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Article

The Impact of Digital Customer Experience on Repurchase Intention: The Mediating Role of Satisfaction and the Moderating Factor of Digital Culture

Suhaib B Bani Kinana[1]

[1] Faculty of Economics & Business, Complutense University of Madrid, Madrid, Spain, Email: suhaibba@ucm.es

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Abstract

This paper explores the effect of digital customer experience on repurchase intention, with customer satisfaction playing the role of the mediator and digital culture playing that of the moderator. Based on the Customer Experience Theory and Theory of Planned Behavior, the current work suggests a conceptual framework that provides insights into the transformation of digital experience into actual behavior in digitally mature contexts. The data used in the empirical analysis were obtained through questionnaire surveys of 397 digitally active consumers in Spain and analyzed with partial least squares structural equation modeling (PLS-SEM). It was found that digital customer experience has a significant positive effect on both customer satisfaction and repurchase intention. Customer satisfaction mediates positively the effect of digital customer experience on repurchase intention. However, contrary to initial hypothesis, no moderating effect of digital culture was observed. Therefore, in digital mature context, the effect of digital customer experience on consumers' repurchase behavior appears to be fairly similar regardless of the level of digital culture readiness. These findings contribute to the literature by providing a multi-layered explanation of how digital experience translates into behavior through satisfaction. From the managerial perspective, this study can be instrumental in improving digital customer experience in order to enhance repurchase behavior.

Keywords: digital customer experience; customer satisfaction; repurchase intention; digital culture.

1. Introduction

Customer experience in the modern digital markets is no longer an exclusive functional service delivery concept but a multidimensional and multifaceted phenomenon that involves cognitive, emotional, and behavioral reactions to the customer journey (Lemon & Verhoef, 2016; Klaus, 2013).

The research in electronic commerce and digital services emphasizes the fact that interface design, usability, and perceived service quality have a positive impact on customer assessment and intention to repeat behavior (Parasuraman et al., 2005; Hoehle & Venkatesh, 2015). Nevertheless, much of the available literature is inclined to study these relations in a straightforward and linear way and does not take into account multifaceted psychological processes that digital experiences are converted into repurchase behavior (Fernandes & Barfknecht, 2020; Hsu et al., 2015).

There is empirical evidence that a positive experience in the digital environment leads to satisfaction, which strengthens the intent to repurchase and loyalty (Bilgihan et al., 2013; Chen & Wang, 2016; Yoo et al., 2013). However, the conclusions are still quite scattered, and there is a lack of agreement on how satisfaction serves as an intervening variable in the context of integrated experiential frameworks, especially when it is discussed in relation to contextual and cultural moderators (Thakur, 2019; Brashear-Alejandro et al., 2016; Ahmad et al., 2022).

The next, but not the most developed, aspect in this area is digital culture (DC), that is, the expression of shared values, norms, and behavioral orientations towards digital technologies in a particular social setting (Venkatesh et al., 2012; Sivathanu, 2019; Yang et al., 2012). Although previous researchers have recognized that cultural and technological predisposition influence technology adoption and use, there is a lack of empirical research on how DC moderates the relationship between digital customer experience (DCE) and satisfaction (Alalwan et al., 2017; Supotthamjaree & Srinaruewan, 2021). This exclusion is especially relevant to the European digital markets, including Spain, where digital maturity is high, and consumer expectations and usage patterns are diverse (Izquierdo-Yusta et al., 2021; San-Martin et al., 2019).

It is to fill these gaps that the current study combines Customer Experience Theory with the Theory of Planned Behavior to formulate and empirically test a comprehensive model that explains repurchase intention (RI) in the digital setting. This study provides a more nuanced insight into the way in which DCE leads to RI and under what conditions by considering customer satisfaction (CS) as a mediating variable and DC as a moderating variable. The study is methodologically based on a quantitative approach based on structural equation modeling (SEM) and path analysis, which gives strong empirical evidence, of a Spanish consumer sample (Hair et al., 2021; Podsakoff et al., 2003; Chou & Hsu, 2016).

In this regard, the main aim of the proposed research is to examine how DCE affects RI, the mediating effect of CS, and the moderating effect of DC. The research questions that the study attempts to address are as follows: How does DCE influence RI in digital settings? What is the extent to which this relationship is mediated by CS? And what role does the DC play in changing the impact of the DCE in CS? Answering these questions, this study will make the theoretical contribution to the existing body of literature on DCE and provide practical implications to managers who want to achieve sustainable repurchase behavior in digitally driven markets.

2. Literature Review

2.1 Digital Customer Experience in Digital Contexts

The customer experience concept has changed significantly with the spread of digital technologies, where one-dimensional service experiences have been replaced by multi-touchpoint experiences developing through digital channels (Zeithaml et al., 2000; Klaus, 2013; Lemon & Verhoef, 2016). Recent research builds up on this perspective by identifying experiential aspects like emotional involvement, cognitive stimulation, and perceived control in the context of the digital environment (Heller et al., 2019; Hoehle & Venkatesh, 2015; Izquierdo-Yusta et al., 2021). Although it is widely accepted that DCE is multidimensional, the literature is still disjointed on the joint effects of these experiential elements on downstream behavioral consequences, specifically RI in various cultural backgrounds (Klaus & Nguyen, 2013; Verhoef et al., 2015).

2.2 Digital Customer Experience and Customer Satisfaction

CS has been now and then placed at the heart of evaluative results of digital interactions. The early research defined satisfaction as a cognitive–affective reaction that occurs as a result of the comparison between expectations and perceived performance of electronic services (Fang et al., 2011; Amin, 2016). Nevertheless, a number of researches observe that satisfaction is no longer a direct consequence of functional quality, but rather an experience that is influenced by experiential and relational signals in digital exchanges (Chen & Wang, 2016; Nambisan & Watt, 2011; McLean & Osei-Frimpong, 2019). This implies that integrative models that describe satisfaction as a process of connecting digital experience with behavioral intentions should be considered, not as a concept in itself.

