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Research Article

Key Factors for In-Store Smartphone Use in an Omnichannel Experience: Millennials vs. Nonmillennials

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The in-store use of smartphones is revolutionizing the customer journey and has the potential to become an important driver in the omnichannel context. This paper aims at identifying the key factors that influence customers' intentions to use smartphones in-store and their actual behavior and to test the moderating effect of age, differentiating between millennials and nonmillennials, as millennials are considered digital natives and early adopters of new technologies. We applied the UTAUT2 model to a sample of 1043 Spanish customers, tested it using structural equations, and performed a multigroup analysis to compare the results between the two groups. The results show that the model explains both the behavioral intention to use a smartphone in a brick-and-mortar store and use behavior. The UTAUT2 predictors found to be most important were habit, performance expectancy, and hedonic motivation. However, the study shows that the only difference between millennials and nonmillennials with regard to the use of smartphones in-store is the effects of behavioral intention and habit on use behavior. The study adds to the existing knowledge by providing evidence in support of the validity of UTAUT2 as an appropriate theoretical basis to explain effectively behavioral intention, specifically the in-store use of smartphones.

1. Introduction

Omnichannel retailing has dramatically changed the way customers shop. Nowadays, consumers increasingly simultaneously use multiple channels and touchpoints during their customer journey and demand that they should be connected and integrated to enjoy a holistic and seamless shopping experience [1]. In this new scenario, the smartphone has become a powerful tool. Customers are mobile dependent and prefer to consult their phones rather than salespersons to carry out different tasks in-store, such as searching for product information and prices, checking product ratings, comparing products, and paying; they also use them to consult family and friends for advice [2–4]. Moreover, they have the potential to become important drivers in the omnichannel context due to their importance as initiators for conversion to other touchpoints or channels.

As Marriott et al. [5] highlight, business managers stress the importance of understanding customer behavior. This is crucial for the successful management and development of m-shopping in the retail industry [6].

M-shopping is defined by many authors as a subsidiary of m-commerce: the online purchase of products or services using a smartphone [7–13]. However, for the purpose of this research, we use a wider definition of m-shopping, which includes browsing, searching, purchasing, and comparing products using smartphones [5, 14–16]. M-shopping is a critical part of m-marketing as it empowers shoppers by allowing them to research product characteristics from multiple sources and carry out tasks such as checking product availability and prices, compare different brands and offers, and read user opinions and reviews [17–19]. In addition, m-shopping encompasses the use of smartphones in prepurchasing activities such as finding directions to the store and checking opening hours [20].

Previous research has shown that consumers' intention to use smartphones in-store positively affects purchase intention, especially when they are used to compare prices and obtain discount coupons [21]. However, there is a lack of research into the motivations for in-store smartphone use. Thus, following the suggestion of Venkatesh et al. [22], this study seeks to bridge that gap by examining the applicability of the UTAUT2 model to explain consumer use of smartphones in a physical store. Additionally, previous literature has discussed the moderating effect of age, demonstrating that young people are more innovative and more likely to accept new technologies than older people (e.g., [12, 16, 23, 24]). Due to m-shopping and omnichannel retailing literature being in its infancy, practical and theoretical understanding remains limited. For this reason, this study's aim is twofold: first, to identify the key factors influencing customers' intentions to use smartphones in-store to gain an accurate understanding of customer m-shopping acceptance behavior and their actual behavior in an omnichannel context, and, second, to test the moderating effect of age, differentiating between millennials and nonmillennials.

The paper is organized into four sections. The first offers an overview of the literature describing the conceptual foundation for the acceptance and in-store use of smartphones. The second describes the sample and the methodology employed. The third reports the results. Finally, the main conclusions and implications are discussed in the context of future research.

2. Theory of Acceptance and In-Store Use of Smartphones: Model and Hypotheses

Our research framework is based on the unified theory of acceptance and use of the technology (UTAUT2) model [22], which is an extension of the original UTAUT model [25]. We select the UTAUT2 model because it provides an explanation for information and communication technology (ICT) acceptance and use by consumers and can be applied to different technologies and contexts [22]. Moreover, Marriott et al. [5] gave us three more reasons to use the UTAU T2 model. First, "UTAUT2 was created in relation to mobile utilization." Second, "UTAUT2 incorporates the cost-benefit factors of *performance expectancy* and *effort expectancy*." Third, "UTAUT2 accounts for voluntary situations and allows for time factors to be considered." Under this model, a customer's intention to accept and use a new technology is affected by seven factors: *performance expectancy* (PE), *effort expectancy* (EE), *social influence* (SI), *facilitating conditions* (FC), *hedonic motivation* (HM), *price value* (P), and *habit* (HA).

Although the model has been used previously to explain customer behavior in the context of mobile commerce (e.g., [26, 27]), to our knowledge, little attention has been paid to the in-store omnichannel shopping context [28]. Thus, this study examines the applicability of the UTAUT2 model specifically to explain consumers' use of smartphones, while in a physical store, in an omnichannel context. In the following paragraphs, we describe the main constructs of the research model.

Performance expectancy is defined as the degree to which using a technology will provide benefits to the consumer in performing certain activities [22]. Performance expectancy adapted to omnichannel stores considers how consumers perceive the benefits they receive by using smartphones while in a physical store. This variable has been shown to be one of the strongest predictors of behavioral intention to adopt m-commerce and an influence on omnichannel shopping behavior (e.g., [7, 17, 28]). Thus, the following hypothesis is proposed:

H1. Performance expectancy positively affects behavioral intention to use a smartphone in-store.

