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Research Article

Revolutionizing User Experience: How AI-Driven Interactivity Enhances Perceived Quality and Loyalty in E-Commerce

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ABSTRACT

Introduction: Artificial Intelligence is reshaping e-commerce by enabling personalized and responsive web interactions. In Morocco's expanding digital environment, user-oriented technologies are increasingly integrated into online shopping platforms. Yet, it remains uncertain whether these systems align with Moroccan user expectations and behaviors in digital commerce.

Objectives: This study aims to investigate the influence of AI-powered interactivity on user experience in Moroccan e-commerce platforms. Specifically, it evaluates how these technologies affect perceived service quality, user satisfaction, and customer loyalty.

Methods: Using the Thüring & Mahlke UX framework, a mixed-method research design was implemented. Data was collected through surveys and interviews involving Moroccan e-commerce users. Analytical methods included both qualitative thematic analysis and quantitative statistical evaluation to assess the impact of interactivity on user perceptions.

Results: Findings indicate that AI-driven interactivity significantly improves the overall user experience by increasing satisfaction and fostering repeat visits. Users perceive higher service quality and exhibit stronger intentions to reuse platforms that integrate interactive AI features.

Conclusions: AI-enhanced interactivity emerges as a key factor in strengthening customer loyalty and engagement in Moroccan e-commerce. The study provides actionable insights for developers and business owners seeking to leverage AI for competitive advantage. It also contributes to the broader understanding of User Experience theory in emerging digital economies.

Keywords: Artificial intelligence (AI), Human-Computer Interaction (HCI), Interactivity, Loyalty, Quality of Service, User Experience (UX).

INTRODUCTION

With the rapid increase in digital adoption in Morocco, consumer behavior has undergone a significant transformation, particularly in online purchasing habits. Moroccan users are becoming increasingly familiar with e-commerce platforms, shifting their buying preferences from traditional retail to digital marketplaces. According to the Interbank Monetics center (CMI), e-commerce websites and associated billers in Morocco processed 25.2

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million online payment transactions in September 2023, amounting to 8.7 billion dirhams. This represents a notable 23% increase in both transaction volume and value compared to the previous year. Such growth underscores the rising importance of digital commerce in Morocco's economy (1).

However, despite this expansion, several obstacles delay the full adoption of digital transactions. Moroccan consumers continue to face challenges related to trust, payment security, and lack of digital experience (2). Additionally, platform usability and user experience (UX) remain critical factors influencing technology acceptance (3). In this evolving several UX-related challenges persist, such as the lack of empirical research on how AI interactivity affects perceived quality and consumer trust, the variability in UX expectations based on user demographics and digital literacy, and the absence of standardized evaluation frameworks for AI-enhanced platforms. Furthermore, skepticism toward AI-powered decision-making remains prevalent, particularly in developing markets like Morocco, where user trust is still evolving.

As UX plays a crucial role in shaping consumer behavior in digital environments, this research explores the influence of AI-driven interactivity on user experience within Moroccan e-commerce platforms. Interactivity, particularly through AI-powered personalization and real-time adaptation, is identified as a key UX criterion that enhances service quality, user satisfaction, and brand loyalty. AI facilitates intelligent automation, dynamic content personalization, and enhanced responsiveness, ultimately shaping a more engaging and seamless user journey. Given the challenges associated with AI-driven UX, this study seeks to investigate the relationship between AI interactivity and perceived UX quality, analyze how UX quality influences customer loyalty, and evaluate the mediating effects of user emotions and the moderating effects of demographic and behavioral factors.

This research provides a comprehensive evaluation of how AI-driven interactivity enhances user perceptions of quality and customer loyalty in Moroccan e-commerce. Unlike prior studies that primarily focus on AI's technical advancements, this study develops a theoretical model linking AI interactivity, UX quality, and loyalty, combining qualitative insights from industry experts with quantitative validation using Structural Equation Modeling (PLS-SEM). By addressing the unique UX challenges present in the Moroccan digital market, the study offers a localized perspective on AI-driven user experiences. Integrating expert interviews with large-scale survey analysis, this research bridges the gap between AI design choices and consumer behavior. The findings offer valuable insights for businesses, UX designers, and digital strategists seeking to optimize AI-powered e-commerce experiences.

The rest of this paper is structured as follows: Section 2 reviews existing literature on AI interactivity, UX quality, and loyalty. Section 3 details the methodology, including data collection and analytical techniques. Section 4 presents the results, while Section 5 discusses key findings, comparisons with existing research, and practical implications. Finally, Section 6 concludes with study limitations and future research directions.

LITERATURE REVIEW

One of the primary challenges digital brands faces is providing high-quality service to satisfy customers and drive usage or purchase intent. Customer perception plays a pivotal role for brands, as it reflects how users interpret their environment based on sensory input, influencing their judgment [1]. Zeithaml defines perceived service quality as an overall judgment resulting from a comparison between perceived and expected performance [2].

UX, as a multidimensional concept, is central to evaluating perceived service quality. It represents the personal and subjective evaluation of the interaction between users and digital platforms, generating cognitive and emotional responses that shape perceptions of the experience [3], [4], [5].

