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Structural Equation Modeling of User Interface Design, User Experience, and Online Purchase Behavior: The Mediating Role of Perception

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ABSTRACT

This study develops and empirically tests a structural equation model to examine how user interface design and user experience influence online purchase behavior, with user perception mediating the relationship in an e-commerce context. Drawing on an integrated theoretical framework that combines the Stimulus – Organism - Response paradigm, the Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology 2, user interface user experience -related attributes, including visual appeal, interactivity, perceived ease of use, perceived usefulness, and perceived security, are conceptualized as exogenous latent constructs within a mediated structural system. Data from 523 consumers in Vietnam were analyzed using covariance-based structural equation modeling. The measurement model demonstrates satisfactory reliability and convergent and discriminant validity, while the structural model exhibits acceptable fit indices. The results support all hypothesized relationships, with interactivity and perceived usefulness emerging as the strongest predictors of user perception.

Furthermore, user perception is confirmed as a significant mediator linking design-related attributes to online purchase behavior. From a methodological standpoint, this study contributes to the structural equation modeling literature by illustrating the specification and validation of a mediated latent variable model, with particular emphasis on measurement validation and indirect effect estimation within a unified SEM framework. These findings provide insights into how design-related factors can be modeled to explain behavioral outcomes in digital environments.

KEYWORDS

Online purchase behavior, Economics, Econometrics, Social Sciences, E-commerce, Structural equation modeling (SEM), User Interface, User Experience.

1. Introduction

The rapid expansion of e-commerce has substantially reshaped consumer behavior across digital markets, particularly in emerging economies where technological adoption is accelerating (Dwivedi, et al., 2021; Verhoef, et al., 2009). In Vietnam, the increasing use of internet-enabled devices and mobile platforms has driven a marked rise in online shopping activities, positioning e-commerce as a central component of the retail landscape. As competition among digital platforms intensifies, firms can no longer rely solely on traditional drivers such as price and product availability; instead, greater emphasis has been placed on how users interact with and experience digital environments (De Keyser, et al., 2020; Lemon & Verhoef, 2016). In this context, user interface (UI) design and user experience (UX) have emerged as critical determinants of consumer engagement and decision-making processes in online environments (Bleier, et al., 2019; Rose, et al., 2012).

Although UI and UX are closely related, they capture different aspects of user interaction within digital systems (Hassenzahl & Tractinsky, 2006). UI design reflects the structural and visual configuration of a platform, including layout, navigation, and interactivity, whereas UX encompasses users' broader cognitive and affective responses throughout the interaction process (Hassenzahl & Tractinsky, 2006; Norman, 2013). Prior research suggests that these constructs jointly shape user perception, influencing evaluations of usefulness, ease of use, trust, and satisfaction (Cyr, et al., 2006; Davis, 1989; Kim, et al., 2008). However, the mechanisms through which UI and UX translate into behavioral outcomes remain insufficiently specified, particularly in models that explicitly account for indirect effects and latent relationships (Hair, et al., 2010; Kline, 2016).

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Existing research on online consumer behavior has largely relied on established theoretical frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh, et al., 2012). While these models provide valuable insights into the cognitive determinants of technology adoption, they are often applied in isolation and tend to emphasize direct relationships between technological attributes and behavioral outcomes (Bagozzi, 2007; Benbasat & Barki, 2007). As a result, they may not adequately capture the process-oriented and multidimensional nature of user interaction in digital environments, particularly when mediated relationships are involved (Hair, et al., 2010; Zhao, et al., 2010).

The Stimulus-Organism-Response (S-O-R) framework offers a useful theoretical lens to address this limitation by conceptualizing environmental stimuli such as UI and UX attributes as antecedents of internal cognitive states, which in turn influence behavioral responses (Eroglu, et al., 2001; Mehrabian & Russell, 1974). Recent studies have applied this framework in digital contexts, highlighting the importance of mediating constructs such as perception, trust, and satisfaction in explaining online consumer behavior (Bleier, et al., 2019; Rose, et al., 2012). Nevertheless, empirical research that integrates these elements into a unified latent variable structural model remains limited, particularly in studies that emphasize rigorous model specification and validation procedures (MacCallum & Austin, 2000; Marsh, et al., 2004).

In addition, most SEM-based studies in this domain have been conducted in developed markets, with relatively limited empirical validation in emerging economies such as Vietnam (Dwivedi, et al., 2021). Consumer behavior in such contexts is often shaped by distinct cultural and institutional characteristics, including heightened sensitivity to trust and perceived risk (Gefen, et al., 2003; Pavlou, 2003). These contextual factors may influence how users interpret UI and UX attributes and how such interpretations translate into behavioral outcomes, underscoring the need for context-specific validation of structural models.

After that, these observations point to several important gaps in literature. First, there is a lack of integrated modeling approaches that capture UI/UX attributes, user perception, and behavioral outcomes within a single coherent latent variable framework (Hair, et al., 2010; Kline, 2016). Second, the mediating role of user perception as a key psychological mechanism remains underexplored, particularly in models that seek to explain how design-related factors influence behavior (Zhao, et al., 2010). Third, empirical evidence based on covariance-based structural equation modeling (CB-SEM) in emerging e-commerce markets remains limited, raising concerns about the generalizability of existing findings (Marsh, et al., 2004).

To address these gaps, this study develops and tests a structural equation model that integrates constructs derived from the S-O-R framework, TPB, and UTAUT2. The model examines how UI design and user experience influence online purchase behavior through the mediating role of user perception, with UI/UX-related attributes conceptualized as exogenous latent constructs within a unified structural system (Hair, et al., 2010; Kline, 2016).

From a methodological perspective, this study contributes to the structural equation modeling literature by demonstrating the specification and validation of a mediated latent variable model, with particular emphasis on measurement validation and indirect effect estimation within a covariance-based SEM framework (MacCallum & Austin, 2000; Masuda et al, 2022). In doing so, the study provides additional insight into how complex relationships among design-related constructs can be modeled to explain behavioral outcomes in digital environments.

