African Journal of Human Resources, Marketing and Organisational Studies (AJHRMOS)
E-ISSN 3050-2292 (Online); ISSN 3050-2284 (Print)

Indexed by EBSCO and SABINET

Volume 3, Number 1, June 2026

Pp 129-150

Artificial Intelligence and Customer Experience in Morocco: Efficiency, Transparency, and the Limits of Automation

DOI: https://doi.org/10.31920/3050-2292/2026/v3n1a6

Salma Haddououmouloud
0009-0002-2958-724X,
LARMODAD, Department of Economics,
Faculty of Law, Economics and Social
Sciences Souissi, Mohammed V University, Rabat, Morocco
Email: salma_haddououmouloud@um5.ac.ma

Hicham Belmaati
National Institute of Social Action (INAS),
Tangier, Morocco
Email: Hicham.belmaati@inas.social.gov

Abstract

Artificial intelligence is reshaping how organisations interact with customers, yet its effects on satisfaction, acceptance, and loyalty remain poorly understood in non-Western markets. This study addresses that gap directly, drawing on a structured cross-sectional survey of 350 Moroccan consumers across e-commerce, banking, and telecommunications. Using multiple linear regression to test four hypotheses, we find that: AI efficiency is positively associated with satisfaction ($\beta = 0.52$, $p < 0.001$), transparency and security are positively associated with acceptance ($\beta = 0.48$, $p < 0.001$), and personalisation is positively associated with loyalty ($\beta = 0.61$, $p < 0.001$). The absence of human support is negatively associated with satisfaction ($\beta = -0.39$, $p = 0.002$), suggesting a boundary condition of satisfaction in AI-mediated contexts. These findings identify human–machine balance as a key boundary condition of AI-mediated customer experience.

Keywords: *Artificial Intelligence (AI), Customer Experience, Technology Acceptance, Customer Loyalty, Transparency*

Introduction

Chatbots handle complaints at midnight. This is demonstrated by recommendation engines that anticipate consumer desires, and predictive analytics that identify potential churn before individuals consciously decide to terminate their relationship. These are not future possibilities; they are already running in Moroccan e-commerce platforms, banks, and telecoms operators (Ameen et al., 2021; Chen & Prentice, 2024). Research in this area largely confirms what practitioners already suspect: AI is associated with improved efficiency, enables personalisation as perceived by consumers, and correlates with higher perceived quality of service interactions (Prentice et al., 2020; Ivanov & Webster, 2019). However, the same literature highlights a persistent tension: as interactions become more automated, consumers increasingly worry about data privacy, data utilisation, and whether they can trust a system that operates ceaselessly but lacks genuine understanding (Siau & Wang, 2018). Real-time personalisation and predictive engagement are now technically possible at a scale unimaginable five years ago, but so are the risks: algorithmic bias, unexplainable decisions, and data governance gaps that erode the very trust these systems depend on (Bahangulu & Owusu Berko, 2025).

To explain these relationships, the study draws on three complementary theoretical perspectives. SERVQUAL explains how AI-related efficiency and responsiveness may be associated with customer satisfaction. TAM and UTAUT provide a framework for understanding how transparency and perceived security relate to the acceptance of AI-enabled services. Trust theory further explains how personalisation and perceived reliability may be positively associated with customer loyalty. Each framework captures a different layer of the same problem: SERVQUAL focuses on service quality perceptions, TAM/UTAUT explains technology adoption behavior, and trust theory connects personalisation to relational outcomes. Together, they suggest that while AI can enhance service experiences, the complete absence of human support weakens perceptions of empathy and reliability, thereby lowering customer satisfaction.

To examine these questions, we surveyed 350 Moroccan consumers across three sectors (e-commerce, banking, and telecommunications) and tested four hypotheses centred on satisfaction, acceptance, loyalty, and the limits of automation. The Moroccan context provides an important setting for examining these relationships due to its rapid digital transformation and sector-specific investments in AI, particularly in banking digitalisation, telecom infrastructure, and e-commerce expansion since 2020. However, despite this technological progress, most empirical research on AI and customer experience continues to originate from Western and East Asian contexts, leaving emerging economies underexplored in how consumers evaluate AI-enabled services and how established drivers of satisfaction and loyalty apply.