Thüring & Mahlke UX model highlights this holistic approach, identifying three key UX components: instrumental qualities (such as perceived usefulness and usability), non-instrumental qualities (including aesthetics and motivational aspects), and emotional responses to the system's use [6]. These elements are viewed as outcomes of the interaction between the user and the system, shaped by system features, user characteristics, and the task or context.

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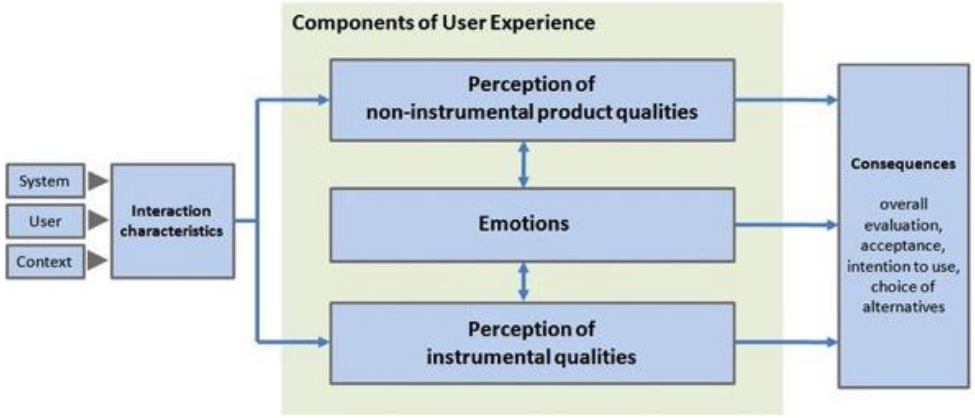

Figure 1: Thüring & Mahlke UX Model

High-quality service is directly linked to customer satisfaction and loyalty. Numerous studies have shown that perceptions of service quality impact purchase decisions, repeat purchase intentions, and customer loyalty [7], [8], [9].

Several models measuring perceived service quality have identified common attributes, such as tangible elements, reliability, helpfulness, credibility, communication, safety, competence, courtesy, consumer understanding, and accessibility of services [10].

[11] Identifies several success factors for digital platforms, including download speed, navigation, content quality, interactivity, and helpfulness, all of which contribute to user satisfaction, usage frequency, and reuse intentions. Interactivity, in particular, enhances the user experience by increasing personalization and responsiveness [12].

In the digital context, usability is considered the most critical dimension of human-computer interaction (HCI). In literature, Usability includes mostly ease of navigation, speed, and interactivity as main factors [13]. Ease of navigation refers to the amount of time and effort required to complete tasks [14], while speed refers to how quickly pages load [11], [13], [15], [16]. Interactivity is defined by [17] as the extent of bidirectionality, speed, mutual control, and responsiveness in online communication, which enhances both consumer and business experiences.

The role of interactivity in improving UX is widely supported by [16], [18], [19], because facilitating customer interactions and strengthening customer-brand relationships leads to enhanced perceived service quality. [20] Highlight that digital marketing enables personalized, real-time interactivity and two-way communication, further enhancing customer experiences and creating added value in the experiences.

The interest in interactivity is multiple. As a part of the flow concept [21], which is a total immersion focused on motivation and generating emotions that directly impact the user experience [22], interactivity gives continual sequences of facilitated answers in the web, and leads to an intrinsic pleasure, accompanied by a loss of consciousness and self-reinforcement [23]. Immersive experiences, that put customers in states of flow thanks to interactivity, increase intrinsic motivation and promote the use and appreciation of technology.

Interactivity is crucial in digital platforms, manifesting in multiple ways, such as in searching and navigation, by providing an advanced search features, dynamic filters and personalized navigation to make it easy for users to find what they are looking for ; in content personalization, due to the personalized recommendations based on past user behaviors ; in reviews and comments by sharing user's experience, viewing those of others and creating social interaction on the platform ; in social interactivity by integrating social networks to share experiences directly on social profiles ; and, most important; in Chatbots and Virtual Assistance by offering instant support, answering users questions in real-time and helping on problem's solving. Interfaces that include a virtual agent (Chatbot) are more engaging, more attractive and more fun than those that do not [24]. Their presence reinforces the interactions between the user and the site [25], generates positive emotions, increases perceived value and leads to favorable behaviors [13].

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Adopted since 2016 by e-commerce platforms in advanced digital countries such as India or Southeast Asia; where e-commerce is growing rapidly; AI plays central role in Interactivity because it redefines UX experiences with more personalized content [26]. It enables real-time adaptation of experiences, thereby improving the platform's responsiveness and personalization. It also helps automate processes and create dynamic interfaces, such as chatbots, recommendation engines, and voice assistants. These intelligent systems collect Data to respond instantly to users' needs and anticipate their preferences by analyzing their behavioral data [27]. This leads to smoother interactions and increased user engagement, thereby enhancing customer satisfaction and loyalty in e-commerce [13], [28].