2. Literature Review

Theoretical Background

User interface

In the context of e-commerce, UI design refers to the visual and interactive architecture that enables users to navigate and interact with digital platforms (Cyr, et al., 2006; Kim, et al., 2008) It encompasses elements such as layout, navigation structure, and system interactivity, which collectively determine the usability and accessibility of the platform (Shneiderman & Plaisant, 2010). From a modeling perspective, UI design can be conceptualized as a latent construct reflected by multiple observable indicators, including visual appeal, interactivity, perceived ease of use, and perceived usefulness (Cyr, et al., 2006; Davis, 1989). This conceptualization aligns with the principles of latent variable modeling, where unobservable constructs are inferred from measured indicators while accounting for measurement error (Bollen, 1989; Hair, et al., 2010). These attributes play a critical role in reducing cognitive effort and facilitating efficient task completion, thereby shaping users' initial evaluations of the system (Norman, 2013).

Dimensions of UI

User interface design represents the set of system-level attributes that shape how users interact with digital platforms. Prior research in human–computer interaction and information systems suggests that effective interfaces are characterized by a combination of visual, structural, interactive, and informational elements that collectively facilitate user interaction and task completion (Norman, 2013; Shneiderman, et al., 2016).

First, from a visual perspective, users are strongly influenced by the aesthetic quality of the interface, including layout, color schemes, typography, and visual organization. These elements contribute to users' initial impressions and perceptions of professionalism and credibility (Cyr, et al., 2006; Tractinsky, et al., 2000). In digital commerce environments where direct physical inspection is absent, visual appeal becomes particularly important in attracting attention and encouraging continued interaction.

Second, the level of interactivity determines how responsive and engaging the system is during user interaction. Interactive features such as search tools, filters, live chat, recommendation systems, and real-time feedback mechanisms enhance users' sense of control and involvement while improving communication between users and the platform (Bleier, et al., 2019; Eroglu, et al., 2001). Higher levels of interactivity are therefore associated with more engaging and dynamic shopping experiences.

Third, interface design must support perceived usefulness by enabling users to complete shopping-related tasks effectively and efficiently. In e-commerce settings, usefulness is reflected in the extent to which the platform facilitates product search, information comparison, order processing, and transaction completion. Prior studies indicate that systems perceived as useful are more likely to encourage positive evaluations and continued usage behavior (Davis, 1989; Venkatesh, et al., 2012).

Finally, effective interfaces should also promote perceived ease of use by minimizing the cognitive effort required to learn and operate the platform. Clear navigation structures, intuitive layouts, and user-friendly functionalities help users interact with the system smoothly and efficiently (Davis, 1989; Shneiderman, et al., 2016). Interfaces perceived as easy to use are more likely to reduce frustration and enhance overall interaction quality.

Overall, these dimensions represent the key characteristics through which users evaluate the quality of digital interfaces. Accordingly, this study conceptualizes UI as comprising four core components: visual appeal, interactivity, perceived usefulness, and perceived ease of use. This specification captures both the aesthetic and functional aspects of interface design while maintaining theoretical coherence and parsimony within the structural model. From a structural equation modeling perspective, these dimensions are specified as first-order constructs reflecting a higher-order UI factor, allowing for a parsimonious representation of interface design within the proposed SEM framework.

User experience

Complementing UI design, UX captures the broader cognitive and affective responses that arise throughout the interaction process (Hassenzahl & Tractinsky, 2006; Norman, 2013). UX extends beyond functional usability to include emotional engagement, satisfaction, and perceived value, reflecting how users interpret and evaluate their interaction with a digital platform over time (Bleier, et al., 2019; Rose, et al., 2012). In structural equation modeling terms, UX can also be represented as a multidimensional latent construct, incorporating both utilitarian and hedonic components that jointly influence user perception and subsequent behavior (Lemon & Verhoef, 2016). The specification of such multidimensional constructs requires careful attention to measurement validity and construct operationalization, as emphasized in SEM literature (Hair, et al., 2010; Kline, 2016).

These constructs are particularly relevant in the context of e-commerce platforms, which function as complex socio-technical systems enabling transactions, information exchange, and customer engagement (Laudon & Traver, 2018). The evolution of these platforms from early web-based systems to mobile and AI-enabled environments has increased the importance of design-related factors in shaping user behavior (Chaffey, 2019; Huang & & Rust, 2018). As digital environments become more sophisticated, understanding how UI and UX operate as latent constructs within a structural model becomes essential for explaining variation in consumer responses (MacCallum & Austin, 2000).

Dimensions of UX

User experience (UX) is widely understood as a multidimensional construct reflecting users' evaluative responses to their interaction with digital systems. Prior research in technology adoption and human–computer interaction suggests that these evaluations are primarily shaped by cognitive, functional, and risk-related considerations (Davis, 1989; Hassenzahl & Tractinsky, 2006; Venkatesh, et al., 2012).

First, from a cognitive perspective, users assess the ease of use of a system, which determines the effort required to learn and operate it. Second, from a functional standpoint, users evaluate the usefulness of the system in achieving their goals efficiently. Third, in online environments characterized by uncertainty, security and privacy concerns play a critical role in shaping trust and willingness to engage in transactions (Gefen, et al., 2003; Pavlou, 2003). Finally, digital interaction is inherently dynamic, and the level of interactivity influences users' sense of control, engagement, and responsiveness of the system (Bleier, et al., 2019; Eroglu, et al., 2001).

Taken together, these dimensions capture the key mechanisms through which users evaluate their experience with digital platforms. Accordingly, this study conceptualizes UX as comprising four core components: interactivity, perceived usefulness, perceived ease of use, and perceived security. This specification allows the construct to reflect both functional and experiential aspects of user evaluation while maintaining parsimony within the structural model. From a structural modeling perspective, these dimensions can be represented as first-order constructs reflecting a higher-order UX factor, enabling a parsimonious yet theoretically grounded specification

Theoretical Frameworks

To examine the effects of UI and UX design on online purchase behavior within e-commerce platforms, this study adopts an integrated theoretical framework that combines the S–O–R paradigm, the TPB, and the UTAUT2. These frameworks are selected for their complementary strengths in explaining relationships among environmental stimuli, internal cognitive states, and behavioral outcomes (Dwivedi, et al., 2021; Venkatesh, et al., 2012).

