary step before proceeding with the assessment of the structural model, collinearity was examined in order to ensure that it does not bias the results. The obtained VIF values are all below 5, thus ensuring that collinearity was not a relevant issue in this study.

4.2. Assessment of the explanatory power and predictive relevance of the model

According to the procedures detailed by Hair et al. (2022), the explanatory power of the model can be evaluated by assessing the magnitude of the R^2. In fact, the "R^2 measures the variance that is explained in each of the endogenous constructs […] -and therefore-is a measure of the model's explanatory power" (Shmueli et al., 2019). In this regard, Hair et al. (2022) suggest that R^2 values of 0.75, 0.50 and 0.25 indicate substantial, moderate and weak explanatory power, respectively, while R^2 values of 0.90 and higher are indicative of overfit. With these premises in mind, in this study R^2 values of 0.725 and 0.541 were obtained for the two final endogenous constructs, namely trust and self-disclosure, indicating a moderate explanatory power of the proposed model for these constructs. On the other hand, lower R^2 values were obtained for the first two endogenous variables, namely perceived control and privacy concern (0.433 and 0.072, respectively), suggesting a weak explanatory power for these constructs. However, acceptable R^2 values are based on the context and in some disciplines an R^2 value as low as 0.10 is considered satisfactory [and] R^2 is a function of the number of predictor constructs (Hair et al., 2022), therefore the R^2 needs to be interpreted taking into account the context of the study. In light of this, considering that this research examines a complex social phenomenon, we have to assume that several variables, which cannot be examined altogether in one single study, can affect (and be explanatory of) privacy concern, explaining the resulting low R^2 value. In line with Shmueli et al. (2019), while the model's in-sample model fit is fairly small according to absolute standards (Hair et al., 2022), we consider it acceptable for this study in light of the model's complexity.

A metric used to measure predictive accuracy is the Stone-Geisser's Q^2 test via the blindfolding procedure, which combines aspects of out-of-sample prediction and in-sample explanatory power (Shmueli et al., 2016). Q^2 values above zero for a specific endogenous construct indicate the predictive accuracy of the structural model for that construct. Q^2 values higher than 0, 0.25 and 0.50 show small, medium and large predictive relevance of the PLS-path model, respectively. The findings show that all the Q^2 values were greater than zero, enabling to confirm that the estimated model has a good predictive relevance. More specifically, the Q^2 values obtained for the 'perceived control', 'trust' and 'self-disclosure' constructs were 0.34, 0.51 and 0.35, thus showing large and medium predictive relevance of the model for these constructs, while the Q^2 value for the 'privacy concern' construct was 0.05, suggesting a small predictive power for this construct.

Since the R^2 only indicates the model's in-sample explanatory power, the model's out-of-sample predictive power should be assessed using the *PLSpredict* procedure, which was developed by Shmueli et al. (2016) and involves estimating the model on an analysis sample and evaluating its predictive performance on data other than the analysis sample, referred to as a holdout sample (Hair et al., 2022). In implementing this procedure, following Shmueli et al. (2019), the total data set is randomly divided into k equally sized subsets of data, setting $k = 10$ and using ten repetitions. Based on the guidelines provided by Hair et al. (2022), when it comes to interpreting *PLSpredict* results, the researcher should focus on the model's key endogenous construct, and the *Q2predict* statistic is to be evaluated first. In this study, the *Q2predict* values were all above zero, showing that the predictions outperform the most naïve benchmark, which is conceptualized as the indicator means from the analysis sample (Shmueli et al., 2019). In addition, since the prediction error distribution is fairly symmetric, the procedure recommended by Shmueli et al. (2019) and Hair et al. (2022) consists of comparing the PLS-SEM_RMSE values with the naïve benchmark (based on the linear regression model, LM) produced by *PLSpredict*. In this regard, the minority of indicators in the PLS-SEM model estimated in this study yields higher prediction errors compared to the naïve LM benchmark, thus confirming a medium predictive power (Table 5).