AI technologies have been widely adopted in various markets, transforming customer and business behavior. The academic community has also shown increased interest in AI adoption at both the organizational and individual levels [29], [30]. A study by [31] in the healthcare field revealed that customers seek control and empowerment while using digital devices, preferring autonomy over passive interactions. AI-enhanced interactivity plays a critical role in providing users with a sense of control and autonomy. Furthermore, Interactivity, supported by intelligent technologies, contributes to a more seamless experience, and generates emotional engagement, a key factor in fostering customer loyalty in online environments [6].

As a part of the interactivity, AI currently has a major contribution to digital platforms. Firstly, personalization is improved because AI analyzes browsing and purchase data and offers personalized product recommendations, special offers, and content tailored to individual user preferences. AI can also handle simple tasks like checking product availability, answering FAQ or even solving some complex problems. In searching, AI provides enhanced search, like search engines used on e-commerce sites to understand natural language, correct spelling mistakes, and provide relevant search results based on user intent. It also helps with predictive analysis to forecast consumer trends and needs by analyzing historical data, allowing businesses to better manage inventory, plan promotions, and personalize offers. Thanks to AI, Chatbots are enhanced because of automated support, where the AI-powered chatbots can understand and answer customer questions conversationally, providing 24/7 support. Lastly, AI can provide an Improved UX by optimizing the user experience while adjusting the interface and content of the site in real-time, based on user behavior; for example, by changing the layout to highlight specific products or simplifying the checkout process.

In a study driven in Indonesia, researchers [32] examined the factors influencing the adoption of AI in e-commerce UI/UX design using the Technology Acceptance Model (TAM) [33]. The results highlight the significant role of perceived usefulness and ease of use in consumer adoption of AI-driven features, such as personalized recommendations and dynamic interfaces. They also found that integrating AI into UI/UX design enhances user satisfaction, improves engagement, and fosters trust, which are critical for long-term customer retention in e-commerce. In another hand, a study driven in India [26] revealed that e-commerce websites using AI-features can track customer preferences in real-time ; and organizations that adopt this AI model see significant sales growth and customer satisfaction. This research underscores the significance of AI in improving sales and customer service by tracking user preferences and behavior instantly.

In sum, Interactivity on e-commerce websites, enhanced by artificial intelligence, aims to create a seamless, personalized, and engaging user experience, which can improve customer satisfaction, increase conversion rates, and build brand loyalty. But are those advantages perceived by the Moroccan user?

METHODOLOGY

Our study is conducted within the emerging framework of UX and consumer behavior in Moroccan e-commerce platforms. We observed a scarcity of research in this area, highlighting the unexplored nature of the field. To address this gap, we adopt a mixed-method approach, combining both qualitative and quantitative techniques. The integration of these methods, known as triangulation, enhances research validity [34]. This study investigates how AI-driven interactivity enhances perceived quality and loyalty in Moroccan e-commerce, necessitating a mixed-methods approach to comprehensively explore both qualitative insights and quantitative validation. Rooted in a post-positivist epistemological stance, our research follows a hypothetico-deductive framework, where an exploratory qualitative phase informs a structured quantitative analysis. The qualitative phase aimed to identify key

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UX determinants and interactivity factors through semi-structured interviews with seven Moroccan experts in UX, AI, and digital marketing. These experts, selected through purposive sampling with a minimum of 10 years of experience, provided in-depth perspectives that guided the development of our survey instrument. The interviews, averaging 48 minutes, were conducted both face-to-face and online, and responses were analyzed using thematic content analysis via TROPES software, chosen for its efficiency in categorizing UX perceptions and extracting research hypotheses.

The quantitative phase sought to empirically validate the relationships between AI-driven interactivity, perceived quality, and customer loyalty. A structured survey, comprising 72 questions, was administered to 376 respondents, selected through convenience and snowball sampling across social media, professional networks, and face-to-face interactions. The sample predominantly consisted of young, digitally active individuals (72.6% aged 18-24), ensuring relevance to the target population of e-commerce users. The survey underwent a rigorous pre-testing process, involving an expert review and pilot testing with 64 participants, leading to refinements in question clarity and measurement validity. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the causal relationships between UX quality, interactivity, and loyalty. Model validity was confirmed using Goodness-of-Fit (GoF = 0.563), with additional bootstrapping (1,000 resamples) to test path significance. We also conducted moderation and mediation analyses following the Baron and Kenny (1986) methodology, which consists of the following four steps:

1. Testing the direct effect of the explanatory variable (X) on the dependent variable (Y).
2. Testing the direct effect of the explanatory variable (X) on the mediator variable (M).
3. Testing the indirect effect (in the regression model) of the explanatory variable (X) on the dependent variable (Y), considering the effect of the mediator variable (M).
4. Determining whether the mediation is partial or complete by comparing the direct and indirect effects of X on Y before and after introducing the mediator variable (M).

This analysis revealed that positive emotions mediated UX quality and loyalty, whereas negative emotions and user characteristics (age, expertise, shopping culture) had no significant moderation effects.

Our methodological approach ensures a rigorous, multi-faceted examination of the impact of AI-driven interactivity on customer experience. The qualitative phase provided rich contextual insights, enabling the quantitative study to test and generalize findings across a broader population. The combination of expert interviews, thematic content analysis, structured surveys, and PLS-SEM modeling allows for a comprehensive understanding of AI's role in enhancing perceived quality and customer retention in the evolving Moroccan e-commerce landscape.