The S-O-R framework provides a foundational structure for modeling the influence of environmental factors on behavior by conceptualizing external stimuli as antecedents of internal psychological states, which subsequently drive behavioral responses (Eroglu, et al., 2001; Mehrabian & Russell, 1974). In this study, UI and UX attributes are treated as stimulus variables, while user perception represents the organism component, and online purchase behavior constitutes the response. This structure is consistent with latent variable modeling approaches that explicitly distinguish between exogenous and endogenous constructs within a structural system (Bollen, 1989; Hair, et al., 2010). However, prior research suggests that S-O-R alone provides limited specificity in modeling the cognitive mechanisms underlying behavioral intention (Bleier, et al., 2019; Rose, et al., 2012).

To address this limitation, the TPB is incorporated to capture the cognitive determinants of behavioral intention, including attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). TPB has been widely applied in studies of technology adoption and online behavior, demonstrating strong predictive power in explaining intention-based outcomes (Pavlou, 2003; Pavlou & Fygenson, 2006). Nevertheless, TPB does not explicitly account for system-related stimuli or experiential factors, which are central to interactions with digital platforms.

The UTAUT2 framework further extends the analysis by incorporating consumer-oriented constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit (Venkatesh, et al., 2012). This model is particularly relevant in e-commerce contexts, where both utilitarian and hedonic motivations influence user engagement and purchase decisions (Dwivedi, et al., 2021). However, similar to TPB, UTAUT2 primarily emphasizes direct relationships between cognitive beliefs and behavioral outcomes, offering limited insight into the mediating psychological processes that link design-related factors to behavior.

While earlier models such as the Technology Acceptance Model (TAM), highlight perceived usefulness and ease of use as key determinants of technology adoption (Davis, 1989), they are often insufficient for capturing the multidimensional and process-oriented nature of user interaction in contemporary digital environments (Bagozzi, 2007; Benbasat & Barki, 2007). As a result, relying on a single theoretical framework may lead to an incomplete representation of the mechanisms underlying online consumer behavior.

In response to these limitations, this study integrates S-O-R, TPB, and UTAUT2 into a unified structural model that enables the simultaneous estimation of relationships among latent constructs. Within this framework, UI and UX attributes are conceptualized as exogenous latent variables, user perception functions as a mediating latent construct, and online purchase behavior is modeled as the endogenous outcome variable. This structure allows for the examination of both direct and indirect effects, consistent with established approaches to mediation analysis in SEM (MacKinnon, et al., 2004; Zhao, et al., 2010).

From a methodological perspective, this integrative approach contributes to the structural equation modeling literature by demonstrating how multiple theoretical frameworks can be operationalized within a single latent variable system. In particular, the model emphasizes rigorous measurement validation and the estimation of indirect effects, while also evaluating overall model fit in light of ongoing discussions regarding appropriate fit-index criteria (Marsh, et al., 2004; Kline, 2016).

3. Methodology

Research Design

The research process was implemented through two main stages: theoretical research and empirical research. This sequential approach ensured both the theoretical rigor of the proposed model and the empirical validation of the relationships among latent constructs within the SEM framework.

Step 1: Theoretical Development

Starting from the research context, the authors identified the problem based on research gaps found through the analysis and synthesis of previous studies, along with reviewing theories explaining scientific laws related to the research problem; from there, they established a theoretical model and designed a preliminary scale to measure the research concepts.

Step 2: Formal Research

Formal research aims to test the model and hypotheses about the relationships in the proposed model. The order of implementation in this step is: i) conducting a formal survey with the completed scale; ii) analyzing the collected data using the analytical tools SPSS and AMOS. Specifically, the data will be processed through reliability and scale validity testing (Cronbach's Alpha, EFA), confirmatory factor analysis (CFA) to confirm the model's suitability, and finally, analysis of relationships within the model using structural equation modeling (SEM). The research results are presented in detail to test hypotheses and discuss the implications of the study for theory and practice. Finally, iii) the study provides recommendations, practical implications, and directions for further research.

- Phase 1: Qualitative Research

From the proposed research model and draft scale, the authors conducted a panel discussion with 25 experts who are qualified professionals working in the field of e-commerce. Based on expert feedback, the author refined the model and scale, then conducted a focus group discussion with 15 research subjects to assess whether the wording was clear and fully expressed, thereby refining and finalizing the model and scale.

Phase 2: Quantitative Research

The order of implementation in this phase is: i) Large-scale survey with the official scale; ii) Screening of unsatisfactory responses; iii) Frequency statistics to obtain general information of the research sample; iv) Testing using Cronbach's Alpha coefficient; v) Conducting exploratory factor analysis (EFA); vi) Regression analysis to check for multicollinearity; vii) Conducting confirmatory factor analysis (CFA) ; viii) Processing the structural equation modeling (SEM). Based on the research findings, the author concludes and offers suggestions for practical application in research.

Data Collection

The primary data collection tool was an electronic questionnaire designed to suit the research objectives. This questionnaire was validated using input from professors at the economics university in Vietnam, who also consulted with experts knowledgeable on the subject. To assess the internal consistency and reliability of the data collection tool, the study calculated Cronbach's alpha reliability coefficients for the 7 concept scales (with 32 items), which ranged from 0.811 to 0.903 (>0.7), with no value greater than 0.95, indicating acceptable reliability. Several improvements were then made to the tool to enhance the language, style, content, and formatting of the questionnaire, which was then administered to 570 research participants, who formed the primary sample. Participants were asked to rate their level of agreement with each questionnaire item on a five-point Likert scale. After data cleaning, the remaining 523 valid surveys were included in the validation and analysis.