Beyond its technological development, Morocco offers a distinctive case where digital transformation interacts with historically embedded relational service norms. Customer relationships in banking and commerce have traditionally been grounded in interpersonal trust and human accountability, which may shape expectations toward AI-enabled services. Internet penetration now exceeds 90% (ANRT, 2024). Rather, AI systems that lack transparency or eliminate human contact may encounter resistance because they violate culturally grounded expectations of interpersonal accountability. In such a setting, trust functions not only as a technological evaluation criterion but also as a socially embedded mechanism that governs consumer interpretations of transparency, risk perception, and the perceived requirement for human intervention in AI-mediated interactions. This tension between rapid automation and relational trust makes Morocco an ideal context for exploring the boundaries of AI-driven customer experience.

This study addresses three research questions:

To what extent do AI efficiency, transparency, and personalisation associate with customer satisfaction, technology acceptance, and loyalty among Moroccan consumers?

Do these associations vary across e-commerce, banking, and telecommunications sectors?

Does the complete absence of human backup in AI-powered services negatively affect customer satisfaction?

Together, these questions allow us to assess whether satisfaction and loyalty frameworks developed in Western and East Asian contexts generalize to an emerging digital economy and where they require adjustment.

Theoretical framing, literature review, and hypothesis development

According to Haenlein & Kaplan, (2021) AI is the capability of a system to correctly interpret external data, learn from such data, and use that learning to achieve specific goals through flexible adaptation. This definition highlights the adaptive capacity to generate value from data gathered during client communications.

AI corresponds with improvements in the customer journey by enabling omnichannel and real-time interactions across touchpoints, which collectively contribute to more consistent and adaptive customer experiences (Lemon & Verhoef, 2016). In this context, (Grewal et al., 2020) further emphasise that AI enables the large-scale deployment of intelligent and adaptive experiences.As such, Wirtz et al. (2018) incorporate AI into a typology of intelligent service systems, shifting its role from a mere efficiency tool to a service partner that learns and reacts holistically in interactions with customers. This evolution is closely linked to hyper-personalisation strategies in digital marketing , where AI supports engagement, relevance, and customer experience while raising ethical concerns related to data use and transparency (Kumar et al., 2024). Because AI simultaneously affects service quality, technology adoption, and relational trust, no single framework is sufficient to explain its impact on customer experience. Various models from relationship marketing and information systems explain how AI reshapes customer relationship dynamics, particularly through the evaluation of service quality and customer experience. In this context, SERVQUAL remains a foundational framework as it conceptualises service quality through the gap between customer expectations and perceived performance (Parasuraman et al., 1988). However, in AI-mediated environments, its traditional dimensions such as reliability, responsiveness, and empathy are reinterpreted to reflect automated and data-driven interactions. Building on this perspective, Prentice et al. (2020) extend SERVQUAL by incorporating the specific characteristics of intelligent technologies and automated service encounters. At the experience level, the customer journey framework proposed by Lemon & Verhoef (2016) further structures these interactions into pre-purchase, purchase, and post-purchase stages, highlighting the temporal nature of AI touchpoints. Complementing these views, (Chen & Prentice, 2024) integrate AI into service research through a multidimensional model that distinguishes between AI experience, AI functions, and AI services, thereby providing a more comprehensive understanding of how AI is associated with both operational processes and customer perceptions.

The Technology Acceptance Model (TAM) and its extension UTAUT are used to explain how perceived usefulness and ease of use translate AI system exposure into actual adoption behaviour, which ultimately conditions satisfaction and loyalty outcomes. Models related to technology acceptance (Davis, 1989; Venkatesh et al., 2003) help to elucidate the conditions for AI adoption. These frameworks highlight key determinants, including, ease of use, social influence and perceived risk, as influential factors in user acceptance of these emerging technologies. In this study, TAM and UTAUT are particularly useful for explaining how transparency and perceived security reduce resistance to AI adoption and facilitate continued engagement with AI-enabled services. Dissonance theory explains user resistance when AI performance falls short of expectations, particularly in relation to transparency and data protection (Sulastri, 2023). This dissonance perspective directly supports H2 (transparency reduces resistance) and H4 (human backup prevents dissonance in high-stakes situations). Research indicates that AI augments operational efficiency and personalisation, but human touch should never be completely eliminated in emotionally-charged or complex service situations, underpinning the need for a balanced "human-in-the-loop" customer experience design approach (Mariani et al., 2024). Regulatory pressure is also reshaping how organisations approach AI deployment. In emerging digital economies such as Morocco, regulatory institutions play a central role in shaping perceived trust and legitimacy of AI systems, particularly in the banking and telecommunications sectors. In such contexts, institutional trust inherently shapes the customer experience, since perceptions of AI reliability depend heavily on confidence in regulatory oversight and digital governance.