Effort expectancy is described as the degree of ease/effort associated with the consumers' use of technology [22]. Perceived ease of use has been demonstrated to be a significant influence on the intention to use mobile commerce (e.g., [5, 7, 12, 17, 27]). In addition, this factor is a key determinant of purchase intention in an omnichannel context [28]. In keeping with these previous works, we propose the following:

H2. Effort expectancy positively affects behavioral intention to use a smartphone in-store.

Social influence is defined as how "consumers perceive that important others (e.g., family and friends) believe that they should use a particular technology" ([29], p. 73). In the case of m-shopping, previous literature suggests that social influence encourages m-shopping acceptance behavior [12, 16, 24, 30]. Moreover, younger consumers are more susceptible to technology adoption due to social media [23]. Adapting social influence to omnichannel shopping, we hypothesize that behavioral intention to use devices in-store is likely to be influenced by friends, family, role models, and celebrities. Therefore, the following hypothesis is proposed:

H3. Social influence positively affects behavioral intention to use a smartphone in-store.

Facilitating conditions are the consumers' perceptions of the resources and support available to perform a behavior [25, 31]. Previous studies demonstrate that a favorable set of facilitating conditions results in greater intention to use shopping apps [5, 27]. We hypothesize that when the consumer has a favorable perception of the facilitating conditions, it will lead to smartphone use in-store during either, or both, the prepurchase and purchase stages. Thus, we have the following:

H4a. Facilitating conditions positively affect behavioral intention to use a smartphone in-store.

H4b. Facilitating conditions positively affect the use behavior of smartphones in-store.

Hedonic motivation is defined as the pleasure or enjoyment derived from using a technology [22]. Previous literature has shown the influence of hedonic motivation on the intention to use m-shopping (e.g., [7, 8, 16, 17]).

However, Juaneda-Ayensa et al. [28] did not find that hedonic motivation-influenced purchase intention in the omnichannel context. As there are different results with respect to this variable, we hypothesize that the higher the consumers' perceived enjoyment is when they use their smartphones in-store, the higher will be their behavioral intention to use them. Thus, we put forward the following hypothesis:

H5. Hedonic motivation positively affects behavioral intention to use a smartphone in-store.

Habit is described as the extent to which people tend to perform behaviors automatically because of learning [32]. This concept, which is a new construct in the UTAUT2 model, has been considered a predictor of behavioral intention to use mobile apps [16, 27]. In addition, Kim [33] demonstrated that habit influenced the actual use of mobile apps and data services. However, Juaneda-Ayensa et al. [28] did not find that habit-influenced purchase intention in the omnichannel context. Taking into account the different results recorded in the literature and that the use of mobile devices is a part of the daily lives of shoppers, we hypothesize the following:

H6a. Habit positively affects behavioral intention to use smartphones in-store.

H6b. Habit positively affects use behavior of smartphones in-store.

The price value is defined as the consumers' cognitive tradeoff between the perceived benefits of the use of internet data and the monetary cost of using them [22]. Thus, we hypothesize that if the perception of the price value when accessing data on the internet using smartphones in-store has greater benefits than the perceived monetary cost (e.g., data cost and other types of service charges), consumers are more likely to access them. Therefore, the following hypothesis is proposed:

H7. Price value positively affects behavioral intention to use a smartphone in-store.

Behavioral intention is the main antecedent of use behavior, and it has a direct effect on individuals' actual use of a given technology [34]. Several studies in different contexts confirm the relationship between intention to perform a behavior and actual behavior [17, 35–37]. Thus, the following hypothesis is proposed:

H8. Behavioral intention positively affects the use behavior of smartphones in-store.

3. The Moderating Role of Age: Millennials vs. Nonmillennials

Previous literature has demonstrated that shopping behavior and the use of new technologies during the customer journey are influenced by sociodemographic variables such as gender, age, and education (e.g., [22, 38, 39]). Regarding age, previous studies have shown behavioral differences between "millennials" and "nonmillennials" [40–42]. Millennials are the generation born between the early 1980s and the early 2000s [43]. They are considered the first high-tech generation because they are early adopters of technological devices and expert Internet users. They are known as digital natives, as opposed to the members of the previous generation, who are called digital immigrants [44].

Previous research has noted that young people integrate smartphones into their daily lives, while older people generally use them for basic functions [45]. Some studies identify a relationship between the age of consumers and the probability that they will use smartphones and mobile technologies during their shopping journeys [45–50]. Although many works have studied this influence, there is no consensus on the relationship between the age of consumers and the probability that they will use new technology in their shopping journeys [49]. The study of how age can influence the way in which a consumer accepts and uses new technology is included in the UTAUT2 [22] as a moderating effect of the influence of facilitating conditions, hedonic motivation, habit, and price value on behavioral intention; however, the authors did not include the influence of age on performance expectancy, effort expectancy, and social influence. Although no works have studied the influence of age using the UTAUT2 model, we have found some works studying the influence of age using the UTAUT model. Regarding the influence of age as a moderator variable in technology acceptance, effort expectancy is stronger for older consumers [25, 50]. Lian and Yen, [48], in their study into online shopping drivers and barriers for older adults, concluded that the major online shopping driving forces are performance expectancy and social influence. Due to the lack of consensus regarding this moderating effect and the lack of works specifically regarding the use of smartphone in the omnichannel context, we would like to develop further debate in this area. For this reason, we studied the moderating role of age by differentiating the two groups, millennials and nonmillennials. Specifically, regarding m-shopping, some studies have shown that younger consumers are more likely to accept m-shopping than older consumers [16, 23, 24] and that the intention to use smartphones in-store positively affects the use behavior more in young people [51]. Due to the limited papers that discuss this moderating effect in the omnichannel shopping process, we incorporate it through the following hypotheses:

H9. Age ("millennials" vs "nonmillennials") plays a moderating role in the relationship between the seven exogenous variables and intention to use smartphones in-store.