Data Analysis

The study used SPSS and AMOS software to undertake an analysis of the quantitative data collected through the electronic questionnaires. The analysis included a basic demographic analysis and the computation of means and response values for items. The Response values were provided by participants based on a five-point Likert scale: strongly disagree, disagree, neutral, agree, and strongly agree. The data were processed through reliability and validity testing (Cronbach's Alpha, EFA), confirmatory factor analysis (CFA) to validate the model's fit, and finally, analysis of relationships within the model using structural equation modeling (SEM) to analyze the relationship within the model and the role of cognitive latent variables in the correlation of UI and UX factors to online user behavior.

Description of the study sample

The demographic profile of the respondents indicates that the sample adequately reflects the characteristics of active e-commerce consumers in Vietnam (Table 1). In terms of gender, the sample included both male (47.22%) and female (52.78%) participants with a relatively balanced distribution, allowing for broader representation of online shopping behaviors across genders.

Regarding age, the majority of respondents were concentrated in the young and middle-aged groups, particularly individuals between 18 and 35 years old. Specifically, 38.81% are in the 18-24 age group, 41.49% are in the 25-34 age group, and 4.59% are under 18 years old. This finding is consistent with the demographic structure of digital consumers in Vietnam, where younger users represent the most active segment in online shopping activities and digital platform engagement. Conversely, the 35-44 age group accounts for 11.09%, while the group over 44 accounts for only 4.02%. This low percentage reflects that middle-aged and older people participate less in e-commerce shopping, possibly due to technological barriers or traditional shopping habits.

With respect to the residential area, respondents were drawn from different regions across Vietnam, including urban, suburban, and rural areas. Most participants resided in urban areas (67.5%) where internet penetration, smartphone usage, and e-commerce adoption are comparatively higher, while in suburban and rural areas, the rates were significantly lower, at 20.65% and 11.85%, respectively.

In terms of income level, respondents represented diverse income groups, ranging from low to high monthly income categories. The inclusion of multiple income segments enhances the generalizability of the findings by capturing differences in purchasing power and online consumption behavior.

Concerning online shopping platforms, participants reported experience using major e-commerce platforms commonly operating in Vietnam, including Shopee, Lazada, Tiki, and TikTok Shop. These platforms represent the dominant digital commerce ecosystem in Vietnam and provide an appropriate context for examining the effects of UI design and UX on online purchase behavior.

Overall, the sample characteristics suggest that the collected data are appropriate for investigating consumer perceptions and purchasing behavior in the Vietnamese e-commerce environment.

Characteristics	Category	Frequency (N)	Percentage (%)
Gender	Male	247	47.22
	Female	276	52.78
Age	Under 18	24	4.59
	18–24 years old	203	38.81
	25–34 years old	217	41.49
	36–44 years old	58	11.09
	Above 45 years old	21	4.02
Residential Area	Urban	353	67.5
	Suburban	108	20.65
	Rural	62	11.85
Monthly Income	Under 5 million VND	93	17.78
	5–10 million VND	184	35.18
	10–20 million VND	169	32.32
	Above 20 million VND	77	14.72
Main E-commerce Platform Used	Shopee	193	36.9
	Lazada	92	17.59
	Facebook	69	13.2
	TikTok Shop	73	13.96
	Retail website	96	18.35
Total		523	100

Table 1: Demographic Characteristics of Respondents (N=523)

4. Results

Testing the reliability and suitability of the research model.

Cronbach's Alpha reliability coefficient

According to the proposed research model, there are 7 conceptual scales: visual appeal (VA), interactivity (IU), usefulness (PEOU), ease of use (PU), security (PS), perception (P), and purchasing behavior (B). Thus, there are 7 concepts measured across 32 observed variables, whose reliability needs to be assessed using total-variable correlation coefficients and Cronbach's Alpha.

The analysis results (Tab 2) show that all 32 observed variables have total variable correlation coefficients ranging from 0.598 to 0.894 (> 0.5), thus meeting the acceptance requirements. The Cronbach's Alpha reliability coefficients for the 7 conceptual scales range from 0.811 to 0.903 (>0.7), with no value greater than 0.95; therefore, it can be concluded that all 9 scales meet the reliability requirements.

Observed Variable	Mean of Scale if Item Deleted	Variance of Scale if Item Deleted	Total Correlation	Cronbach's Alpha if Item Deleted
Visual Attractiveness (VA) Cronbach's Alpha =0.895				
IU1	16.55	6.325	0.751	0.869
IU 2	16/55	6.302	0.768	0.866
IU 3	16.55	6.493	0.729	0.874
IU 4	16.55	6.375	0.756	0.868
IU5	15.53	6.629	0.700	0.881
2. Interactivity with User (IU), Cronbach's Alpha = 0.903				
IU1	15.66	6.451	0.781	0.876
IU 2	15.69	6.484	0.771	0.879
IU 3	15.69	6.436	0.783	0.876
IU 4	15.65	6.585	0.754	0.892
IU5	15.65	6.765	0.697	0.894
3. Perceived Ease of Use (PEU), Cronbach's Alpha = 0.811				
PEU1	11.81	3.785	0.619	0.767
PEU2	11.80	3.981	0.598	0.776
PEU3	11.78	3.786	0.650	0.752
PEU4	11.84	3.770	0.646	0.754
4. Perceived Usefulness (PU), Cronbach's Alpha = 0.858				
AT1	12.08	4.069	0.749	0.800
AT2	12.13	4.259	0.666	0.834
AT3	12.07	4.063	0.722	0.811
AT4	12.11	4.236	0.675	0.831
5. Perceived Security (PS), Cronbach's Alpha = 0.866				
PS1	11.34	3.902	0.705	0.861
PS2	11.30	3.576	0.631	0.873
PS3	11.27	3.010	0.718	0.862
PS4	11.39	3.039	0.691	0.863
PS5	11.28	3.254	0.674	0.835
6. Perception (P), Cronbach's Alpha = 0.845				
P1	11.25	3.489	0.664	0.811
P2	11.27	3.216	0.732	0.781
P3	11.22	3.438	0.653	0.816
P4	11.24	3.441	0.677	0806
7. Buying Behavior (B), Cronbach's Alpha = 0.882				
B1	16.37	6.930	0.739	0.852
B2	16.32	6.950	0.723	0.855
B3	16.38	7.149	0.708	0.859
B4	16.34	6.959	0.719	0.856
B5	16.35	7.095	0.694	0.862