RESULTS

QUALITATIVE RESEARCH

To understand the impact of Interactivity and AI features on platform's using behavior, qualitative interviews were conducted with 7 Moroccan experts in e-commerce, UX, and Marketing fields. They were invited to evaluate the importance of interactivity in the user experience on Moroccan e-commerce websites. An interview guide has been drawn up and the interviews have been faithfully transcribed in the form of verbatims and assessments. The interviews lasted an average of 45 minutes. The verbatims collected were subjected to a content analysis through the TROPES analysis tool.

Our findings confirm the importance of interactivity in influencing perceptions of service quality and user engagement. Personalized and interactive designs enhance the perceived quality of digital platforms, as noted by several experts:

"*A dynamic and interactive design gives the buyer the impression that the site is alive.*" Expert 3

« *… The presentation of the interface is important, especially its consistency and the layout, ensuring key content is visible without scrolling*" Expert 7

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«*Moroccans value human interactions, so any feature that simulates these exchanges enhances the experience.* » Expert 2

The importance of the interactivity of the website and its customization in the perceived quality has been highlighted in the figure below:

Figure 2: Interactivity – UX Perceived Quality

Experts also highlighted AI's potential to improve user behavior, particularly for less tech-savvy users :

"*One barrier to Moroccan e-commerce adoption is the lack of online assistance, which is more prevalent in Europe. Automatic purchase assistance is essential for users uncomfortable with digital interfaces*" Expert 5

The link between UX quality and usage intent is clear:

" *A functional, user-friendly site creates a positive experience and encourages customers to return*." Expert 4

" *Companies must prioritize user experience, designing intuitive interfaces to simplify navigation, product searches, and the checkout process to drive online sales*." Expert 6

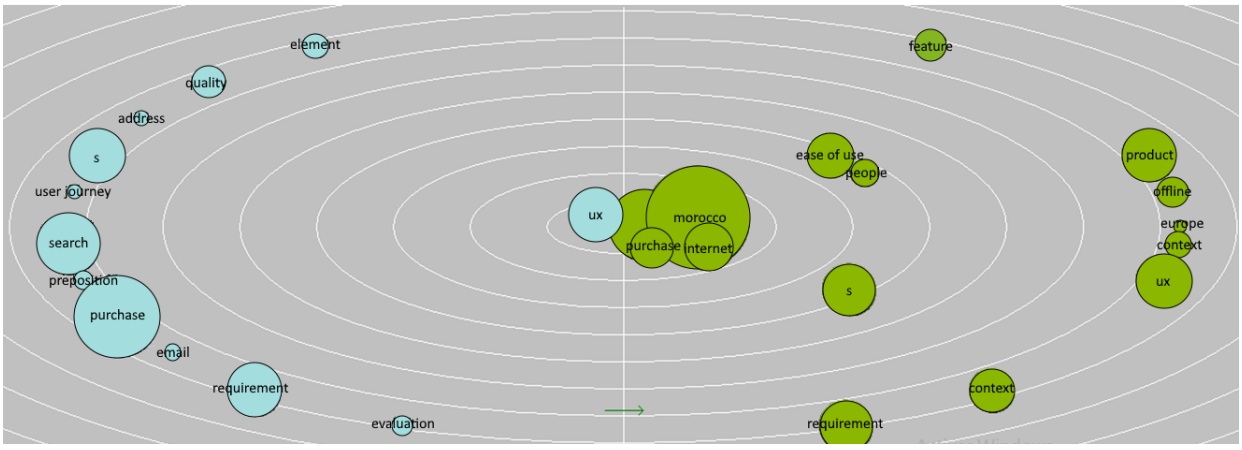

Figure 3: UX Perceived Quality – Purchase / use Intention

RESEARCH MODEL

The Based on our literature review and qualitative research, we have developed a theoretical model in which interactivity plays a major experiential role. This model suggests that interactivity significantly influences the user's perception of service quality, ultimately shaping their loyalty in a digital platform. This model is schematized according to the following figure :

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Figure 4: Research Model

H1: The interactivity of a website positively affects the perception of the quality of the platform

H2: The positive perception of the quality of the website has a positive influence on website loyalty4

QUANTITATIVE RESEARCH

Our quantitative study aims to validate the hypotheses identified through qualitative research by analyzing the causal relationships between the variables in our conceptual model. These include usability, interactivity, perceived UX quality, and consumer loyalty.

To ensure robust findings, a structured survey was conducted with 376 participants, all of whom had made at least one online purchase within the six months preceding the study. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and regression analysis with SPSS. The PLS approach was chosen due to its ability to handle complex relationships and exploratory research designs where theory development is ongoing[35].

The operationalization of interactivity and UX perceived quality was adopted from the Minge et al. (2017) meCUE questionnaire. Based on Thüring and Mahlke's (2007) UX model, a commonly used UX assessment scale a widely accepted UX evaluation scale. Similarly, loyalty measurement was based on validated scales from previous studies [6], [7], [9], [36], [37], [38], [39]. Moreover, scales of [6], [38], [39], [40] have been tested on e-commerce websites. The different used items are detailed in Table 1. The use of these frameworks allows for the theoretical anchoring of our research in existing UX literature, ensuring consistency with prior work in human-computer interaction and e-commerce studies. Table 1 presents the detailed research instruments.