2.3 Satisfaction and Repurchase Intention

The concept of RI has received extensive research as a major predictor of continuity of relationships in digital markets. The existing literature regularly shows that satisfied consumers have higher RIs, recommendation intentions, and loyalty intentions in the online settings (Chiu et al., 2014; Liu et al., 2011). Other studies that combine satisfaction with trust, perceived value, and habit also indicate that satisfaction works together with cognitive and social variables to influence repeat purchase behavior (Chou & Hsu, 2016; Hsu et al., 2015; Yoo et al., 2013). However, although satisfaction is often taken as a predictor of RI, less research empirically examines the mediating role of satisfaction between experiential antecedents and behavioral consequences within a single structural model (Bilgihan et al., 2013; Brashear-Alejandro et al., 2016; Thakur, 2019).

2.4 Moderating Role of Digital Culture

A new body of literature is focusing on the significance of DC and norms associated with technology in influencing consumer reactions to digital services. Even though engagement, value co-creation, and habit are some of the moderators that have been explored in the digital experience research (Ahmad et al., 2022; Thakur, 2019; Supotthamjaree & Srinaruewan, 2021), the moderating effect of DC itself on the experience-satisfaction relationship is under-researched. The gap is especially obvious in the European context, where digital maturity may not always correspond to homogenous experiential judgments (Izquierdo-Yusta et al., 2021; San-Martin et al., 2019; Vásquez & Vera-Martinez, 2020).

2.5 Research Gap and Contribution

The existing literature confirms the significance of DCE, satisfaction, and RI but contains three major gaps: poor integration of these constructs into one explanatory model, inadequate empirical research on satisfaction as a mediating variable, and neglect of DC as a contextual moderator. With the help of filling these gaps, the current research formulates and validates an extensive model based on the Customer Experience Theory and the Theory of Planned Behavior, using SEM and path analysis on the Spanish consumer data. In this way, the research can help advance theoretical knowledge in the area of digital customer behavior and provide practical implications to companies that have to work in the digitally intensive markets.

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Framework

The Customer Experience Theory is a conceptual framework that views experience as an overall assessment that occurs as a result of customer interactions in touchpoints, with functional cues (e.g., service quality, usability) and affective-cognitive reactions that contribute to subsequent behavior (Zeithaml et al., 2000; Klaus, 2013; Lemon & Verhoef, 2016). These touchpoints are also present in the digital realm, as they are applied to websites, mobile apps, and interactive service interfaces, and thus, interface quality, perceived security, and usability become key experience-building mechanisms that affect how customers perceive the value and relational outcomes (Parasuraman et al., 2005; Chang & Chen, 2009; Hoehle & Venkatesh, 2015). To supplement this experiential perspective, TPB gives a behavioral rationale according to which experiences influence intentions: judgment of outcomes and the perceived control influence the development of intentions, and the RI is the likely result of positive experience judgments (Venkatesh et al., 2012; Yang et al., 2012; Sivathanu, 2019). The combination of these views indicates that DCE must affect RI directly via positive reviews of the digital experience and indirectly via satisfaction as a summary of evaluation that integrates experience into behavioral preparedness (Bilgihan, 2016).

3.2 Hypotheses Development

3.2.1 Digital Customer Experience and Repurchase Intention

The impact of DCE on the RI is theorized to occur due to the reduction of friction, perceived value, and relational confidence through high-quality digital interactions, which in turn increases the probability of repeating the purchase behavior. The repeat purchase intentions of customers in e-commerce environments are always associated with positive attitudes towards utilitarian and hedonic value and lower perceived risk, which are highly influenced by experiential quality of digital interface and service process (Chiu et al., 2014; Kim & Lennon, 2013). It has also been found that intention to continue dealing with the same provider is strengthened by trust-building characteristics and perceived reliability in the online environment, which makes experience a determinant of relationship continuity (Gefen et al., 2003; Bilgihan, 2016; Vásquez & Vera-Martínez, 2020).

H1: *DCE positively impacts RI.*

3.2.2 Digital Customer Experience and Customer Satisfaction

The Customer Experience Theory view of satisfaction is a cumulative assessment of previous engagements and, therefore, ought to be elevated in situations where the digital experience is coherent, efficient, and emotionally reassuring. The electronic service quality tradition focuses on the fact that e-satisfaction is determined by the responsiveness, reliability, and efficiency of the system, which match the perceived performance with customer expectations (Parasuraman et al., 2005; Amin, 2016; Anderson & Srinivasan, 2003). It is also empirically demonstrated that the quality of digital interaction, including usability and the overall experience of the services, contributes to the increase in satisfaction in online and mobile settings by increasing perceived value and minimizing the cost of effort (Hoehle & Venkatesh, 2015; Fernandes & Barfknecht, 2020; Hsu & Lin, 2016).

H2: *DCE positively impacts CS.*

3.2.3 Customer Satisfaction and Repurchase Intention

The Theory of Planning Behavior consistent logic postulates that the more customers perceive the results as positive, the more they will have intentions to repeat the behavior; satisfaction thus acts as a proximal attitudinal predictor of RIs. Studies on online business show that satisfaction is a strong indicator of e-loyalty and repeat patronage, but its impact may be contingent on situational circumstances and relationship factors (Liu et al., 2011). Research that combines satisfaction and trust and justice perceptions also indicates that satisfaction integrates various evaluative cues into a RI (Fang et al., 2011; Chou & Hsu, 2016; Hsu et al., 2015).

H3: *CS positively impacts RI.*

3.2.4 The Mediating Role of Customer Satisfaction

In addition to direct effects, experience-intention relationships will presumably be partially mediated by satisfaction since satisfaction embodies the general evaluation of the digital experience, and it is the psychological mediator between experience attributes and behavioral continuity. Previous studies suggest that digital experiences influence the outcome of loyalty by intervening evaluative and relational processes including satisfaction, engagement, and perceived value (Bilgihan, 2016; Fernandes & Barfknecht, 2020; Ahmad et al., 2022). Likewise, the models of RI emphasize that experiential stimuli cannot be effective on their own, but instead, they affect repurchase by initially modifying internal evaluations that drive the repetition of behavior (Chiu et al., 2014; Chou & Hsu, 2016). This reasoning suggests that there must be a mediated route in which DCE leads to satisfaction, which enhances RI.