Table 2: Summary of Cronbach's Alpha Coefficients of the Components

Exploratory Factor Analysis (EFA)

The results of the EFA, conducted using the Principal Axis Factoring extraction method with Promax rotation, indicate that the research data satisfied all requirements for factor analysis. Specifically, the KMO measure reached 0.879 (> 0.5), demonstrating that the correlations among the observed variables were sufficiently strong and that the dataset was appropriate for EFA (Hair, et al., 2010). In addition, Bartlett's Test of Sphericity produced a chi-square value of 8836.425 with a significance level of Sig. = 0.000 (< 0.05) (Figure 1), indicating that the observed variables were significantly correlated and suitable for identifying underlying factor structures (Tabachnick & Fidell, 2013).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.879
Bartlett's Test of Sphericity	Approx. Chi-Square	8836.425
	df	496
	Sig.	.000

Figure 1. Results of KMO and Bartlett's Test

The findings further revealed that (Figure 2) the Total Variance Explained (TVE) was 60.294%, exceeding the recommended threshold of 50%, suggesting that the extracted factors accounted for 60.294% of the variance in the dataset (Hair, et al., 2010). Moreover, the minimum Eigenvalue was 1.069 (> 1), satisfying Kaiser's criterion and confirming that the number of extracted factors was consistent with the proposed theoretical model (Kaiser, 1974).

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6.794	21.232	21.232	6.409	20.029	20.029	4.924
2	4.342	13.570	34.803	3.972	12.414	32.443	3.851
3	3.139	9.809	44.611	2.739	8.559	41.002	3.783
4	2.591	8.096	52.707	2.171	6.784	47.785	2.705
5	2.433	7.603	60.311	2.020	6.314	54.099	3.525
6	1.705	5.328	65.638	1.298	4.056	58.155	2.288
7	1.069	3.341	68.979	.685	2.139	60.294	5.086

Figure 2. Results of Total Variance Explained

Furthermore, all observed variables exhibited factor loadings greater than 0.5, indicating satisfactory convergent validity and strong representation of their corresponding latent constructs. Therefore, no observed variables were removed from the research model (Figure 3).

	Factor 1	2	3	4	5	6	7
VA2	.830						
VA3	.810						
VA1	.790						
VA4	.790						
VA5	.716						
IU3		.836					
IU1		.828					
IU4		.810					
IU2		.808					
IU5		.752					
PS4			.791				
PS2			.754				
PS1			.739				
PS3			.735				
PS5			.733				
PU1				.835			
PU3				.794			
PU2				.750			
PU4				.719			
P2					.804		
P1					.798		
P4					.735		
P3					.681		
PEU3						.743	
PEU4						.742	
PEU2						.701	
PEU1						.701	
B2							.763
B5							.717
B1							.713
B3							.676
B4							.647

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Figure 3. Results of Pattern Matrixa

Testing for Multicollinearity

Variance Inflation Factor (VIF) is an indicator used to assess the presence of collinearity in regression models. The smaller the VIF, the less likely multicollinearity is to occur. Hair et al. (2010) suggest that a VIF of 10 or higher indicates strong multicollinearity (Hair, et al., 2010). Researchers should strive to keep the VIF as low as possible, as even VIFs of 5 or 3 can indicate significant multicollinearity. According to Nguyen Dinh Tho (2010), in practice, if VIF > 2, caution is needed because multicollinearity may occur, leading to biased regression estimates (Tho, 2010) .

Figure 4 shows that the variance inflation factor (VIF) is < 10. Therefore, it can be concluded that there is no multicollinearity in the model.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	.300	.254		1.179	.239		
	F_IU	.014	.034	.014	.421	.674	.870	1.149
	F_VA	.636	.033	.609	19.297	.000	.962	1.040
	F_PEU	-.009	.033	-.008	-.268	.789	.963	1.038
	F_PU	-.029	.032	-.029	-.906	.366	.924	1.082
	F_PS	.279	.034	.268	8.263	.000	.915	1.093
	F_P	.038	.038	.035	1.001	.317	.773	1.294

a. Dependent Variable: F_B

Figure 4. Testing for multicollinearity results

Confirmatory Factor Analysis – CTA

The results of the structural equation analysis (CTA) showed that the overall model had a Chi-square/df ratio of 1.558 (≤ 3). Furthermore, other fit indices also met the required thresholds: GFI = 0.926 (≥ 0.8), Tucker-Lewis Index (TLI) = 0.968 (≥ 0.9), Comparative Fit Index (CFI) = 0.971 (≥ 0.9), and RMSEA = 0.033 (≤ 0.8). Therefore, the proposed model showed a good fit to the data (Figure 5).

In addition, all relationships between the study constructs were statistically significant (p-value < 0.05), indicating that the elements in the overall model exhibited strong discriminant validity. Meanwhile, comparing the square root of AVE with the correlation coefficients between the structures, the research team found that all two-variable correlations were smaller than the square root of AVE, satisfying the discriminant validity requirement. These results are summarized in Table 3.