Table 1: Research Instruments

Variable	Dimension	Indicator	Variable	Dimension	Indicator
Usability	**Interactivity**	INT1. This website offers personalization	**UX perceived Quality: Instrumental qualities**	**Usefulness**	U1. The features of this website are perfectly adapted to my objectives of use
		INT2. This website can treat me as a unique individual and meets my specific needs			U2. I consider this website to be extremely useful
		INT3. This website provides content tailored to each person.			U3. With the help of this website, I can achieve my usage goals.
		INT4. This website tracks my actions to			

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		evaluate my progress during navigation.			
Global Loyalty	**Loyalty to the website**	LOY1. I wouldn't trade this website for any other	**UX perceived Quality: Non-instrumental qualities**	**Design**	D1. The website is creatively designed
		LOY2. Compared to this website, the other websites look less sophisticated			D2. The design of this website looks attractive
		LOY3. I will not hesitate to come back to this website again			D3. This website has a sleek visual design
	Use intent	UI1. If I could, I would use this website regularly		**Status**	S1. Using this website gives me a better image with those around me
		UI2. I can't wait to use this website again			S2. Thanks to my use of this website, I am perceived differently
		UI3. When I use this website, I sometimes lose track of time			S3. My friends and family may well be envious of my use of this website
	Purchase Intent	PI. I will be buying products on this website		**Commitment**	C1. This website is so useful that I can't live without it
	Word of Mouth	WOM1. I will speak well of this website			C2. If I lost this website, I would be very affected
		WOM2. I will speak well of this website to those around me			C3. This website is like a friend to me.
		WOM3. I will encourage my family and friends to visit this website			
	Global Evaluation	GE. How would you rate this website as a whole?			

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EXPLORATORY FACTOR ANALYSIS AND RELIABILITY ASSESSMENT

Before hypothesis testing, exploratory factor analysis (EFA) and reliability assessments were conducted to verify construct validity. Table 2 provides a summary of factor loadings and internal consistency.

To ensure construct validity, Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA). The Kaiser-Meyer-Olkin (KMO) values for all constructs exceeded the 0.6 threshold, confirming sample adequacy, while Bartlett's test of sphericity ($p < 0.001$) validated the suitability of factor analysis. After item purification, the retained scales demonstrated strong internal consistency, with Cronbach's alpha values above 0.80, confirming reliability.

To refine the measurement instruments, certain items were removed from the Perceived UX Quality and Global Loyalty scales. This decision was guided by low factor loadings (< 0.50) and the need to enhance the precision of construct measurement. The final set of constructs showed strong discriminant and convergent validity, ensuring the robustness of subsequent analyses.

The table 2 demonstrates the robustness and reliability of the scales used to measure Usability; through Interactivity; Perceived UX Quality, and Global Loyalty. High KMO values (respectively 0.793, 0.821, and 0.685) and significant Bartlett's tests (respectively 0.833, 0.820, and 0.883) across all variables confirm the adequacy as well as the factorability of the data. The retained constructs demonstrated strong internal consistency, with Cronbach's alpha values above 0.80, indicating high reliability.

Table 2: Factorization and reliability

Variable	Indicator	Performance quality		Cronbach's alpha	Eliminated items
Usability	Interactivity	**KMO = ,793**	**Bartlett Sig 0.00**	**,833**	**0**
UX Perceived Quality	Instrumental and non-instrumental qualities	**KMO = ,821**	**Bartlett Sig 0.00**	**,820**	**7**
Global Loyalty	Loyalty to the website	**KMO = ,685**	**Bartlett Sig 0.00**	**,883**	**3**

REGRESSION ANALYSIS AND HYPOTHESIS TESTING

To examine the direct relationships between explanatory variables and perceived UX quality, a regression analysis was conducted. Table 3 presents the results. The model significantly explains the variance in UX quality and loyalty, with ANOVA F-values of 54.703 ($p < 0.001$) and 139.360 ($p < 0.001$), respectively. The results confirm that:

- Interactivity positively influences UX perceived quality ($\beta = 0.339$, $p < 0.001$), supporting H1.
- UX perceived quality significantly impacts consumer loyalty ($\beta = 0.521$, $p < 0.001$), confirming H2.

These findings highlight the critical role of AI-driven interactivity in shaping UX perceptions and fostering brand loyalty in e-commerce.

These findings confirm the validity of our assumptions, emphasizing the pivotal role of interactivity and perceived UX quality in fostering customer loyalty on e-commerce websites. The results align with prior theoretical frameworks, reinforcing that AI-driven interactivity enhances user engagement, which in turn strengthens brand attachment. The strong correlation between UX quality and loyalty highlights UX as a key driver of long-term customer retention, supporting established models in digital marketing, service quality research. These insights further validate the notion that seamless, interactive, and AI-enhanced user experiences contribute to higher

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satisfaction levels, increased platform usage, and stronger customer-brand relationships, particularly in emerging digital markets like Morocco.