H4: *CS mediates the relationship between DCE and RI.*

3.2.5 The Moderating Role of Digital Culture

The notion of DC within this paper is defined as an individual's situational predisposition towards digital technology that influences perceptions and evaluations of the digital experience. Building on technology acceptance literature, social influence theories, beliefs and attitudes, and trust orientations literature, responses to the use of digital technologies will depend on the extent of readiness for using digital technologies. This means that the same digital experience can be viewed positively or negatively depending on readiness for digital interaction (Alalwan et al., 2017).

On the theoretical level, DC will act as a boundary condition that regulates the way individuals perceive and interpret digital experiences. Individuals with high DC characterized by knowledge, confidence, and positive attitude towards technology will have the ability to interact efficiently with the digital environment. It will enable them to gain maximum value from their interaction with digital technology, and the same DCE will result in greater satisfaction among such individuals. For people with low DC, there may be confusion, cognitive effort, or negative evaluations. Thus, the effect of DCE on satisfaction levels will be weakened. Therefore, the effect of DCE on CS will be strengthened by DC.

H5: *DC modifies the relationship between DCE and CS.*

3.2.6 Positioning and Contribution of the Framework

This framework moves a step further than previous models of digital commerce by explaining both the evaluative mechanism (satisfaction as mediator) and the contextual boundary condition (DC as moderator) of RI in Figure 1. This overcomes drawbacks of previous studies that tend to assume the experience-repurchase associations are homogeneous across settings and do not specify the psychological mediation between experience and intention (Klaus & Nguyen, 2013; San-Martin et al., 2019). The proposed model can be empirically tested with the help of SEM and path analysis to offer a rigorous foundation of assessing the proposed relationships in the Spanish market and provide theoretically based and managerially applicable insights into designing digital experiences, which can be effectively transformed into repeat purchase behavior (Hair et al., 2021; Podsakoff et al., 2003; Lemon & Verhoeff, 2016).

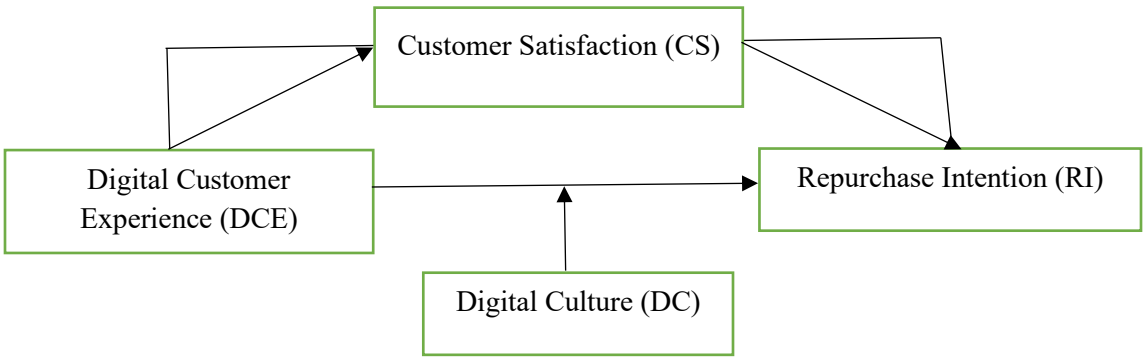

Figure 1: Conceptual model

4. Methodology

4.1 Research Design

The research design used in this study was a quantitative, cross-sectional study in order to empirically investigate the association between DCE, CS, DC, and RI. An approach based on surveys was deemed suitable due to the nature of the study that aimed at testing theoretically based hypotheses, which are based on the Customer Experience Theory and the Theory of Planned Behavior, which focus on quantifiable perceptions, assessments, and behavioral intentions (Venkatesh et al., 2012). Path analysis and SEM were used to evaluate both direct and mediating relationships together with moderating relationships in a single analytic model and to rigorously test complex causal paths and latent constructs by controlling measurement

error (Hair et al., 2021). This methodological decision was in line with previous studies of DCE and RI that focus on theory testing and model validation in digital settings (Bilgihan, 2016; Chou & Hsu, 2016).

4.2 Population and Sample

The target group was the users of digital platforms in Spain with the previous experience of online purchasing or online interactions with the digital services. The country of interest was Spain because it is highly mature in terms of digital market and has heterogeneous consumer expectations, which allows exploring the influence of experiential and cultural impact (San-Martin et al., 2019; Izquierdo-Yusta et al., 2021). Non-probability purposive sampling method was used to make sure that the respondents had adequate digital experience to assess the constructs being studied. Out of the 540 online questionnaires sent, 397 valid and complete responses were obtained, which gave a response rate of about 73.5. This was a sufficient sample size that met minimum requirements of SEM and was considered sufficient to estimate the parameters and test the hypothesis (Hair et al., 2021).

4.3 Data Collection Instruments

The structured online questionnaire, which was given via Microsoft Forms, was used to collect data. Each measurement item was measured in terms of a five-point Likert scale between strongly disagree and strongly agree, which has been extensively justified in digital service and consumer behavior studies (Anderson & Srinivasan, 2003; Bilgihan, 2016). DCE was assessed with five items that measured the evaluative as well as the experiential aspects of digital interactions, RI was assessed with five items that measured behavioral continuity, CS was assessed with four items that measured the overall evaluative judgment, and DC was assessed with four items that measured predispositions towards digital technologies (Parasuraman et al., 2005). The survey system was also set to receive submissions upon completion of all items, and thus, missing data and incomplete responses were reduced. The data collection processes were conducted in line with the principles of research ethics, where the respondents were assured of anonymity, voluntary participation, and confidentiality of the entire research process (Podsakoff et al., 2003).