This hypothesis is divided into the following:

H9a. Age plays a moderating role in the relationship between performance expectancy and intention to use smartphones in-store.

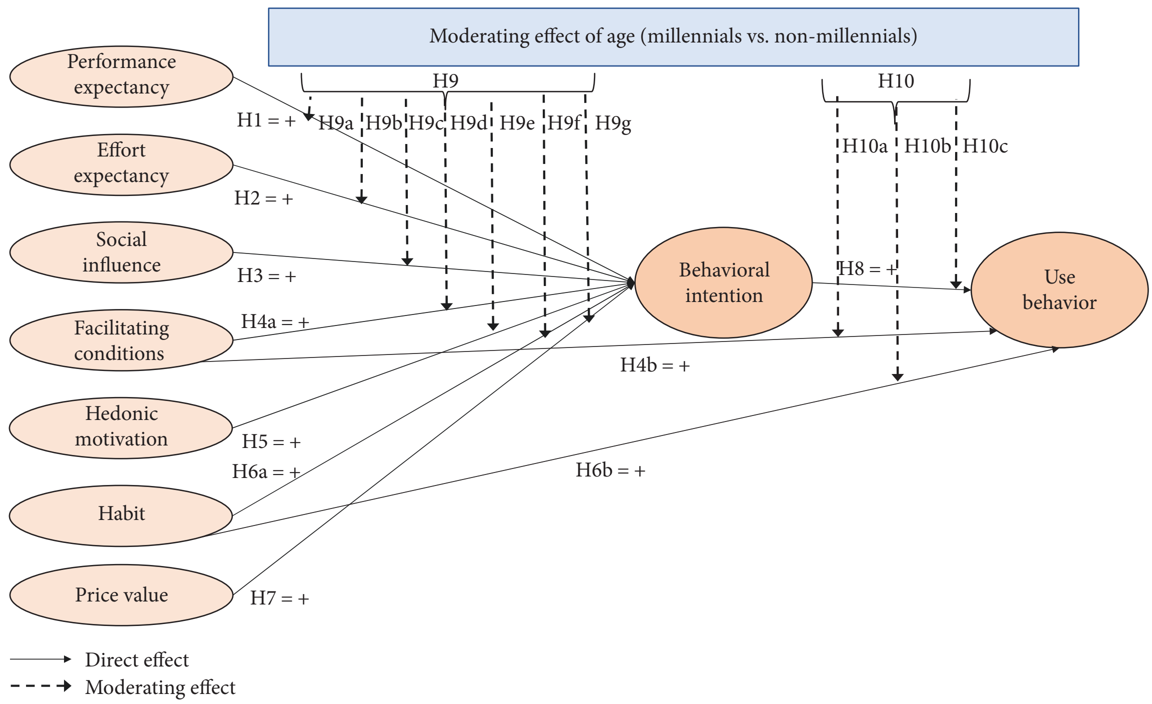

Figure 1: Research model.

H9b. Age plays a moderating role in the relationship between effort expectancy and intention to use smartphones in-store.

H9c. Age plays a moderating role in the relationship between social influence and intention to use smartphones in-store.

H9d. Age plays a moderating role in the relationship between facilitating conditions and intention to use smartphones in-store.

H9e. Age plays a moderating role in the relationship between hedonic motivations and intention to use smartphones in-store.

H9f. Age plays a moderating role in the relationship between habit and intention to use smartphones in-store.

H9g. Age plays a moderating role in the relationship between price value and intention to use smartphones in-store.

H10. Age (“millennials” vs “nonmillennials”) plays a moderating role in the relationship between the three antecedents of the use behavior of smartphones in-store.

H10a. Age plays a moderating role in the relationship between facilitating conditions and the real behavior of using smartphones in-store.

H10b. Age plays a moderating role in the relationship between habit and the real behavior of using smartphones in-store.

H10c. Age plays a moderating role in the relationship between behavioral intention and the real behavior of using smartphones in-store.

To determine the impact of the different constructs on the behavioral intention to use a smartphone and use behavior, we developed a model with nine hypotheses related to the effect of age on customers’ in-store use of their smartphones in an omnichannel context (Figure 1).

4. Research Method

4.1. Data Collection Procedure. Data were collected using a personal survey focusing on Spanish customers who use smartphones in physical stores. The measurement scale was adopted from Venkatesh et al. [22], and we developed the items related to use behavior from the results of previous reports [52, 53]. The performance expectancy, effort expectancy, facilitating conditions, and habit constructs are each composed of four items. Social influence, hedonic motivation, price value, and behavioral intention are each comprised of three items. Questions were answered on an eleven-point Likert scale, with 0 referring to totally disagree and 10 referring to totally agree. The instrument was pretested on four university marketing professors, and as a result, modifications were made to improve the content and make it more understandable and consistent. Thereafter, we conducted a pilot study with two groups (millennials and nonmillennials), using a paper version. The data were collected in November 2017. The sample consisted of 1043 individuals. Of the surveys collected, 40.7% were millennials (between 18 and 35 years) and 59.3% were nonmillennials

Table 1: Profile of respondents.