4.3. Structural (inner) model assessment and hypotheses testing

Once the preliminary steps (measurement model, explanatory power and predictive relevance) have been carried out, the structural (inner) model was assessed to test the hypotheses. The findings (see Fig. 2) suggest that the overall goodness-of-fit (SRMR = 0.046) of the estimated model was acceptable. Perceived customer care was found to be positively and significantly related to both perceived control ($\beta_{pcare \rightarrow pcontrol} = .658$; $t = 17.159$, $p = .00$) and trust ($\beta_{pcare \rightarrow trust} = 0.511$; $t = 8.662$, $p = .00$), thus providing empirical support to H1 and H4. Likewise, the results also indicate that the relationship between perceived control and trust is positive and significant ($\beta_{pcontrol \rightarrow trust} = .363$; $t = 5.963$, $p = .00$). Therefore, H2 also gathered empirical support. On the contrary, perceived control was found to be negatively related to privacy concern ($\beta_{pcontrol \rightarrow pconcern} = -0.269$; $t = 4.715$, $p = .00$), confirming H3. Similarly, the findings indicate that there is a significantly negative relationship between privacy concern and trust ($\beta_{pconcern \rightarrow trust} = -.144$; $t = 3.796$, $p = .00$), thus providing statistical proof to confirm H5. Finally, trust was found to be strongly, positively and significantly related with self-disclosure ($\beta_{pcontrol \rightarrow trust} = 0.736$; $t = 20.618$, $p = .00$). These findings are in full support of H6 and demonstrate that building trust is a key element to trigger a customer's greater proneness to disclosure and share information with retailers.

To test the mediation effects posed in the conceptual model, we applied the two-step method developed by Zhao et al. (2010). In this regard, the first step consists of determining the significance of the indirect effect, while the second step aims at determining the type of effect and/or of mediation. With these premises, the results revealed that the indirect effects of both perceived customer care ($\beta = .57$; $t = 14.868$; $p = .00$) and privacy concern ($\beta = -0.106$; $t = 3.647$; $p = .00$) on self-disclosure are significant. Moreover, following the second step procedures, the evaluation of the direct effects of both perceived customer care ($\beta_{pcare \rightarrow sdisc} = .23$; $t = 0.23$; $p = .81$) and privacy concern ($\beta_{pconcern \rightarrow sdisc} = -0.08$; $t = 1.69$; $p = .10$) on self-disclosure were found to be not significant. Taken together, these findings satisfy the condition for the full mediation of trust on the impact of perceived customer care and privacy concern on self-disclosure.

Following the same procedures, a test for mediation effect of perceived control on the link between perceived customer care and trust revealed that, while the indirect effect of perceived customer care on trust was positive and significant ($\beta_{pcare \rightarrow trust} = 0.264$; $t = 6.597$; $p = .00$), the direct effect was also positive and significant (as shown earlier), suggesting a complementary/partial mediation effect. Likewise, a positive and significant ($\beta_{pcontrol \rightarrow trust} = 0.039$; $t = 2.839$; $p = .005$) indirect effect of perceived control on trust emerged; however, the direct effect was also positive and significant, thus suggesting a complementary/partial mediation effect.

5. Discussion and conclusion

As a result of the pandemic, we have observed that retail businesses have taken a leap towards electronic commerce to continue operating despite having their establishments closed to the public or having limited capacity. More specifically, in March and April 2020, the digitization of firms was undoubtedly accelerated due to the restrictions. There was an increase in online purchases such as pharmacy products and consumption followed a similar pattern to the increase in COVID cases (Guthrie et al., 2021). As a consequence, once the firms launched on the online market, we observed a long-term growth trend in the