5. Data Analysis and Result

5.1 Descriptive Analysis

5.1.1 Demographic Profile

The demographic features of the respondents that took part in the study are given in Table 1. The sample size was 397 valid responses, and gender distribution was rather balanced, as females were 52.9 percent of the sample, and males comprised 47.1 percent. Regarding age, most of the respondents were within the economically and digitally active age brackets with 25 to 34 years (28.5) and 35 to 44 years (24.7) being the most prevalent ones, and the respondents aged 18 to 24 years (22.4) coming in close. This age distribution represents the representation of active users of digital platforms, more prone to online purchasing and online services, which is also similar to previous studies in digitally mature markets (San-Martin et al., 2019; Izquierdo-Yusta et al., 2021). The relatively low percentage of the respondents who are aged 55 and older (8.8) is consistent with the available evidence that indicates a lower intensity of digital interaction among older consumer groups (Venkatesh et al., 2012).

In terms of education level, the sample has well-educated respondent population, with 42.8% having Bachelor degree and 26.2% having a Master degree, with 10.6% having a PhD. This type of distribution is suitable when researching DCE because higher education levels tend to be more correlated with the familiarity and confidence in the use of digital platforms and technologies (Alalwan et al., 2017; Sivathanu, 2019). Regarding behavioral involvement, the majority of the respondents stated that they frequently engaged in digital purchasing behavior, with 34.3% of respondents indicating that they made digital purchases or used digital services 4–6 times per month and 16.4% of the respondents making purchases or utilizing digital services more than 6 times per month, which suggests that the sample is highly exposed to digital experiences. Moreover, smartphones have become the primary device of digital interactions (81.1%), and this tendency helps to focus on the mobile-centered nature of the modern digital consumption behavior that is thoroughly reported in the studies of digital commerce and mobile services (Hoehle & Venkatesh, 2015; Hsu & Lin, 2016). In general, the demographic characteristics indicate that the sample is ideal in exploring DCE, satisfaction, and RI in a digitally advanced setting.

Table 1: Demographic profile of the respondents

Question	Answer	Frequency	Percent	Cumulative Percent
Gender	Male	187	47.1	47.1
	Female	210	52.9	100.0
	Total	397	100.0	
Age Group	Under 18	4	1.0	1.0
	18–24	89	22.4	23.4
	25–34	113	28.5	51.9
	35–44	98	24.7	76.6
	45–54	58	14.6	91.2
	55 and above	35	8.8	100.0
	Total	397	100.0	
Level of Education	High school or less	81	20.4	20.4
	Bachelor's degree	170	42.8	63.2
	Master's degree	104	26.2	89.4
	PhD	42	10.6	100.0
	Total	397	100.0	
Monthly Digital Purchase Frequency	Once or less	94	23.7	23.7
	2-3 times	102	25.7	49.4
	4-6 times	136	34.3	83.6
	More than 6 times	65	16.4	100.0
	Total	397	100.0	
Primary Device	Smartphone	322	81.1	81.1
	Computer / Laptop	47	11.8	92.9
	Tablet	28	7.1	100.0
	Total	397	100.0	

5.1.2 Descriptive Statistics for Variables

Table 2 shows the descriptive statistics of the key constructs under analysis in the present research study, namely, DCE, CS, RI, and DC. The means reveal that the overall perceptions of DCE (M = 3.33, SD = 0.86), CS (M = 3.27, SD = 0.88), and RI (M = 3.20, SD = 0.77) among the respondents were moderate to moderately high. These results indicate that the assessment of respondents about their online

communication was generally positive, which indicates the sufficient quality of the experience and the sufficient level of the desire to continue to communicate with online platforms. These average scores are aligned with previous empirical studies in the digital commerce and service setting, which tend to indicate moderate to high ratings of experience, satisfaction, and behavioral intentions among active digital users (Bilgihan, 2016; Chiu et al., 2014).

Table 2: Descriptive statistics of the study variables

Descriptive	N	Mean	SD	Skewness	Std. Error	Kurtosis	Std. Error
DCE	397	3.3349	0.8571	-0.522	0.14	0.259	0.279
CS	397	3.2738	0.8814	-0.421	0.14	-0.286	0.279
RI	397	3.1980	0.7715	-0.690	0.14	0.705	0.279
DC	397	2.3676	0.9142	1.063	0.14	0.629	0.279
Valid N (list-wise)	397						

DC, in turn, had a lower mean score (M = 2.37, SD = 0.91), which suggests that there was a variation in the predisposition of respondents to the digital technologies and the digital norms. This difference confirms the idea of DC as a contextual variable instead of a uniformly distributed characteristic of consumers, which explains why it should be used as a moderating variable in the proposed model (Venkatesh et al., 2012; Sivathanu, 2019). Analysis of skew and kurtosis values shows that the values of skew and kurtosis are not very high, which means that there are no drastic deviations in the normality of the data, and it is appropriate to use such data in partial least squares structural equation modeling (PLS-SEM) analysis (Hair et al., 2021). Namely, skew values were between -0.690 and 1.063, and the kurtosis values were not outliers, indicating that the distributions of responses are not skewed or peaked.

5.2 Measurement Model Assessment

The measurement model was tested to determine the reliability and validity of the reflective constructs before testing the structural relationships. Table 3 shows that all item loadings were above the suggested value of 0.70 with a range of 0.765 to 0.899, which implies that the indicators have strong item reliability and that all indicators measure the construct they are supposed to measure. The findings indicate that the measurement items are effective in capturing the latent variables as per the stipulated guidelines of PLS-SEM analysis (Hair et al., 2021). The high factor loadings in DCE, CS, RI, and DC are consistent and justify the suitability of measurement scales applied in this research.