Characteristics	Frequency		Percentage (%)	
	Millennials	Nonmillennials	Millennials	Nonmillennials
Gender				
Male	219	309	51.5	50.0
Female	206	309	48.5	50.0
Level of education				
Primary education	54	160	12.7	25.9
Secondary education	261	214	61.4	34.6
University studies	110	244	25.9	39.5
Mobile data plans				
Yes	418	539	98.4	87.8
No	7	79	1.6	12.8

(older than 36 years). Table 1 summarizes the profile of the respondents.

4.2. Data Analysis Process. To test the hypotheses about the significance of the relationships in the model and the multigroup analysis, we used PLS-SEM (partial least square-structural equation modeling) [54]. Our objectives were to predict the intention to use mobile technology in a store in an omnichannel environment and identify the key drivers that explain use and use behavior. Hair et al. ([55], p. 144) recommend using PLS-SEM "if the goal is predicting key target constructs or identifying key 'driver' constructs," as in our case. Similarly, other authors suggest that PLS-SEM is appropriate when the research has a predictive purpose [56–59] and an explanatory purpose [60], as is the case with our study.

In this study, age is a categorical variable that integrates two groups: millennials and nonmillennials. The moderating influence of age has been analyzed through a multigroup analysis [61].

5. Results

5.1. Measurement Model. The reliability and validity of the measurement model were analyzed. We tested the measurement model in the general model to be able later to maintain the structure when executing the two models for the millennials and nonmillennials.

Subsequently, the structural model was analyzed and the effects of the exogenous variables on the endogenous variables were checked. Finally, a multisample analysis was carried out.

In the analysis of the measurement model, reliability and convergent and discriminant validity were verified. Regarding the reliability of the indicators, most factor loadings were >0.70 and had t values > 1.96, but two did not [62]. These two exceptions could be considered for removal based on composite reliability (CR) and convergent validity (AVE). Regarding the reliability of the scales used to measure the factors, the CR coefficient should, to establish internal consistency, be higher than 0.7 [63]. As to convergent validity, the AVE must be >0.5 [63]. The results in Table 2 show that all the constructs fit these criteria. Given that the requirements of reliability and convergent validity have been met, we decided to maintain the indicators with loadings in the range of 0.4–0.7 [54]. Discriminant validity was measured by two methods. First, it was measured by comparing the correlation among constructs and the square root of the AVEs [64]. Secondly, we used the heterotrait-monotrait (HTMT) ratio, which has been established as a superior criterion [65]. The present study uses the more conservative level of 0.85 to assess discriminant validity. In Table 3, it can be seen that in all the cases the square root of the AVEs is greater than their corresponding intercorrelations and that all results are below the critical value of 0.85. Accordingly, both criteria for achieving discriminant validity are satisfied. These results allow us to confirm that the measuring instrument is reliable and valid.

5.2. Assessment of the Structural Model. First, we assessed the structural model for collinearity between items using the variance inflection factor (VIF) values (Table 4) [63]. The VIF values of this analysis are lower than 3.3 in all cases (complete model and millennial and nonmillennial models), so there are no problems of multicollinearity [66].

We now discuss the effects of the exogenous variables on behavioral intention and real behavior. Regarding the structural model, we analyzed (i) the R^2 (coefficient of determination), (ii) the Q^2 (predictive relevance of the model), and (iii) the algebraic sign, magnitude, and significance of the path coefficients [67]. The results show that the model has the capacity to explain both behavioral intention and use behavior. Overall, for the millennials, the variables performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value explain 71.8% of the variation in behavioral intention ($R^2 = 0.718$). For the nonmillennials, the R^2 is 0.685. Chin [68] argues that R^2 values of 0.67, 0.33, and 0.19 can be considered substantial, moderate, and weak, respectively. Thus, following this prescription, our research model "substantially" explains variations in behavioral intention to use smartphones in-store. The R^2 for use behavior was 0.498 for millennials and 0.546 for nonmillennials. In this case,

Table 2: Assessment results of the measurement model.

Construct/associated items	Loading	CR > 0.7	Cronbach's alpha	AVE > 0.5
Performance expectancy (PE)		0.951	0.890	0.830
PE1	0.902			
PE2	0.929			
PE3	0.896			
PE4	0.917			
Effort expectancy (EE)		0.958	0.941	0.851
EE1	0.902			
EE2	0.943			
EE3	0.949			
EE4	0.895			
Social influence (SI)		0.959	0.935	0.886
SI1	0.930			
SI2	0.956			
SI3	0.938			
Facilitating conditions (FC)		0.879	0.816	0.647
FC1	0.835			
FC2	0.846			
FC3	0.815			
FC4	0.714			
Hedonic motivation (HM)		0.969	0.951	0.911
HM1	0.949			
HM2	0.967			
HM3	0.948			
Price value (P)		0.943	0.910	0.847
P1	0.921			
P2	0.943			
P3	0.897			
Habit (HA)		0.947	0.926	0.818
HA1	0.919			
HA2	0.912			
HA3	0.857			
HA4	0.928			
Behavioral intention (BI)		0.981	0.972	0.946
BI1	0.973			
BI2	0.974			
BI3	0.971			
Use behavior (UB)		0.916	0.890	0.613
UB1	0.866			
UB2	0.701			
UB3	0.891			
UB4	0.896			
UB5	0.642			
UB6	0.823			
UB7	0.604			

the research model "moderately" explains the variations. Thus, the study demonstrates that UTAUT2 is appropriate to explain the in-store use of smartphones in an omnichannel context and explains variations in behavioral intention and use behavior [65]. Regarding the predictive power of the model, we used the Q^2 provided by PLS predict. Our results gave us 0.689 for the millennials and 0.651 for the nonmillennials for behavioral intention. For use behavior, it was 0.416

Table 3: Discriminant validity.