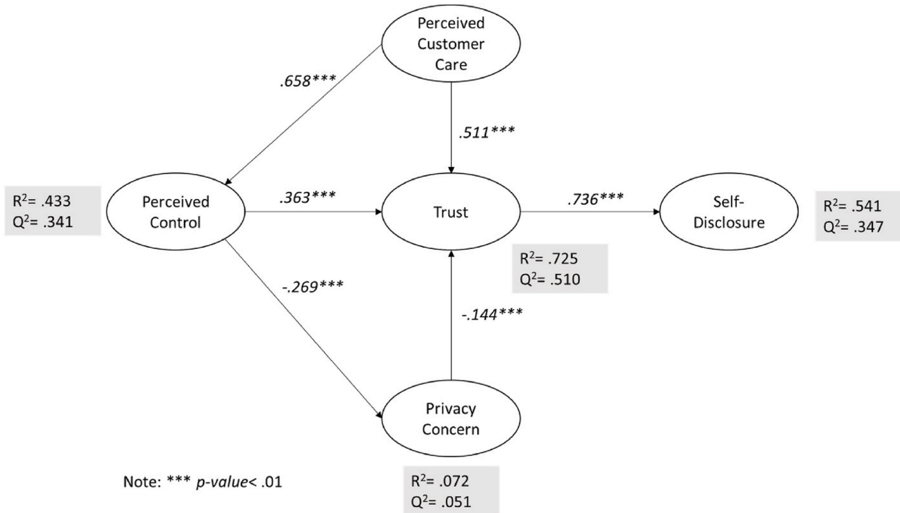

Fig. 2. Estimated structural model.
Source: The authors

online retail sector (Szász et al., 2022). In this context, our research aims to measure the explanatory variables of online self-disclosure, and its relationship with customer care. However, the relationships explored between the variables should remain even if the socio-sanitary situation changes, as long as digitization does not disappear, as previous studies indicate.

This research aimed to address the shortcomings regarding the scarce literature on care management in retailing. For this purpose, the digitization of the firms is considered an opportunity to explore how the companies take care of their customers by engaging in appropriate behaviors towards them (Northington et al., 2021). We focus on a specific sphere of care management, namely customer care and its relationship with customers' privacy-related behaviors. More precisely, this study pioneers the demonstration of the role of *perceived customer care* as a crucial determinant of customers' personal data *perceived control.* In this regard, the more that the customers perceive that the firm is caring of them, the greater the control they perceive over their personal data. This outcome follows previous findings on health care management, where the perceived support from professionals (for example, their responsiveness to wishes) and organizations (for example, the organization's accessibility) were found to affect perceived control (Claassens et al., 2014).

We consider this a very relevant result, as the *perceived control* would also increase *trusting beliefs*, which is a central construct on our behavioral model. These findings are consistent with the ones obtained in previous studies, which have found that users' *perceived control* of the information they share has a positive effect on *trust* (Krasnova et al., 2010; Mosteller and Poddar, 2017). Similarly, *perceived control* would decrease *privacy concern,* as we proposed in the model. It means that increasing the perceived control regarding customers' personal data would diminish their concerns about their privacy, as stated in the literature (Sheehan and Hoy, 2000; Taddei and Contena, 2013; Mosteller and Poddar, 2017). A first managerial implication of this result is that retailers should consider ways to improve individuals' *perceived control* of their data, which becomes a key antecedent of our behavioral model. For example, the firm could provide customers with information on how to change or control the privacy default settings in the e-commerce platform. Another example would be to provide customers with very specific information on how to protect them from phishing.

Turning back to *perceived customer care,* we must underline the positive direct relationship with *trusting beliefs*. This means that when customers perceive that the firm cares about them, they consequently increase their confidence in the seller. More interestingly, when it comes to taking advantage of the beneficial effect of *perceived customer care* in terms of higher *self-disclosure*, it is paramount to build *trust*, since it acts as a mediator. That is to say, when the customer perceives a higher level of *customer care,* he/she will show a higher proneness to disclose information only when he/she trusts in the firm. These findings confirm previous research (Uthamaputhran et al., 2022) regarding the positive correlation between *customer care* and *trust* and open a path for improving firms' customer relationship management. Therefore, managers who aim to master care management should increase the attention given to online *perceived customers' care*. In this sense, recommendations should lead the managers to provide information on how the company cares about their customers. For example, through the use of explicit messages about how the retailer protects the customer.

Regarding the last predictor of *trusting beliefs* in our model, we find that *privacy concern* decreases confidence in how the firm would handle customers' privacy. This result confirms the ideas introduced by previous literature (Malhotra et al., 2004; Wirtz & Lwin, 2009). Customers worried about how the company uses their data would decrease their level of confidence in how it keeps their best interests in mind. In this regard, firms should explore how to decrease customers' concerns about their privacy. For example, they could provide them with information on how the firm is caring about their privacy and protecting their personal data.

All these managerial implications revolve around the importance of care management in retailing and the benefits that this can bring to the consumers' perception of the retailer, and to consumers' trust, which is our first main contribution.