Table 3: Measurement model assessment

Construct	Indicator	Factor Loading	Cronbach's Alpha	CR (rho_A)	CR (rho_C)	AVE
Customer Satisfaction (CS)	**CS.1**	0.784	0.844	0.847	0.895	0.682
	CS.2	0.861				
	CS.3	0.815				
	CS.4	0.841				
Digital Culture (DC)	**DC.1**	0.839	0.862	0.938	0.903	0.7
	DC.2	0.899				
	DC.3	0.765				
	DC.4	0.837				
Digital Customer	**DCE.1**	0.817	0.885	0.888	0.915	0.684
	DCE.2	0.818				

Experience (DCE)	**DCE.3**	0.841				
	DCE.4	0.799				
	DCE.5	0.861				
Repurchase Intention (RI)	**RI.1**	0.771	0.869	0.876	0.905	0.655
	RI.2	0.808				
	RI.3	0.838				
	RI.4	0.802				
	RI.5	0.825				
Interaction Term	**DC × DCE**	1				

Cronbach alpha, composite reliability (rho_A), and composite reliability (rho_C) were further used to test internal consistency reliability. Table 3 indicates that Cronbach's alpha values were between 0.844 and 0.885, which is above the acceptable level of 0.70, and this means that there is a satisfactory internal consistency among the indicators of each construct. On the same note, the values of composite reliability (rho_A and rho_C) were all greater than 0.80, which ensured the strong construct reliability. These results align with the previous studies of digital service and customer experience that note the significance of strong reliability tests in evaluating latent constructs of perceptions, evaluations, and behavioral intentions (Bilgihan, 2016; Amin, 2016; Hair et al., 2021).

The average variance extracted (AVE) was used to measure convergent validity. According to Table 3, the value of all constructs was above the recommended value of 0.50, and the values were between 0.655 and 0.700. This means that every construct has more than 50 percent of its indicators explained by it, which is a good sign of sufficient convergent validity. These findings are consistent with the existing body of research in the field of digital commerce and online service settings, where the focus is placed on the fact that experiential and attitudinal constructs must exhibit a high level of convergent validity in order to be able to interpret structural relations meaningfully (Chiu et al., 2014; Fernandes & Barfknecht, 2020; Vásquez & Vera-Martínez, 2020).

Table 4: Discriminant validity (HTMT) matrix

HTMT	CS	DC	DCE	RI	DC × DCE
CS					
DC	0.236				
DCE	0.788	0.195			
RI	0.821	0.153	0.788		
DC × DCE	0.155	0.139	0.072	0.032	

The heterotrait-monotrait ratio (HTMT) was used to test the discriminant validity as well as the Fornell-Larcker criterion. Table 4 indicates that all the HTMT values were below the conservative value of 0.90, which means that there was a satisfactory discriminant validity among the constructs. In addition, Table 5 demonstrates that the square root of the AVE of each construct was greater than that of other constructs, which also confirms the discriminant validity. The combination of HTMT and Fornell-Larcker criteria enhances the validity test and aligns with the best practices in PLS-SEM research on the investigation of complex experiential and behavioral models (Hair et al., 2021; San-Martin et al., 2019; Izquierdo-Yusta et al., 2021).

Table 5: Discriminant validity (Fornell–Larcker criterion)

Fornell–Larcker Criterion	CS	DC	DCE	RI
CS	**0.826**			
DC	0.199	**0.837**		
DCE	0.682	0.178	**0.827**	
RI	0.711	0.146	0.707	**0.809**

Lastly, the indicators were evaluated on the variances of the indicators, which is referred to as variance inflation factor (VIF) values, which are presented in Table 6. The VIF values fell below the conservative 3.3, which means that the measurement model did not have multicollinearity problems. This implies that the indicators add some distinct information to their respective constructs and that the estimated parameters are stable and reliable. The VIF of the interaction term (DC × DCE) of 1.000 indicates the use of a two-step method of modeling moderation effects, which is typically used in PLS-SEM research to eliminate collinearity bias (Hair et al., 2021; Thakur, 2019). In general, the findings prove that the measurement model has sufficient reliability and validity, which will be a good basis of the further structural model analysis.

Table 6: Collinearity statistics (VIF)

Indicator	VIF	Indicator	VIF
CS.1	1.687	**DC.1**	1.926
CS.2	2.28	**DC.2**	2.179
CS.3	1.792	**DC.3**	1.839
CS.4	2.175	**DC.4**	2.304
RI.1	1.945	**DCE.1**	2.075
RI.2	1.934	**DCE.2**	2.113
RI.3	2.213	**DCE.3**	2.298
RI.4	2.127	**DCE.4**	2.134
RI.5	1.983	**DCE.5**	2.534
DC × DCE	1		

5.3 Structural Model Assessment

Figure 2 shows the estimated structural model with standardized path coefficients and coefficient of determination (R^2) of the endogenous constructs. The findings demonstrate that DCE has a positive significant impact on CS and a moderate direct impact on RI, with CS having an additional positive impact on RI. The values of R^2 show that the model accounts for 46.6 percent of the variation in CS and 60.1 percent of the variation in RI, implying that it is a strong model. These results correspond to the Customer Experience Theory and previous empirical studies that suggest that digital experiences represent an important antecedent of satisfaction and subsequent behavioral intentions in digital environments (Bilgihan, 2016; Lemon & Verhoef, 2016; Vásquez & Vera-Martínez, 2020).

Figure 3 shows the bootstrapping results of the structural model with statistical significance of the hypothesized relationships. The findings affirm that the DCE to CS and CS to RI paths are statistically significant, which does support the mediating nature of satisfaction in the experience to repurchase relationship. Conversely, the interaction term between the DC and the DCE does not show a significant

effect on the RI, showing that the DC does not have a direct moderating effect on the relationship between the two. These results can be compared to previous research that indicates that cultural and technological inclinations have a major impact on evaluative processes and do not directly affect behavioral intentions (Venkatesh et al., 2012; Sivathanu, 2019; Thakur, 2019).