	PE	EE	SI	FC	HM	HA	P	BI	UB
PE	**0.911**	0.596	0.593	0.560	0.720	0.691	0.385	0.757	0.742
EE	0.559	**0.922**	0.359	0.811	0.621	0.531	0.410	0.545	0.567
SI	0.554	0.337	**0.941**	0.404	0.585	0.573	0.294	0.573	0.559
FC	0.492	0.710	0.355	**0.804**	0.599	0.448	0.487	0.532	0.485
HM	0.679	0.558	0.552	0.531	**0.955**	0.770	0.405	0.743	0.689
HA	0.644	0.499	0.534	0.394	0.726	**0.904**	0.319	0.829	0.774
P	0.354	0.380	0.272	0.420	0.376	0.294	**0.920**	0.383	0.364
BI	0.721	0.521	0.546	0.477	0.714	0.789	0.360	**0.973**	0.735
UB	0.682	0.521	0.511	0.417	0635	0.707	0.323	*0.686*	**0.783**

Note: values on the main diagonal are the square roots of the AVEs. Below the diagonal: correlations between the factors. Above the diagonal: ratio HTMT.85 criterion.

Table 4: Full collinearity VIFs.

	Total	Millennials	Nonmillennials
VIF behavioral intention			
PE	2.332	2.149	2.221
EE	2.449	1.946	2.290
SI	1.641	1.722	1.655
FC	2.229	1.869	2.177
HM	2.910	2.201	3.206
HA	2.422	2.118	2.495
P	1.280	1.215	1.253
VIF use behavior			
FC	1.296	1.219	1.258
HA	2.648	2.719	2.346
BI	2.893	2.928	2.560

for millennials and 0.501 for nonmillennials. Table 5 also shows the explained variance of each factor for each group. It can be seen that the direct effects of effort expectancy (−0.045) and price value (−0.002) are negative for millennials. They are negative also for nonmillennials for price value (−0.002). According to Falk and Miller [69], "when the original relationship between the two variables is so close to zero, the difference in the signs simply reflects random variation around zero." In summary, the results support seven of the hypotheses for the millennial group: H1 (regarding the influence of performance expectancy), H3 (social influence), H4a (facilitating conditions), H5 (hedonic motivation), H6a (regarding habit), H8 (behavioral intention), and H7 (regarding the influence of habit on use behavior). H2 (effort expectancy), H7 (price value), and H4b (regarding the influence of facilitation conditions on use behavior) were rejected, as the relationships were not significant. With regard to the nonmillennials, support was found for seven hypotheses, H1, H5, H6a, H7, H8, H4b, and H6b, while no significant differences were found for H2, H3, and H4a (Table 5).

5.3. Multigroup Analysis. We carried out a multigroup analysis to verify the moderating effect of age on intention to use smartphones in-store and real behavior. For this purpose, the sample was split into two groups, millennials and nonmillennials. We followed a three-step procedure to analyze the measurement invariance of composite models (MICOM). Following the proposals of Henseler et al. [70], we first checked configural invariance, then compositional invariance, and finally, we assessed the equal means and variances.

As Table 6 illustrates, partial measurement invariance for both groups was achieved for all model variables, thereby allowing multigroup comparison between groups.

We next performed two nonparametric tests, Henseler's test [70] and the permutation test. These were used as both are nonparametric tests, and they fit well with the nonparametric character of PLS-SEM [71].

Table 7 shows the p values of Henseler's tests in the P_{H} column. The last column of the table shows the p values of the permutation test. In this test, the differences are only significant at the 5% level if the p value is less than 0.05. We used 5000 permutations and 5000 bootstrap resamples. Henseler's test shows significant differences between millennials and nonmillennials only in the effect of price value on behavioral intention and habit on use behavior. The permutation test, which is considered the best technique [72], confirms the lack of significance of the differences shown in the results, except in the case of the relationship between behavioral intention (H10c) and habit (H10b) on use behavior of smartphones in-store in an omnichannel context.

5.4. Assessment of Predictive Validity Using PLSpredict. With the objective of producing valid predictions of behavioral intention and use behavior, we used PLSpredict for the general model and the millennial and nonmillennial models. We carried out the new PLSpredict technique using SmartPLS software version 3.2.7.

In general, for the simple models with minimal theoretical constraints, PLSpredict allows predictions very close to those obtained by using LM [59]. This study follows this approach and Felipe et al.'s [73] to assess the predictive performance of the PLS path model for the indicators and constructs. We obtain the mean absolute error (MAE), the root mean squared error (RMSE), and the Q^2 for indicators. Moreover, we also obtained the Q^2 for the constructs behavioral intention and use behavior.

In order to assess predictive performance, we carried out the benchmark procedures developed by the SmartPLS team

Table 5: Effect of endogenous variables, p values, and support for the hypotheses.