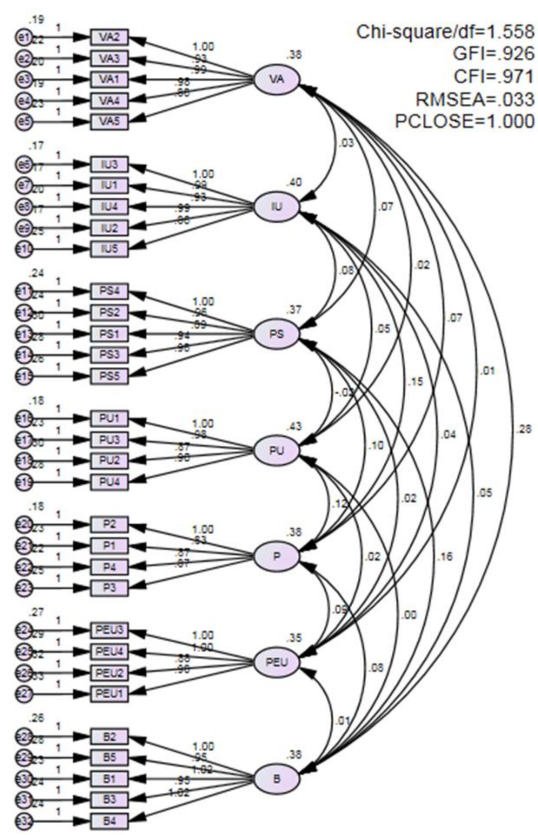

Figure 5. CFA overall model results

Construct	VA	IU	PS	PU	P	PEU	B
VA	0.794						
IU	0.065	0.807					
PS	0.176	0.204	0.752				
PU	0.051	0.127	-0.053	0.778			
P	0.178	0.390	0.263	0.298	0.761		
PEU	0.020	0.096	0.046	0.042	0.235	0.720	
B	0.737	0.123	0.425	-0.001	0.212	0.021	0.774

Note: Bold diagonal values represent the square root of the Average Variance Extracted (AVE); off-diagonal values represent the correlation coefficients between constructs

Table 3: Discriminant Validity

To assess the convergence of the model, the research team used Cronbach's Alpha (CA) coefficient and composite reliability (CR). The results showed that all Cronbach's alpha values exceeded the acceptable threshold of 0.7, and the composite reliability of the structures ranged from 0.811 to 0.903. Additionally, all extracted mean variance (AVE) values were > 0.5 and ranged from 0.518 to 0.630 (Table 4). According to Hair et al. (2018), the structure assessment scale was considered to have achieved convergent validity (Hair, et al., 2018).

Construct	Item	Std.loadings	CA	CR	AVE
VA	VA2	0,821	0,895	0,895	0,63
	VA3	0,777			
	VA1	0,807			
	VA4	0,813			
	VA5	0,749			
IU	IU3	0,839	0,903	0,903	0,652
	IU1	0,833			
	IU4	0,797			
	IU2	0,829			
	IU5	0,733			
PS	PS4	0,781	0,866	0,867	0,565
	PS2	0,769			
	PS1	0,705			
	PS3	0,737			
	PS5	0,765			
PU	PU1	0,837	0,858	0,859	0,605
	PU3	0,799			
	PU2	0,723			
	PU4	0,746			
P	P2	0,826	0,845	0,846	0,579
	P1	0,727			
	P4	0,754			
	P3	0,733			
PEU	PEU3	0,749	0,811	0,811	0,518
	PEU4	0,74			
	PEU2	0,677			
	PEU1	0,711			
B	B2	0,773	0,882	0,882	0,599
	B5	0,744			
	B1	0,799			
	B3	0,765			
	B4	0,788			

Table 4. Convergent Validity

In summary, the CFA results indicate that the overall model fits the market data, and the scales for the research concepts meet the required evaluation standards. This result provides a basis for the author to test the proposed theoretical model further.

SEM Analysis

Testing direct relationships

The standardized estimation results of the main parameters presented in Table 5 show that the standardized regression coefficient β of the independent variables with the intermediate variable (user perception) and the intermediate variable with the dependent variable (user behavior) ranges from 0.134 to 0.286 (>0), p-value <= 0.003, with a significance level of 5%, it can be confirmed that there is a direct relationship between the independent variables and the intermediate variable and between the mediating variable and the independent variable.

Relationship	β	S.E	CR	P-VALUE
P ← VA	0,134	0,044	3,021	0,003
P ← IU	0,286	0,046	6,245	0,000
P ← PS	0,201	0,048	4,208	0,000
P ← PU	0,238	0.044	5,471	0,000
P ← PEU	0,192	0.049	3,908	0,000
B ← P	0,251	0.051	4,889	0,000

Note: β: regression coefficient, SE: standard error, CR: critical value, P-VALUE: significance level

Table 5. Regression coefficients (standardized) of direct relationships in the model

Test Mediating Relationships

Analyzing the relationship between the latent constructs in the model using the Bootstrap technique shows that the confidence interval does not contain 0 between the independent variables and the intermediate variable, with a P-value < 0.05, proving the existence of an indirect relationship from the independent variables of UI and UX to the dependent variable behavior through the intermediate variable of perception.

Relationship	S.E	Lower	Upper	P-VALUE
B ← P ← VA	0,034	0,009	0,067	0,005
B ← P ← IU	0,072	0,041	0,111	0,001
B ← P ← PS	0,049	0,024	0,088	0,001
B ← P ← PU	0.063	0,035	0,091	0,001
B ← P ← PEU	0.045	0,025	0,078	0,001

B ← P ← PEU 0.045 0,025 0,078 0,001

Table 6. Regression coefficients (standardized) of mediating relationships in the model

The results of structural analysis of the linear model normalizing the indirect relationship between variables in the model show that the main model with 523 degrees of freedom achieves compatibility with market data through satisfactory indices, including Chi-square = 1033.866 (P = 0.000); GFI = 0.900; CFI = 0.931; and RMSEA = 0.050.

Overall, SEM results testing the relationships in the main model show that there are 5 hypotheses representing direct relationships that are accepted at the p-value < 0.05 significance level. In addition, the coefficient β for all variables is positive, demonstrating the impact relationships with the dependent variable of shopping behavior through the cognitive mediator variable. This variable is most influenced by the interaction variable with a coefficient β = 0.286, and has the lowest impact level, with β = 0.134 from the visual attractiveness variable (Figure 6).