Table 3: Regression analysis

Indicator	B (standardized coefficient)	T-value	P-value	Variance explained (r^2)	Adjusted r^2	F-statistic	Model significance
Usability - interactivity	0.339	7.221	<0.000	0.306	0.301	54.703	P<0.001
Ux - perceived quality	0.521	11.805	<0.001	0.271	0.27	139.36	P<0.001

STRUCTURAL EQUATION MODELLING (SEM)

To comprehensively assess the relationships within our research model, we employed Structural Equation Modeling (SEM) to analyze direct, indirect, and moderating effects. This approach allows for a holistic evaluation of how interactivity, UX quality, and loyalty interact within Moroccan e-commerce websites. By integrating both measurement and structural modeling techniques, we ensure that our results are statistically robust and theoretically sound.

- A two-step Structural Equation Modeling (SEM) approach was adopted to enhance analytical precision and model validation:
- Measurement Model Assessment – Evaluating reliability, validity, and factor structure to ensure the constructs accurately measure the intended theoretical concepts.
- Structural Model Evaluation – Examining causal relationships between variables, testing model fit, and validating hypothesis-driven paths.

To further ensure the robustness and accuracy of our research findings, we adopt the two-step design method for structural equations as proposed by [41], [42], [43]. In the first step, we evaluate the validity and reliability of the measurement model (external model), ensuring that all constructs meet statistical thresholds for consistency. The second step focuses on the structural model (internal model), which is assessed using five key statistical measures: path coefficients (to test the hypotheses), the coefficient of determination (R^2), predictive relevance (Q^2), and the overall model fit (GoF). This comprehensive approach enhances the validity of our findings and strengthens the theoretical contribution of our study.

The application of PLS-SEM is particularly suited for this study due to its effectiveness in handling complex models with relatively small sample sizes, making it ideal for exploratory research in emerging markets like Morocco. By employing this rigorous approach, we not only validate our conceptual framework but also contribute to the broader discourse on AI-driven interactivity and UX optimization in digital commerce.

MEASUREMENT MODEL RELIABILITY AND VALIDITY

Using SmartPLS, the measurement model was assessed for composite reliability, convergent validity, and discriminant validity. The reliability analysis aimed to examine the correlation between each item and its associated latent construct by assessing the outer loadings generated by the SmartPLS algorithm. This involved testing the measurement model for convergent validity (through Outer Loadings and AVE), discriminant validity (via Cross Loadings), and composite reliability (using Cronbach's Alpha and Composite Reliability).

External loadings should ideally be 0.7 or higher [43], ensuring strong indicator reliability. However, for exploratory research, values between 0.60 and 0.70 are considered acceptable [44]. Several studies further suggest that factor loadings greater than 0.5 yield optimal results [45], [46]. Consequently, our study adopts a threshold of outer loadings > 0.5 to ensure meaningful construct measurement. Table 4 shows outer loading results.

The results indicated:

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- Most outer loadings exceeded 0.70, confirming strong indicator reliability.
- Composite Reliability (CR) values ranged from 0.866 to 0.900 (see Table 5), surpassing the 0.6 threshold, indicating strong internal consistency.
- Average Variance Extracted (AVE) values confirmed convergent validity, demonstrating that constructs adequately explain the variance in observed indicators.
- Discriminant validity was assessed through the Fornell-Larcker criterion and HTMT ratio, ensuring that each construct is statistically distinct from others.

Following the validity assessment, certain items (LOY1, UI3, C3, S2, S3) were removed due to low factor loadings (< 0.50), improving measurement precision. The decision to refine these scales aligns with best practices in psychometric validation, ensuring that only theoretically and empirically robust indicators are retained. Table 6 provides the final reliability and validity measures, reinforcing the robustness and accuracy of our model.

Table 4: Outer loadings results

Indicator	Interactivity	Indicator	Ux perceived quality: instrumental qualities	Indicator	Ux perceived quality: non instrumental qualities	Indicator	Loyalty
				D1.	0.727	Loy1.	0.442
Int1.	0.790	U1.	0.715	D2.	0.662	Loy2.	0.541
				D3.	0.654	Loy3.	0.639
				S1.	0.581	Ui1.	0.667
Int2.	0.863	U2.	0.635	S2.	0.457	Ui2.	0.672
				S3.	0.443	Ui3.	0.365
Int3.	0.803	--------	--------	--------	--------	Pi	0.692
				C1.	0.591	Wom1.	0.822
Int4.	0.791	U3.	0.696	C2.	0.536	Wom2.	0.846
				C3.	0.468	Wom3.	0.861
						Ge.	0.559

Table 5: PLS Algorithm - Composite Reliability Test Results

	Composite Reliability	NOT
Interactivity	0.886	Valid
UX Perceived Quality	0.866	Valid
Global loyalty	0.900	Valid

Table 6: Discriminant validity

		AVE	1	2	3
1	Loyalty	0.507	**0.712**		
2	Interactivity	0.660	0.387	**0.812**	
4	UX Perceived Quality	0.425	0.697	0.421	**0.652**

Note: The values in bold in the main diagonal are the square roots of the AVE

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The AVE test is conducted to assess discriminant validity. While a value greater than 0.5 is generally recommended, [47] suggest that an AVE below 0.5 may be acceptable if convergent validity exceeds 0.8. Table 6 demonstrates that all constructs along the diagonal have values higher than the correlations between constructs in the same row or column, thereby confirming discriminant validity. Additionally, it indicates that all statements have loading values greater than their cross-loadings, confirming their validity.