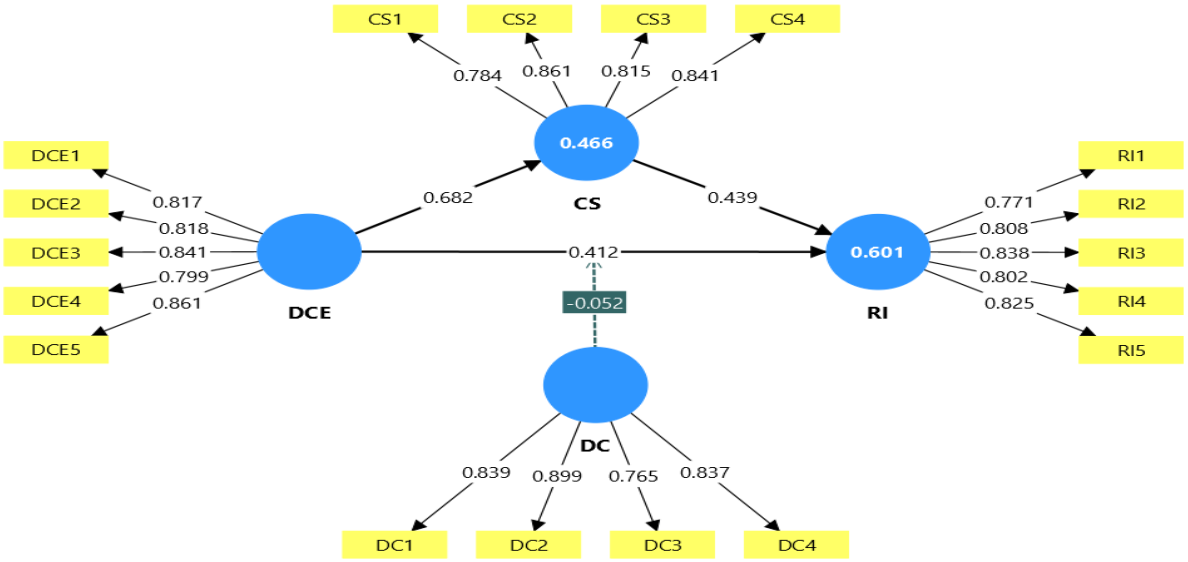

Figure 2: Structural model estimation using PLS-SEM

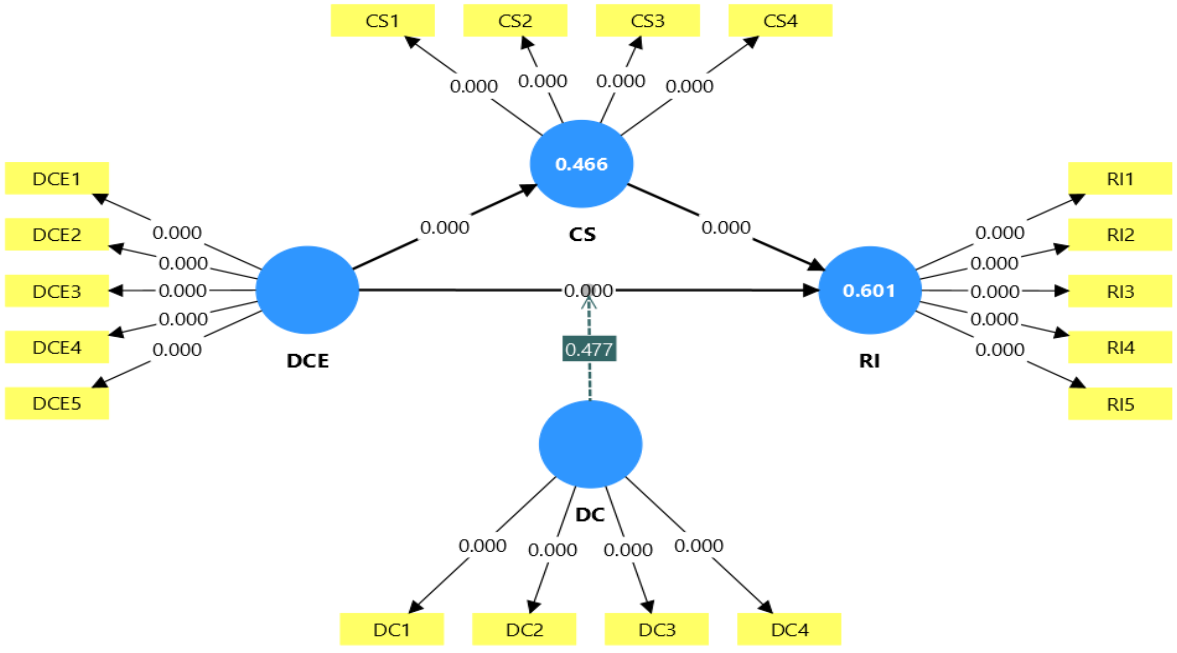

Figure 3: Bootstrapping results of the structural model

Table 7 indicates the model fit indices of the saturated and estimated model. The standardized root mean square residual (SRMR) of both models is lower than the recommended 0.08 value, which means that the model fits well. Further, the d_ULS and d_G values also indicate that there are only slight variations between the saturated and estimated models indicating that the structural relationships are stable. The normed fit index (NFI) values are somewhat lower than the traditional 0.90 standard, but they are still satisfactory in the PLS-SEM research, especially when mediation and moderation effects are included in the model. The overall findings indicate that the suggested structural model is adequate and aligns with the methodological suggestions of assessing the model fit in PLS-SEM studies (Hair et al., 2021).

Table 7: Model fit indices

Fit Index	Saturated Model	Estimated Model
SRMR	0.071	0.073
d_ULS	0.873	0.922
d_G	0.415	0.418
Chi-square	229.453	231.669
NFI	0.797	0.795

5.4 Path Coefficients

Table 8 presents the findings of the structural model through investigating the direct, indirect, and moderating influences of the study constructs. The results have high empirical evidence of the proposed relationships based on the Customer Experience Theory and the Theory of Planned Behavior. On the whole, the findings suggest that DCE is a key factor in the development of RI, whether directly or indirectly, through CS, but the moderating effect of the DC does not have statistical significance.