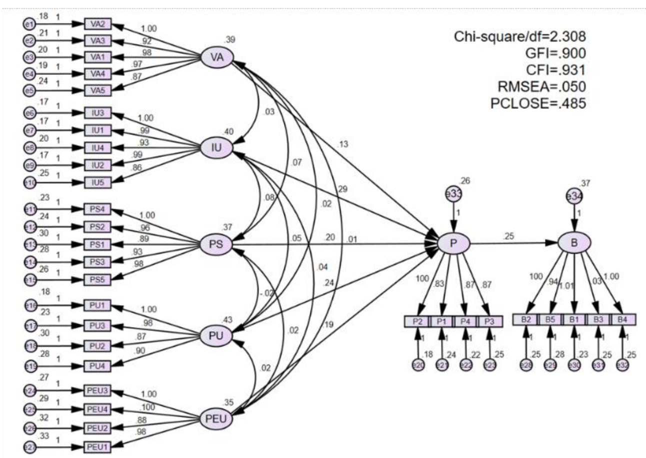

Figure 6. Standardized model SEM results

5. Discussion

Interpretation of Key Findings

This study set out to examine how user interface (UI) design and user experience (UX) influence online purchasing behavior through the mediating role of user perceptions. These findings provide strong support for the proposed structural model and offer several theoretical and methodological insights.

First, the results confirm that both UI and UX have a significant positive impact on user perception. This finding is consistent with the theoretical logic of the S-O-R framework, in which environmental stimuli influence internal cognitive and affective states, which then drive behavioral responses. However, the extent and nature of these impacts are different.

Second, user perception is found to have a significant influence on online purchasing behavior, confirming its role as a mediating mechanism. This result reinforces previous research showing that consumers do not react directly to system attributes but to their interpretation and evaluation of those attributes.

And in particular, the analysis results have shown that the impact of UI and UX on purchasing behavior is largely indirect, operating through user perception. This finding provides empirical support for mediation-based modeling approaches in SEM and emphasizes the importance of incorporating psychological mechanisms into structural models.

Theoretical Implications

This study provides an important theoretical contribution by clarifying the role of interface design (UI) and user experience (UX) elements in influencing consumers' online shopping perceptions and behavior. In the context of e-commerce growing strongly, especially with the rise of online retail platforms, the research has added a scientific perspective on how UI/UX design affects shopping decisions, expanding previous studies on digital consumer behavior.

First, the study identified and measured five important factors in UI/UX, including visual appeal, interactivity, perceived usefulness, and perceived ease of use, and perceived security, to evaluate the influence of these factors on consumer perception. Building a research model based on TAM, UTAUT2 theory, and the S-O-R psychology model framework helps supplement the theoretical basis on the impact of UI/UX on online shopping decisions.

Second, research has demonstrated the mediating role of cognitive factors in the relationship between UI/UX and shopping behavior. This helps clarify how people spend

use to receive and react to interface and experience design elements on e-commerce platforms, and contribute to research on UX and digital consumer behavior in Vietnam.

Third, the research results have determined the influence level and direction of each UI/UX factor on perception and shopping behavior. This finding not only helps expand the theoretical basis of user experience but also creates a premise for further research on UI/UX optimization to enhance experience and increase conversion rates on e-commerce platforms.

Methodological Contributions to SEM

Beyond its substantive findings, this study provides several methodological contributions relevant to structural equation modeling.

First, it illustrates the specification and validation of a mediated higher-order latent variable model, integrating both measurement and structural components within a unified SEM framework. This approach demonstrates how complex constructs such as UI and UX can be operationalized and empirically tested.

Second, the study highlights the importance of distinguishing between system-level constructs, user-level evaluations, and mediating psychological mechanisms. This layered specification improves model clarity and reduces the risk of construct redundancy, a common issue in SEM applications.

Third, by validating the model in an emerging market context, the study contributes to the generalizability of SEM-based research. It demonstrates that theoretically grounded latent variable models can be successfully applied beyond developed markets, while also capturing context-specific behavioral patterns.

Limitations and Future Research

Despite its contributions, this study has several limitations. First, the use of cross-sectional data limits the ability to infer causal relationships over time. Future research could employ longitudinal designs to examine how user perceptions and behaviors evolve with continued platform use.

Second, the study focuses on a single emerging market, which may limit the generalizability of the findings. Comparative studies across different cultural and economic contexts would provide valuable insights into the robustness of the proposed model.

Third, although the model incorporates key UI and UX dimensions, other factors such as personalization, social influence, or platform trust mechanisms may also play important roles and should be considered in future research.

6. Conclusion

This study develops and empirically validates a structural equation model to explain how UI and UX design influence online purchasing behavior through the mediating role of user perception in the context of e-commerce in Vietnam. The findings confirm that both UI and UX have a significant positive impact on user perception, thus positively influencing online purchasing behavior. Importantly, the results demonstrate that the impact of UI and UX is largely indirect, operating through user perception rather than directly influencing behavior. This evidence reinforces the central role of perception as a psychological mechanism linking design-related factors to consumer decision-making and supports mediation-based modeling approaches within the structural equation model.

Despite the achievements, the study also has some limitations that need to be addressed in future research. Future research may further extend the proposed model by incorporating cultural and personalization-related variables as moderating factors. Cultural dimensions such as uncertainty avoidance, collectivism, and trust orientation may influence how consumers perceive and respond to UI and UX attributes in e-commerce environments (Pavlou & Fygenson, 2006; Hoai & Du, 2025). In addition, personalization factors, including personalized recommendations, adaptive interfaces, and perceived customization, may strengthen the effects of UI and UX on user perception and online purchase behavior (Bleier, et al., 2019; Lemon & Verhoef, 2016; Hoai & Du, 2025). Integrating these moderating variables into future SEM frameworks could provide deeper insights into heterogeneous consumer behavior and enhance the explanatory power of the model across different digital commerce contexts.

In summary, this study demonstrates that understanding online purchasing behavior in a digital environment requires not only examining technological attributes but also modeling the psychological processes by which these attributes are interpreted by users. By integrating theoretical perspectives and employing an SEM approach, this study provides a structured and general framework for analyzing digital interactions and consumer behavior, with implications for both academic research and the design of user-centric e-commerce platforms.