	R^2	Q^2	Direct effects	Correlations	Explained variance	p value	Confidence intervals	Support for hypotheses
				Millennials				
Behavioral intention	0.718	0.689						
H1: PE ≥ BI			0.254	0.697	17.70%	0.000	[0.173, 0.337]	H1: supported
H2: EE ≥ BI			−0.045	0.439	−1.98%	0.241	[−0.120, 0.030]	H2: nonsupported
H3: SI ≥ BI			0.075	0.569	4.27%	0.039	[0.003, 0.146]	H3: supported
H4a: FC ≥ BI			0.087	0.424	3.69%	0.014	[0.016, 0.155]	H4a: supported
H5: HM ≥ BI			0.114	0.648	7.39%	0.030	[0.015, 0.220]	H5: supported
H6a: HA ≥ BI			0.514	0.795	40.86%	0.000	[0.428, 0.594]	H6a: supported
H7: P ≥ BI			−0.002	0.232	−0.05%	0.941	[−0.061, 0.054]	H7: nonsupported
Use behavior	0.498	0.416						
H8: BI ≥ UB			0.442	0.683	30.19%	0.000	[0.314, 0.560]	H8: supported
H4b: FC ≥ UB			0.052	0.334	1.74%	0.134	[−0.017, 0.119]	H4b: nonsupported
H6b: HA ≥ UB			0.276	0.645	17.80%	0.000	[0.144, 0.406]	H6b: supported
				Nonmillennials				
Behavioral intention	0.685	0.651						
H1: PE ≥ BI			0.275	0.704	19.36%	0.000	[0.185, 0.364]	H1: supported
H2: EE ≥ BI			−0.002	0.492	−0.10%	0.960	[−0.075, 0.070]	H2: nonsupported
H3: SI ≥ BI			0.036	0.527	1.90%	0.341	[−0.038, 0.112]	H3: nonsupported
H4a: FC ≥ BI			0.064	0.452	2.89%	0.083	[−0.006, 0.137]	H4a: nonsupported
H5: HM ≥ BI			0.132	0.718	9.48%	0.015	[0.025, 0.236]	H5: supported
H6a: HA ≥ BI			0.426	0.757	32.25%	0.000	[0.331, 0.516]	H6a: supported
H7: P ≥ BI			0.074	0.372	2.75%	0.005	[0.022, 0.126]	H7: supported
Use behavior	0.546	0.501						
H8: BI ≥ UB			0.196	0.644	12.62%	0.000	[0.102, 0.302]	H8: supported
H4b: FC ≥ UB			0.112	0.391	4.38%	0.000	[0.064, 0.164]	H4b: supported
H6b: HA ≥ UB			0.526	0.715	37.61%	0.000	[0.412, 0.622]	H6b: supported

[74]: "The Q^2 value, which compares the prediction errors of the PLS path model against simple mean predictions. If the Q^2 value is positive, the prediction error of the PLS-SEM results is smaller than the prediction error of simply using the mean values. Accordingly, the PLS-SEM model offers an appropriate predictive performance." As Table 8 shows, this is true both at construct and at indicator levels for the general model and for the millennial and nonmillennial models.

In addition, if we compare the results of PLS with LM, the differences between PLS and PLS-LM are very small (these differences are shown in the PLS-LM column of Table 8). The Q^2 differences are less than 0.06, which is an indicator of a good predictive capacity; and the differences between RMSE and MAE are around 0.1.

6. Discussion and Conclusions

Technology is changing the way customers shop in the omnichannel era. Smartphones have become essential tools in daily life and are increasingly gaining importance for shopping in brick and mortar stores. More and more people use them to look for information and make purchases. This research explains how customers behave with regard to the in-store use of smartphones. Specifically, this study aims at analyzing the key factors that influence both customers' intention to use their devices in physical stores and their actual use of those devices. It also seeks to deepen this understanding by assessing the differences between the millennial and nonmillennial generations. To this end, the UTAUT2 model [22] was adapted, and its specific applicability to the consumer context was confirmed by applying it to a new technology (in-store use of smartphones). Our research has theoretical implications since the results reveal that the UTAUT2 model holds good predictive power and is able to explain well the behavioral intention and use behavior of smartphones in-store for both groups, millennials and nonmillennials. Although previous researchers have examined m-shopping in general, a few studies have focused on the in-store use of smartphones. Specifically, this research advances the understanding of the antecedents of the use of smartphones in-store in the new omnichannel retailing context, where customers use different channels simultaneously.

The results indicate that habit, performance expectancy, and hedonic motivation are the strongest predictors of in-store smartphone use for both groups (millennials and nonmillennials). This is consistent with the findings of previous studies in other contexts (e.g., [12, 17, 22,

Table 6: Results of the measurement invariance of composite models (MICOM) procedure.

	Step 1	Step 2 Compositional invariance			Step 3a Equal variances				Step 3b Equal means				
Construct	Configural invariance	Original correlation	5%	Partial measurement invariance established	Variance-original difference	2.5%	97.5%	Equal	Mean-original difference	2.5%	97.5%	Equal	Measurement invariance?
PE	Yes	1.000	1.000	Yes	0.573	−0.130	0.121	No	−0.171	−0.112	0.111	No	Partial
EE	Yes	1.000	1.000	Yes	0.850	−0.123	0.121	No	−0.526	−0.121	0.124	No	Partial
SI	Yes	1.000	1.000	Yes	0.185	−0.128	0.120	No	−0.024	−0.133	0.133	Yes	Partial
FC	Yes	0.999	0.997	Yes	0.563	−0.127	0.117	No	−0.577	−0.173	0.168	No	Partial
HM	Yes	1.000	1.000	Yes	0.637	−0.132	0.124	No	−0.079	−0.129	0.128	Yes	Partial
HA	Yes	1.000	1.000	Yes	0.563	−0.128	0.122	No	0.319	−0.192	0.171	No	Partial
P	Yes	1.000	0.999	Yes	0.459	−0.121	0.126	No	−0.424	−0.185	0.171	No	Partial
BI	Yes	1.000	1.000	Yes	0.539	−0.126	0.119	No	0.044	−0.135	0.114	Yes	Partial
UB	Yes	1.000	0.999	Yes	0.599	−0.132	0.123	No	0.106	−0.176	0.148	Yes	Partial

Table 7: Multigroup comparison for the intention to use a smartphone in-store: millennials vs. nonmillennials.