Cross-loadings are evaluated to further assess discriminant validity, ensuring that each construct's indicators display the highest values within their respective columns. Table 7 describes cross-loadings results:

Table 7: Cross-Loadings

	Interactivity	Loyalty	Perceived quality
Int1	0.794	0.312	0.358
Int2	0.862	0.286	0.343
Int3	0.802	0.300	0.320
Int4	0.790	0.359	0.345
Wom1	0.340	0.838	0.593
Wom2	0.334	0.867	0.617
Wom3	0.308	0.874	0.577
Ge	0.299	0.576	0.45
Pi	0.195	0.704	0.476
Ui1	0.253	0.662	0.501
Ui2	0.299	0.652	0.484
Loy2	0.211	0.51	0.303
Loy3	0.212	0.628	0.363
C1	0.240	0.425	0.557
C2	0.199	0.38	0.468
D1	0.332	0.495	0.729
D2	0.304	0.4	0.655
D3	0.386	0.407	0.642
S1	0.334	0.359	0.5
U1	0.261	0.535	0.777
U2	0.211	0.498	0.71
U3	0.271	0.547	0.749

Table 7 confirms that this condition has been satisfied. Therefore, we can conclude that our measurement model exhibits strong discriminant validity.

EVALUATION OF THE STRUCTURAL MODEL

For multiple coefficients, [48] identifies three thresholds for R^2 values. An R^2 greater than 0.1 indicates that the model is relevant. If R^2 falls between 0.05 and 0.1, the model is considered marginally relevant. An R^2 below 0.05 signifies that the model is not relevant. In the second level of analysis, the mean coefficient represents the average of the coefficients of determination observed for the dependent variables.

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Table 8: Coefficients of determination for the research constructs

	R^2	R^2 adjusted
Loyalty	0,486	0,484
Perceived quality	0,519	0,515
Average of r2	0,502	0,499

In our results, the individual coefficients of determination range from 0.486 to 0.519, all exceeding the threshold of 0.1. Therefore, we deem the model to be significant. The average R^2 coefficient is 0.499, indicating a strong level of nomological validity.

Additionally, the GoF (Goodness of Fit) index was utilized to assess the overall research design. Our model's GoF score is 0.563. According to [49], for a model to be considered a valid PLS model, the GoF values should exceed 0.36. This criterion is met, confirming that the measurement scales for the latent variables are both valid and reliable.

Hypotheses Testing

Following the positive evaluation of both our measurement and structural models, we applied the bootstrap technique, as recommended by [43], to assess the significance and relevance of the trajectory coefficients in the structural model. Our hypothesis testing is based on causal analyses among the various research constructs.

To evaluate the research hypotheses, [50] suggests using a Student's T coefficient greater than 1.96 at the 5% significance level. Based on this criterion, we find that both relationships are significant.

As mentioned in table 0, Interactivity (β = 0.207, P = 0.000) shows a positive association with Perceived Quality, thus supporting the hypothesis. Additionally, Perceived Quality (β = 0.697, P = 0.000) significantly influences Fidelity, indicating that H2 is also supported.

The results are illustrated in the following diagram, where the bold links represent highly significant relationships.

Table 9: Structural Equation's results

Hypothesis	Indicator	B	Sample average	Standard deviation	T-value	P-value	Décision
H1	Interactivity ->perceived quality	0.207	0.209	0.042	**11.702**	0	Accepted
H2	Perceived quality -> global loyalty	0.697	0.7	0.037	**18.667**	0	Accepted

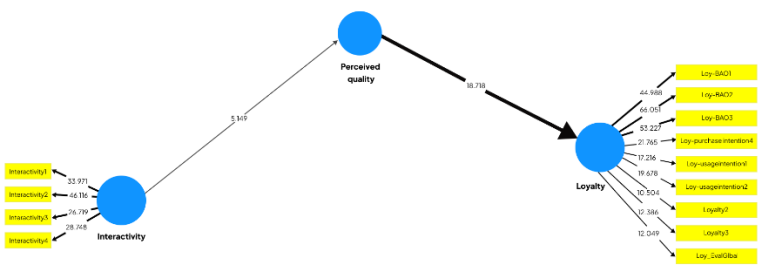

Figure 1 : Final model with validated links

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DISCUSSION

Our research underscores the pivotal role of interactivity in enhancing user experience (UX) on e-commerce platforms, particularly within the Moroccan market. A dynamic and interactive design not only elevates the perceived quality of the platform but also fosters customer loyalty. Features such as a well-structured interface that minimizes excessive scrolling and culturally relevant interactions that foster personal connections are especially valuable in markets like Morocco, where personalized interactions are highly valued. This aligns with findings from studies emphasizing the significance of interactivity in online retail environments (Daou, & Stephan El Khoury, 2025).