Table 8: Structural model results (direct and indirect effects)

Hypothesis	Path	β	Std. Error	t-value	p-value	Result
H1	CS to RI	0.439	0.099	4.413	0.000	Supported
H2	DCE to CS	0.682	0.054	12.717	0.000	Supported
H3	DCE to RI	0.412	0.104	3.972	0.000	Supported
H4	DCE to CS to RI (Indirect)	0.299	0.07	4.256	0.000	Supported
H5	DC × DCE to RI	-0.052	0.073	0.712	0.477	Not Supported

The findings indicate that the CS has strong and positive impact on the RI (β = 0.439, p = 0.000), which confirms H1. This result proves that CS is more likely to result in intentions to remain a customer of digital platforms, and it is not the first study to find that satisfaction is a vital predictor of post-purchase behavior in online settings (Anderson & Srinivasan, 2003; Chiu et al., 2014; Vásquez & Vera-Martínez, 2020). The robustness of such relationship underscores the significance of the evaluative judgments developed in the course of digital interactions in the formation of the future behavioral intentions of consumers.

Moreover, DCE has a high and statistically significant influence on CS (β = 0.682, p = 0.000), which supports H2. The implication of this finding is that positive digital experiences, which can be described as usability, efficiency, and perceived value, make a significant difference in the level of satisfaction of customers. This result is in line with previous research in the field of digital services and e-commerce, which all report that the experiential quality is a major antecedent of satisfaction in online contexts (Amin,

2016; Bilgihan, 2016; Fernandes & Barfknecht, 2020). Also, H3 is supported by the fact that, in addition to their impact via satisfaction, experiential perceptions directly influence the RI (β = 0.412, p = 0.000) as well, which supports H3.

Mediation was also studied by analyzing indirect effects of CS. Table 8 indicates that indirect relationship between DCE and RI through CS is positive and statistically significant (β = 0.299, p = 0.000), which supports H4. This finding supports the fact that CS is a partial mediator between DCE and RI. This, as per the earlier empirical evidence, indicates that digital experiences affect the RI not only directly but also by affecting customer overall evaluative judgments, which, in turn, determine the continuity of behavior (Bilgihan, 2016; Ahmad et al., 2022). The fact that there are both considerable direct and indirect effects means that there is a partial mediation mechanism, which supports the integrative nature of the model proposed.

Surprisingly, the moderating role of DC on the connection between DCE and RI was not statistically significant (β = -0.052, p = 0. 477), and thus the rejection of H5. This result indicates that although DC is an indicator of the predisposition of consumers towards digital technologies, it does not have a significant influence on the translation of digital experience to RI in the context under investigation. This result can point to the fact that in digitally mature markets, including Spain, digital experiences have a comparatively homogeneous impact on consumer behavior despite cultural inclinations towards technology (Venkatesh et al., 2012; Sivathanu, 2019). This has been the finding of previous research, with contextual or cultural moderators not necessarily having a strong effect in cases where baseline digital familiarity was high (Thakur, 2019; Supotthamjaree & Srinaruewan, 2021).

5.5 Structural Model Assessment

Table 9 shows the coefficients of determination (R^2) of the endogenous constructs in the structural model. The findings show that the model accounts for 46.6 percent of the variance in CS and 60.1 percent of the variance in RI, which is a moderate to strong explanatory power. Based on the accepted rules of PLS-SEM, the following R^2 values indicate that the proposed model can be used to offer a significant explanation of the evaluative and behavioral results of the consumers within the digital setting. The comparatively strong explanatory ability of the RI highlights the primary role of the DCE and CS in influencing the repeat purchasing behavior, which is in line with the previous empirical studies in the digital commerce and online service setting (Anderson & Srinivasan, 2003). Besides, the low values of the difference between the R^2 and adjusted R^2 values suggest that there is no overfitting and this also supports the strength of the structural model (Hair et al., 2021).

Table 9: Coefficient of determination (R^2)

Endogenous Construct	R^2	Adjusted R^2
Customer Satisfaction (CS)	0.466	0.46
Repurchase Intention (RI)	0.601	0.584

6. Discussion

The objective of the present study was to investigate the impact of DCE on RI and consider the mediating effect of CS and moderating effect of DC in a digitally mature market. In general, the results are highly

empirical evidence of the central role of DCE in the formation of post-purchase behavior, both directly and indirectly, and have subtle insights into the work of evaluative and contextual processes in the digital consumption context. These findings are consistent with the Customer Experience Theory and Theory of Planned Behavior, which further supports the perception that the behavioral intentions are the result of the cumulative experiential measurements, but not the single experience with the service (Lemon & Verhoeff, 2016; Klaus, 2013).

To begin with, the substantial direct impact of DCE on RI confirms the fact that experiential quality is an effective source of behavioral continuity in the digital setting. The result aligns with the previous studies that show that positive online experiences, which are defined as usability, reliability, and emotional reassurance, decrease perceived risk and enhance relational confidence, which in turn makes the consumers more willing to repurchase (Bilgihan, 2016). In the context of the Customer Experience Theory, this finding highlights the notion that experience is a holistic evaluative judgment, which involves functional and affective cues at digital touchpoints, and which can directly drive future behavior without necessarily going through intermediate attitudinal states (Klaus & Nguyen, 2013; Verhoff et al., 2015; Heller et al., 2019).

Second, the positive correlation between DCE and CS is very strong, which underscores satisfaction as an accumulative appraisal result of the digital interactions. The finding aligns with the established findings in the electronic service quality and e-satisfaction literature, which theorize that system usability, interface quality, and perceived efficiency are the foundation of satisfaction ratings in online contexts (Parasuraman et al., 2005; Amin, 2016). Notably, the scale of this effect indicates that satisfaction is not just a side effect of functional performance but an indicator of more general experiential interpretations of digital interactions by consumers, in line with more recent experiential and relational approaches (Bilgihan, 2016; Fernandes & Barfknecht, 2020; Nambisan & Watt, 2011).