Relationships	Nonmillennials	Millennials	Path coefficient differences	P_H	p value permutation test
H9a: PE ≥ BI	0.275	0.254	0.021	0.635	0.748
H9b: EE ≥ BI	−0.002	−0.045	0.043	0.792	0.477
H9c: SI ≥ BI	0.036	0.075	0.039	0.230	0.457
H9d: FC ≥ BI	0.064	0.087	0.023	0.328	0.678
H9e: HM ≥ BI	0.132	0.114	0.088	0.594	0.837
H9f: HA ≥ BI	0.426	0.514	0.088	0.085	0.186
H9g: P ≥ BI	0.074	−0.002	0.076	0.026	0.055
H10a: FC ≥ UB	0.112	0.052	0.060	0.087	0.135
H10b: HA ≥ UB	0.526	0.276	0.250	0.002	0.003
H10c: BI ≥ UB	0.196	0.442	0.246	0.002	0.006

Notes: $P_H = p$ value Henseler's test.

29, 32, 35]). On the other hand, we did not find significant differences between the groups regarding the effect of effort expectancy on the intention to use smartphones in-store. This result differs from previous studies; this has always been considered one of the variables that most explains the intention to use a new technology. This lack of empirical evidence may be due to the absence of incremental effort perception, on the part of consumers, of in-store mobile use. Both millennials and nonmillennials use mobile phones in their daily lives; therefore, it should not be an additional effort to use them in the purchasing process.

Analyzing the results by group, first focusing on the millennial generation, it can be seen that price value does not influence the intention to use smartphones. This may be because young people do not take into account the price of internet data, as the cost has fallen since Venkatesh's 2012 study. As can be seen in the sample, 98.4% of them access mobile data, which they assume is normal. Another explanation for this result is that the Internet is now widely available due to the introduction of Wi-Fi open access points in cities and in physical stores and more and more of these offer free Wi-Fi. In addition, no significant differences were found regarding the effect of facilitating conditions on use behavior of smartphones in-store. This result is in line with the studies of Baptista and Oliveira [26] and Chopdar et al. [34], but contrary to the findings of Venkatesh et al. [22]. The explanation for this may be that the millennial generation is accustomed to new technologies and devices and they believe that they have enough skills to use their mobile phones and do not give importance to supporting factors.

For the nonmillennial group, social influence did not play a significant role in affecting behavioral intention to use smartphones in-store during the shopping process. The insignificant impact of this construct on behavioral intention suggests that older consumers are not influenced by other people. The explanation for this may be that the use of smartphones is perceived as a private activity. This result is consistent with the studies of Hew et al. [27] and Chopdar et al. [34]. In addition, facilitating conditions have an insignificant impact on intention to use smartphones in-store. A possible explanation for this result may be that today people habitually use mobiles in their daily lives and, therefore, they consider themselves self-sufficient in their use, including in the shopping context.

The results also confirm the influence of behavioral intention on use behavior. In other words, the greater a customer's perceived intention to use a smartphone in-store is, the more likely he or she is to actually use it. This result is in line with the recent studies of Chopdar et al. [34], Escobar-Rodríguez and Carvajal-Trujillo [29], and Venkatesh et al. [22]. Specifically, the proposed model explains 71.8% of the intention to use smartphones in-store by millennials and 68.5% for the nonmillennial group. In addition, the R^2 for use behavior was 49.8% for millennials and 54.6% for nonmillennials. The R^2 results we obtained were "weakly" lower than the variance values obtained by previous studies. For example, Chopdar et al. [34] obtained an R^2 value for BI 0.70 and an R^2 for UB 0.59 for the adoption of mobile shopping apps in the USA and an R^2 for BI 0.63 and an R^2 for UB 0.58 for India; Escobar-Rodríguez and Carvajal-Trujillo [29] obtained values of R^2 on BI 0.60 and R^2 on UB 0.6 for purchasing tickets online; and Venkatesh et al. [22] obtained values of R^2 on BI 0.74 and R^2 on UB 0.52 in the context of mobile technology.

Moreover, the model shows predictive power for the sample used in the research. This means that the model provides more information than noise, and the seven drivers predict accurately the behavioral intention to use smartphones in-store and real behavior.

Regarding the moderating role of age, our results indicate that, although millennials are considered digital natives and early adopters of technological devices, there are no differences between them and nonmillennials in terms of intention to use a smartphone in-store. This result is inconsistent with the findings of Bigne et al. [23] and Yang and Forney, [24]. The only differences found between the groups are in terms of the relationship between the behavioral intention and habit constructs on use behavior of smartphones in-store in an omnichannel context.

With regard to managerial implications, clothing retailers should develop user-friendly, useful, effective, and enjoyable apps and/or responsive websites to provide customers with a complete and seamless shopping experience when using their smartphones, as this research shows that consumers

Table 8: PLS predict assessment.