The integration of artificial intelligence (AI) emerges as a crucial solution for addressing challenges faced by users, particularly those with limited technological proficiency. AI-driven tools, such as automatic purchasing assistance and personalized product recommendations, enhance overall satisfaction by simplifying interactions and guiding users through complex tasks. This approach not only improves usability but also provides businesses with valuable data to tailor their offerings, thereby enhancing customer loyalty. This perspective is supported by recent research highlighting the transformative impact of AI on personalization in e-commerce[16], [18], [19], [26], [32]. This approach not only improves usability but also provides businesses with valuable data to tailor their offerings, thereby enhancing customer loyalty. Recent findings suggest that incorporating e-loyalty features into AI-based recommendation systems significantly enhances recommendation accuracy and strengthens customer engagement [51]. This further validates the role of AI-driven personalization in optimizing user experience and fostering long-term retention.

Furthermore, our research confirms a direct link between perceived UX quality and customer loyalty. A well-designed, AI-enhanced, and intuitive interface that simplifies navigation and the purchasing process fosters repeat visits and purchases. This was also revealed by [32] who attest that the perceived usefulness and ease of use of AI-enhanced features significantly influence user satisfaction and engagement.

In conclusion, integrating AI and ensuring high levels of interactivity and personalization are essential strategies for enhancing UX in Moroccan e-commerce. These elements not only improve immediate satisfaction but also foster long-term user retention, giving professionals a competitive edge in a growing digital marketplace. Consequently, focusing on intuitive design and culturally aligned features will be key to sustaining customer loyalty in this evolving landscape.

In closing, our findings suggest that integrating AI and ensuring high levels of interactivity and personalization are essential strategies for enhancing UX in Moroccan e-commerce. These elements not only improve immediate satisfaction but also foster long-term user retention, giving professionals a competitive edge in a growing digital marketplace. Consequently, focusing on intuitive design and culturally aligned features will be key to sustaining customer loyalty in this evolving landscape.

CONCLUSION

Our results highlight the pivotal role of interactivity in enhancing the user experience (UX) on e-commerce platforms. Interactivity, when paired with artificial intelligence, creates more personalized, responsive, and engaging experiences that directly contribute to both user satisfaction and customer loyalty. AI acts as a crucial component of interactivity by offering automatic assistance, particularly for users with limited technological expertise. This synergy between interactivity and AI not only improves the overall UX but also fosters repeat visits and purchases.

In conclusion, interactivity is a central element in improving UX on e-commerce platforms. AI, as a key driver of interactivity, enables the creation of personalized, reactive, and engaging experiences, significantly boosting user satisfaction and loyalty. For professionals, implementing interactive solutions supported by AI is critical to optimizing user engagement and ensuring their success in an increasingly competitive digital environment. Interactivity, with AI as its foundation, thus becomes a strategic imperative for managers aiming to maximize the performance of their e-commerce platforms.

From a theoretical standpoint, this research reinforces the notion that interactivity is a key vector in improving UX, especially when enhanced by AI-driven solutions. Interactivity, backed by intelligent technologies, not only increases user satisfaction but also plays a vital role in fostering customer loyalty. By combining responsiveness and personalization, AI allows e-commerce platforms to create interactive experiences where users feel valued and understood. This study also enriches the existing literature by showing that interactivity is not merely a technological feature but a strategic component at the heart of UX strategies, and AI is its pivotal factor.

From a managerial perspective, the implications are significant. Companies must prioritize the implementation of AI-supported interactive mechanisms, such as adaptive interfaces, data-driven recommendations, and intelligent chatbots. Such an approach maximizes user engagement, boosts conversion rates, and enhances customer retention.

Thus, interactivity becomes an essential lever not only for capturing users' attention but also for offering a smooth and engaging experience, thereby strengthening a company's competitiveness in the e-commerce sector.

CONFLICTS OF INTEREST

Authors have no conflicts of interest to declare.

DATA AVAILABILITY

All data supporting the findings of this study are available from the corresponding author upon reasonable request.

AUTHOR'S CONTRIBUTION STATEMENT

- Halim Amal: Writing, conceptualization, result analysis, modeling, data curation, original draft.
- Ouiddad Smail: Result analysis, supervision, investigation on challenges, original draft.
- Ait Lamkadem Saad: Reviewing, manuscript draft preparation and final manuscript editing
- El Mountassirr El Khalil: Data validation, statistical analysis, literature review.
- Jeddou El Mehdi : Manuscript adaptation to journal standards, concept translation verification, final formatting and layout
- Mamoudou Bocar Sall : Final verification and proofreading

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APPENDIX

S. No	Abbreviations	Description
1	AI	Artificial Intelligence
2	UX	User experience

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3	CMI	Centre monétaire interbancaire
4	HCI	Human computer interaction
5	FAQ	Frequently Asked Questions
6	UI	User Interface
7	TAM	Technology Acceptance Model
8	KMO	Kaiser Meyer Olkin
9	SEM	Structural Equation modeling
10	PLS	Parial Least Square