References

Ajzen, I. (1991). The theory of planned behavior. Organizational

Behavior and Human Decision Processes, 179-211. doi:https://doi.org/10.1016/0749-5978(91)90020-T

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. Journal of the Association for Information Systems, 8(4), 244–254. doi:https://doi.org/10.17705/1jais.00122

Benbasat, I., & Barki, H. (2007). Quo vadis, TAM? Journal of the Association for Information Systems, 8(4), 211–218., 8(4), 211-218. doi:https://doi.org/10.17705/1jais.00126

Bleier, A. H. (2019). Creating effective online customer experiences . Journal of Marketing, 98-119.

Bleier, A., Harmeling, C, M., Palmatier, R., & W. (2019). Creating effective online customer experiences. Journal of Marketing, 83(2), 98-119. doi:https://doi.org/10.1177/0022242918809930

Bollen, K. A. (1989). Structural equations with latent variables. Wiley. doi:https://doi.org/10.1002/9781118619179

Cyr, D., Head, M., Ivanov, & A. (2006). Design aesthetics leading to m-loyalty in mobile commerce. Information & Management,, 43(8), 950-963. doi:https://doi.org/10.1016/j.im.2006.08.009

Chaffey, D. (2019). Digital marketing: Strategy, implementation and practice (7th ed.). Pearson.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. doi:https://doi.org/10.2307/249008

De Keyser, A., Verleye, K., Lemon, K. N., Keiningham, T. L., & Klaus, P. (2020). Moving the customer experience field forward: Introducing the touchpoints, context, qualities (TCQ) nomenclature. Journal of Service Research, 433-455. doi:https://doi.org/10.1177/1094670520928390

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., . . . & Wang, Y. (2021). Setting the future of digital and social media marketing research. International Journal of Information Management,, 55, 102168. doi:https://doi.org/10.1016/j.ijinfomgt.2020.102168

Eroglu, A., S., Machleit, A., K., Davis, & M., L. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. Journal of Business Research, 54(2), 177-184. doi:https://doi.org/10.1016/S0148-2963(99)00087-9

Gefen, D., Karahanna, E., Straub, & W., D. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly,, 27(1), 51-90. doi:https://doi.org/10.2307/30036519

Hair, F., J., Black, C., W., Babin, J., B., . . . E., R. (2010). Multivariate data analysis (7th ed. Pearson.

Hair, J. F., Black, C., W., Babin, J., B., & Anderson, R. E. (2018). Multivariate data analysis (8th ed.). Cengage.

Hassenzahl, M., & Tractinsky, N. (2006). User experience – A research agenda. Behaviour & Information Technology,, 25(2), 91-97. doi:https://doi.org/10.1080/01449290500330331

Hoai, L. T., & Du, P. T. (2025). The Impact of Cultural Factors on Online Consumer Behavior of Gen Z In Vietnam: A Study In Hanoi, Vietnam. Journal of Ecohumanism, 4(2), 1824-1835. doi:https://doi.org/10.62754/joe.v4i2.6567

Huang, M.-H., & & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172. doi:https://doi.org/10.1177/1094670517752459

John, O. R., & Benet-Martinez, V. (2000). Measurement: Reliability, construct validation, and scale construction. In Handbook of research methods in social and personality psychology (pp. 339-369). Cambridge University Press.

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika , 39(1). doi:https://doi.org/10.1007/BF02291575

Kim, D, J., Ferrin, D, L., . . . R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544-564. doi:https://doi.org/10.1016/j.dss.2007.07.001

Kim, J., D., Ferrin, L., D., Rao, & R., H. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544-564. doi:https://doi.org/10.1016/j.dss.2007.07.001

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Laudon, K. C., & Traver, C. G. (2018). E-commerce: Business, technology, society (14th ed.). Pearson.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96., 60(6), 69-96. doi:https://doi.org/10.1509/jm.15.0420

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. Annual Review of Psychology, 51, 201-226. doi:https://doi.org/10.1146/annurev.psych.51.1.201

MacKinnon, P., D., Lockwood, M., C., Williams, & J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. Multivariate Behavioral Research, 39(1), 99-128. doi:https://doi.org/10.1207/s15327906mbr3901_4

Marsh, W., H., Hau, K.-T., Wen, &., & Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. Structural Equation Modeling: A Multidisciplinary Journal, 11(3), 320-341. doi:https://doi.org/10.1207/s15328007sem1103_2

Masuda et al. (2022). Impacts of influencer attributes on purchase intentions in social media influencer marketing: Mediating roles of characterizations. Technological Forecasting and Social Change, 174(January), 121246.

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Norman, D. A. (2013). The design of everyday things: Revised and expanded editon. New York: Hachette.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101-134. doi:https://doi.org/10.1080/10864415.2003.11044275

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. MIS Quarterly, 30(1), 115-143. doi:https://doi.org/10.2307/25148720

Rose, S., Clark, M., Samouel, P., . . . N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. Journal of Retailing, 88(2), 308-322. doi:https://doi.org/10.1016/j.jretai.2012.03.001

Shneiderman, B., & Plaisant, C. (2010). Designing the user interface: Strategies for effective human–computer interaction (5 ed). Pearson.

Shneiderman, B., Plaisant, C., Cohen, M., Jacobs, S., Elmqvist, N., & Diakopoulos, N. (2016). Designing the user interface: Strategies for effective human–computer interaction (6th ed.). Pearson.

Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Pearson.

Tho, N. D. (2010). Scientific research methods in business: Design and implementation. Social Labor Publishing House.

Tractinsky, N., Katz, S., A., Ika, & D. (2000). What is beautiful is usable. Interacting with Computers, 13(2), 127-145. doi:https://doi.org/10.1016/S0953-5438(00)00031-X

Venkatesh, V., Thong, L., J. Y., Xu, & X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178. doi:https://doi.org/10.2307/41410412

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. Journal of Retailing, 31-41. doi:https://doi.org/10.1016/j.jretai.2008.11.001

Zhao, X., Lynch, G., J., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197-2069. doi:https://doi.org/10.1086/651257