	Construct prediction summary		
		Q^2	
	Complete model	Millennials	Nonmillennials
BI	0.654	0.689	0.651
UB	0.503	0.416	0.501

Indicator prediction summary

Complete model									
		PLS			LM			PLS-LM	
	RMSE	MAE	Q^2	RMSE	MAE	Q^2	RMSE	MAE	Q^2
BI1	1801	1368	0.682	1801	1337	0.682	0.000	0.031	0.000
BI2	1894	1469	0.659	1878	1420	0.665	0.016	0.049	−0.006
BI3	1851	1402	0.679	1859	1383	0.677	−0.008	0.019	0.002
UB1	2111	1640	0.466	2013	1515	0.515	0.098	0.125	−0.049
UB2	2192	1631	0.423	2123	1573	0.458	0.069	0.058	−0.035
UB3	2227	1673	0.396	2179	1618	0.423	0.048	0.055	−0.027
UB4	2296	1667	0.337	2278	1647	0.347	0.018	0.020	−0.010
UB5	2761	2349	0.292	2679	2193	0.334	0.082	0.156	−0.042
UB6	2575	1997	0.253	2581	2001	0.250	−0.006	−0.004	0.003
UB7	2233	1485	0.186	2243	1510	0.180	−0.010	−0.025	0.006
Millennials									
BI1	1808	1394	0.673	1832	1375	0.665	−0.024	0.019	0.008
BI2	1873	1473	0.641	1897	1445	0.632	−0.024	0.028	0.009
BI3	1866	1435	0.67	1926	1438	0.649	−0.060	−0.003	0.021
UB1	2288	1861	0.396	2259	1760	0.411	0.029	0.101	−0.015
UB2	2345	1892	0.372	2316	1836	0.387	0.029	0.056	−0.015
UB3	2409	1937	0.325	2421	1905	0.318	−0.012	0.032	0.007
UB4	2586	2012	0.288	2627	2027	0.266	−0.041	−0.015	0.022
UB5	2964	2532	0.156	2942	2412	0.168	0.022	0.120	−0.012
UB6	2750	2296	0.19	2829	2332	0.142	−0.079	−0.036	0.048
UB7	2540	1879	0.143	2624	1958	0.086	−0.084	−0.079	0.057
Nonmillennials									
BI1	1809	1358	0.642	1839	1350	0.63	−0.030	0.008	0.012
BI2	1921	1471	0.623	1940	1441	0.616	−0.019	0.030	0.007
BI3	1860	1398	0.647	1881	1396	0.639	−0.021	0.002	0.008
UB1	1965	1453	0.453	1900	1384	0.489	0.065	0.069	−0.036
UB2	2076	1427	0.41	2056	1432	0.422	0.020	−0.005	−0.012
UB3	2089	1475	0.408	2075	1472	0.416	0.014	0.003	−0.008
UB4	2068	1405	0.346	2095	1430	0.329	−0.027	−0.025	0.017
UB5	2447	2039	0.313	2466	1987	0.302	−0.019	0.052	0.011
UB6	2436	1761	0.253	2476	1778	0.228	−0.040	−0.017	0.025
UB7	2006	1210	0.196	2024	1259	0.181	−0.018	−0.049	0.015

Notes: BI: behavioral intention. US: use behavior RMSE: root mean squared error. MAE: mean absolute error. PLS: partial least pquares math model. LM: linear model.

perceive both the utilitarian and the hedonic benefits of using their smartphones in-store. Consumers are becoming more and more accustomed to using their mobile phones in their daily lives, and therefore, retailers and managers should facilitate the use of smartphones and integrate them in their physical stores. In this way, when customers are in a store they can get all the information they need about products, inventories, and the possibility of buying online to avoid queues. If all of this information is available in the retailer's app, then this will be registered and the retailers can use this huge amount of data to offer suggestions for future purchases and the personalization of products and offers. Moreover, smartphones increasingly offer the possibility of paying without using a credit card. Therefore, managers are recommended to facilitate this by providing checkouts that integrate this technology. In addition, the management of fashion retail stores with a target market over 35 years of age should bear in mind that these nonmillennials are not influenced by the opinions of others (friends, family, and celebrities), and we recommend that they rethink the use of the resources that they dedicate to hire influencers to publicize their products.

This paper has some limitations. Specifically, the study focuses on clothing retailers and the sample is limited to Spain. Although the sample is very complete in terms of gender, age, and educational level, it would be interesting, to generalize the results, to replicate the study in other sectors and countries with different levels of penetration of smartphone use in-store during the shopping process. In addition, we consider it necessary to rethink the price-value construct, because the reduction in the cost of accessing mobile data has diminished the importance of this cost. Additionally, future papers should analyze the influence of other constructs, such as security and trust, to test whether the inclusion of these variables would improve the predictive value of both behavioral intention and actual in-store smartphone use. It would also be interesting to analyze the influence of other moderating variables, such as gender and personal innovativeness.

Although the mobile phone is revolutionizing the purchasing process, the physical store is still the preferred channel to make purchases. It is important for retailers to think of the physical store not only in terms of sales generation but also as a means of enriching the user's engagement with the consumer experience and the services that can only be offered in the physical channel. Consumers are ahead of retailers: their digitization, in all respects, occurred before the retailers. They enter physical stores, often having researched information online, with more knowledge and demands than ever before. And they expect a brand experience, ahead of the channel. As omnichannel shopping and, more specifically, m-shopping research, remain in their infancy, there are several research gaps, so further work to examine consumer acceptance models is needed.

Data Availability

The database used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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