Our second main contribution in this study is the validation of the central role of *trust* in predicting *self-disclosure*. The positive effect between trust and disclosure supports previous findings (Malhotra et al., 2004; Taddei and Contena, 2013). Moreover, as anticipated earlier, from our results *trust* emerged as a full mediator between *perceived customer care* and *self-disclosure*, and between *privacy concern* and *self-disclosure*.

In addition, this central role of trust has implications for the firms. It strengthens the importance of having confidence in the firm for building favorable relationships with the customer, which would redound in facilitating the information that the last needs to improve his approach to the customer. It could reduce the firm's cost for obtaining the relevant information they need from the customer. Consequently, the firm could offer products that fit the customers' needs better.

Finally, this study has some limitations. First, we focused on Amazon's users for conducting the research and there might have been some specific characteristics that differentiate them from users of other e-commerce platforms. For example, Aliexpress' users might be more willing to wait a longer period of time to obtain the purchased products, however their default level of trust in the platform differs from Amazon's users. This could reduce the transferability of our findings. Consequently, future research could assess this model in other e-commerce platforms to examine the validity of the relationships established in other environments. Secondly, another limitation may derive from the geographical context selected for this study. In this regard, to enhance the external validity of the results, we encourage future research to replicate the assessment of the proposed model in other national contexts. Third, while the relationship between *perceived control* and *privacy concern* has been broadly supported by previous studies (Sheehan and Hoy, 2000; Taddei and Contena, 2013; Mosteller and Poddar, 2017), the obtained explanatory power in this study is fairly low, thus suggesting that there are other antecedent variables of *privacy concern* that have not been considered in this research. In light of this limitation, we recommend that researchers make further efforts in order to study the effects of other variables that can exert an impact on *privacy concern*, enhancing the whole model. Finally, since most managerial implications suggest using specific messages to increase perceived control, but also trust and self-disclosure, future research should focus on framing these messages. By testing different message framings, researchers should provide clues on what does and does not work.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix. Research constructs measurement scales

Scales	Items	Source
Perceived Control (PCONTROL)	• PCONTROL_1 Amazon allows me to control who can get access to my personal information. • PCONTROL_2 Amazon allows me to control what kind of personal information can be accessed by other people. • PCONTROL_3 Amazon allows me to control how my personal information can be used by third parties.	Adapted from Zhao, Lu, & Gupta (2012) and Mosteller and Poddar (2017) (Likert-scale 1 = strongly disagree, 7 = strongly agree)
Perceived Customer Care (PCARE)	• PCARE_1 Amazon would act in consumers' best interests. • PCARE_2 Amazon would be aware of what is consumers want. • PCARE_3 Amazon would devote resources to maintain its relationship with its consumers. • PCARE_4 Amazon would genuinely listen to the demands that people put on it. • PCARE_5 Amazon seems to believe the opinions of consumers are legitimate.	Adapted from Sohn and Lariscy (2012) (Likert-scale 1 = strongly disagree, 7 = strongly agree)
Privacy Concern (PRIVCON)	• PRIVCON_1 I would think twice before providing Amazon with my personal information. • PRIVCON_2 It bothers me when Amazon asks me for personal information. • PRIVCON_3 I would be concerned about giving personal information to Amazon.	Adapted from Malhotra et al. (2004); Pan & Zinkhan (2006); Wirtz & Lwin (2009); Gabisch and Milne (2013) (Likert-scale 1 = strongly disagree, 7 = strongly agree)
Self-Disclosure (SDISC)	• SDISC_1 I am willing to provide personal information when registering with Amazon. • SDISC_2 I am likely to share my personal information when registering with Amazon. • SDISC_3 I would reveal my personal information when registering with Amazon.	Adapted from Malhotra et al. (2004) and Gabisch and Milne (2013) (Likert-scale 1 = strongly disagree, 7 = strongly agree)
Trust (TRUST)	• TRUST_1 I trust Amazon to keep my best interest in mind. • TRUST_2 Amazon is trustworthy. • TRUST_3 I can count on Amazon to protect my privacy.	Adapted from Malhotra et al. (2004); Pan & Zinkhan (2006); Wirtz & Lwin (2009); Gabisch and Milne (2013) (Likert-scale 1 = strongly disagree, 7 = strongly agree)

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