Third, CS was also identified to have a strong and positive impact on RI, which supports its position as an important proximal predictor of behavioral intentions. The given finding is consistent with a large body of empirical literature that suggests that CS leads to increased repeat purchasing, loyalty intentions, and long-term relationships with providers of digital services (Chiu et al., 2014; Liu et al., 2011). In the perspective of the Theory of Planned Behavior, satisfaction may be viewed as an attitudinal judgment that enhances positive intentions by boosting perceived behavioral consequences and decreasing uncertainty regarding repeat transactions (Hsu et al., 2015; Chou & Hsu, 2016).

In addition to these direct relationships, the research is able to offer strong evidence of the mediating nature of CS in the association between DCE and RI. The large indirect impact supports the fact that satisfaction is a psychological process by which experiential stimuli are converted into behavioral intentions. This result confirms integrative theories that experiential inputs affect behavior mostly through internal judgments, including satisfaction, engagement, or perceived value (Bilgihan, 2016). The fact that both the significant direct and indirect effects are present implies that there is partial mediation, meaning that although satisfaction is one of the key pathways, DCE still has an independent motivational power in the context of RI.

The moderating role of DC on the experience-repurchase relationship was not supported as expected. This finding implies that DC does not influence the process of DCE converting into RI in the context of the research. A possible reason is the fact that the Spanish consumers are highly digitally mature, and the

minimum level of familiarity with digital technologies may decrease the range of culture predispositions and diminish the moderation impact (Venkatesh et al., 2012; Sivathanu, 2019; Izquierdo-Yusta et al., 2021). The same observations have been made in earlier studies in which contextual or cultural moderators portrayed a weak impact in technologically advanced settings with the prevalent use of digital technologies (Thakur, 2019; Supotthamjaree & Srinaruewan, 2021; San-Martin et al., 2019).

Combined, these results add to the literature of DCE through the empirical verification of an integrated model that encompasses both evaluative and behavioral processes underlying RI. This study contributes to the literature on the theoretical understanding of digital experience to mature digital market conversion into long-lasting consumer behavior by showing the central role of satisfaction as a mediating factor and elucidating the conditions of the boundary of the DC. In addition, the findings are useful to scholars and practitioners who aim to create digital experiences that can build long-term customer relations based on valuable experiential and evaluative journeys (Lemon & Verhoef, 2016; Bilgihan, 2016; Vasaquez & Vera-Martínez, 2020).

7. Theoretical and Practical Implication

7.1 Theoretical Implications

The current research has a number of theoretical impacts on the literature of DCE and post-purchase behavior. To begin with, the findings contribute to the Customer Experience Theory by empirically confirming that DCE as a direct and indirect antecedent of RI is independent as well as satisfaction-mediated. This confirms the idea that digital experience is a wholesome construct that incorporates functional, cognitive, and affective aspects throughout the customer experience, and not an antecedent of satisfaction (Lemon & Verhoef, 2016; Klaus, 2013; Verhoef et al., 2015). Second, the established partial mediating role of CS moves the previous satisfaction-loyalty models by emphasizing satisfaction as an important psychological transmission pathway through which the digital experiences are codified into behavioral intentions (Anderson & Srinivasan, 2003; Fang et al., 2011; Bilgihan, 2016). Lastly, the non-significant moderating role of DC adds to the theory by proposing the conditions of boundaries where the cultural predispositions toward technology can become inexplicable, especially in digitally mature markets where the baseline digital competence is elevated (Venkatesh et al., 2012; Sivathanu, 2019; Izquierdo-Yusta et al., 2021). Taken together, these results narrow the gaps in the theoretical models by defining the relative importance of experience, evaluation, and contextual variables in the formation of the RI in online settings.

7.2 Practical Implications

Based on the results, there are a number of implications regarding the practical aspects of managing digital service touchpoints. In particular, it is vital that DCE plays a major role in shaping CS and RI. Thus, it is necessary for companies to follow a well-structured approach towards managing their digital touchpoints. To this end, managers are encouraged to work on the design of user experiences by making digital systems easy to navigate, simplify transactions, and increase performance speed. With regard to mobile device usage being the most common way of interacting with websites or applications, firms should adopt a mobile first philosophy in designing their platforms.

Furthermore, it is evident that CS is a mediator in this relationship. Therefore, it is important for organizations to focus on measuring user perceptions in order to ensure that the customer experience is

positive. The implementation of real-time surveys, as well as in-application ratings, could allow companies to track satisfaction levels more effectively, which would help them identify the sources of dissatisfaction and address these issues promptly before they become serious enough to negatively impact users' attitudes towards the firm. It is also recommended that businesses pay attention to creating personalized experiences by implementing recommendation engines powered by data analytics or artificial intelligence solutions. The latter will enable companies to create tailored experiences based on user needs, preferences, and behaviors and, thus, make their interactions more positive and enjoyable.

Lastly, it is worth emphasizing that DC does not moderate the relationships under investigation. Thus, when working in digitally advanced markets, the differences in customer technological predisposition may not play a critical role in the effectiveness of digital marketing approaches. As a result, managers should focus on improving customer experience as a whole, regardless of their clients' technological sophistication.

8. Limitations and Future Research

Although it has made contributions, this study has a number of limitations that leave the way to future research. First, the cross-sectional design does not allow capturing dynamic changes in experience, CS, and intention to repurchase, and longitudinal designs might be the way to go in the future to learn how experience evaluations change across repeated digital interactions. Second, the research was carried out in one national environment, which might restrict the applicability of the results to markets with different levels of digital maturity; future studies can apply the model to cross-cultural or emerging-market environments to further investigate the role of DC in different technological environments. Lastly, the proposed framework can be enhanced in future research by including other experiential or relational constructs, including trust, engagement, or perceived value, to offer a more detailed view of the mechanisms by which DCE affects long-term behavioral outcomes.

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