This study proposes a unified conceptual framework integrating SERVQUAL, TAM/UTAUT, and trust theory, where AI-mediated customer experience is explained through three interdependent mechanisms: operational efficiency, cognitive acceptance, and relational trust. Together, these mechanisms are associated with variations in customer satisfaction, technology acceptance, and loyalty in AI-enabled service environments. This integration also clarifies why the absence of human support, which disrupts SERVQUAL's empathy dimension and trust theory's benevolence, is hypothesised to reduce satisfaction independently of AI's efficiency gains.

Based on this integrated theoretical perspective, four hypotheses are proposed.

H1: AI efficiency is positively associated with customer satisfaction. Perceived satisfaction is enriched by customers' reduced effort and more rapid problem-solving using more streamlined platforms, faster responses, automatic agents, and the integration of service channels (Ameen et al., 2021 ; Chen & Prentice, 2024). According to the SERVQUAL model, improvements across the dimensions of reliability, responsiveness, and customisation positively correlate with heightened consumer satisfaction.

H2: Transparency and security are conceptualised as a unified construct, as both reduce perceived uncertainty and perceived risk in AI-mediated interactions. Prior research suggests that these dimensions are closely interrelated in shaping users' trust and acceptance of digital technologies (Gefen et al., 2003 ; Siau & Wang, 2018), where transparency enhances understanding of system behavior and security reinforces perceived protection of personal data. Together, they are associated with whether AI systems are perceived as sufficiently trustworthy to be adopted.

H3: Personalised customer experiences through AI are positively associated with loyalty. Personalising products to serve the specific needs of clients is associated with loyalty (Lemon & Verhoef, 2016). Automation through AI corresponds with personalised content, is associated with increased brand value, and is associated with both attitudinal and behavioural loyalty (Prentice et al., 2020).

H4:Perceived absence of human support in AI-powered services is associated with lower customer satisfaction, particularly in high-involvement or emotionally sensitive service contexts (Ameen et al., 2021; Tussyadiah, 2020). This construct is treated as unidimensional because removing human backup entirely violates two core assumptions of the theoretical framework. First, SERVQUAL's empathy dimension presumes the availability of human understanding when automated systems reach their limits; second, trust theory suggests that perceived benevolence is difficult to establish in fully automated interactions. Accordingly, the absence of human support is conceptualised as a single condition linked to lower satisfaction even in the presence of high system efficiency.

Taken together, these perspectives suggest that AI-mediated customer experience reflects a dynamic interaction between perceived service efficiency, risk reduction mechanisms, and institutional trust conditions. Figure 1 presents the conceptual framework guiding this study:

Methodology:

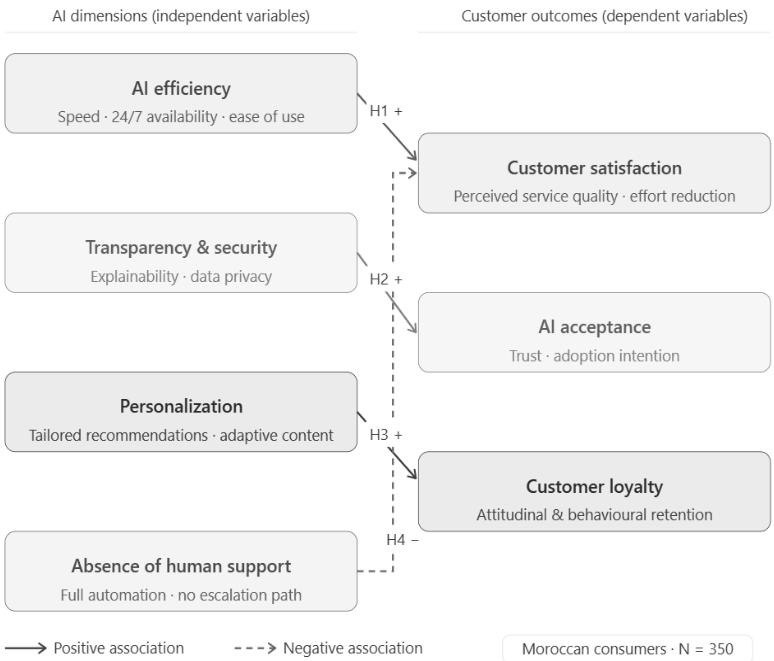

Figure 1: Conceptual framework

This study follows a quantitative explanatory design. Data were collected between January and March 2025 through a self-administered questionnaire distributed online to Moroccan consumers who had used at least one AI-powered service, chatbot, recommendation engine, or automated helpline within the previous six months. Participants were recruited through social media and digital mailing lists. Eligibility was limited to adults aged 18 and over. Sample size was grounded in Slovin's formula: $n = N / (1 + N \cdot e^2)$.

With Morocco's digitally active consumer base numbering in the millions (ANRT, 2024) and a margin of error set at 0.05, the calculation points to a minimum of 384 respondents. Of 370 questionnaires distributed, respondents with no prior experience of AI-powered customer services were excluded, and 350 cleared the screening stage, a 94.6% retention rate that falls slightly short of that threshold yet remains consistent with comparable work in AI consumer research. Table 1 presents the sample demographic characteristics:

Table 1. Sample demographic characteristics (N = 350)

Characteristic	**Category**	**%**
Region	Casablanca-Settat	34
	Rabat-Salé-Kénitra	28
	Marrakech-Safi	15
	Other regions	23
Age	18–24 years	18
	25–34 years	58
	35–44 years	16
	45 years and older	8
Gender	Female	52
	Male	48
Education	Secondary or less	35
	Higher education	65
Number of sectors where the respondent used AI	One sector (e-commerce, banking, or telecom)	27
	Two sectors	32
	Three sectors (all: e-commerce, banking, and telecom)	41

Note. Income was not collected due to the low reliability of self-reported household income in the Moroccan context.
Source: Authors' computation using SPSS (2025)

The questionnaire was originally developed in English, translated into French and Arabic by two bilingual researchers, and back-translated into English by an independent translator to verify conceptual equivalence across language versions (Brislin, 1970). All participants were informed of the study's purpose before taking part. Participation was voluntary, responses were anonymous, and the study was cleared by the relevant institutional ethics committee. The questionnaire covered two areas: respondent profiles and the core model constructs, all measured on a five-point Likert scale. Items were drawn from validated instruments (Ameen et al., 2021; Chen & Prentice, 2024; Siau & Wang, 2018) and spanned satisfaction (4 items), AI acceptance (4), loyalty (3), AI efficiency (3), personalization (3), transparency and security (4), and absence of human support (2). Example items for each construct (5-point Likert scale):- Satisfaction: “The AI-powered service meets my expectations overall.”- AI acceptance: “I am willing to use AI-based customer service again.”- Loyalty: “I will continue using this company’s services because of its AI features.”- AI efficiency: “The AI chatbot resolves my issues quickly.”- Personalisation: “This company offers me relevant recommendations based on my behavior.”- Transparency & security: “I understand how this system uses my personal data.”- Absence of human support: “No human agent is available when I need assistance.”

A pilot with 30 Moroccan consumers confirmed clarity before full deployment. Internal consistency was strong across all constructs: satisfaction ($\alpha = 0.82$), AI acceptance ($\alpha = 0.79$), loyalty ($\alpha = 0.85$), AI efficiency ($\alpha = 0.81$), personalisation ($\alpha = 0.84$), transparency and security ($\alpha = 0.81$), and absence of human support ($\alpha = 0.76$) , all above the 0.70 threshold (Hair et al., 2019). The absence of human support scale relied on only two items. While this is acceptable for reliability, it represents a psychometric limitation that is discussed further in the limitations section.

All analyses were conducted in SPSS. Multiple linear regression served as the primary method for testing H1 through H4, with age, gender, digital literacy, and sector included as control variables. Digital literacy was measured using self-assessment items that captured respondents’ perceived ability to use digital technologies, online platforms, and AI-enabled services in everyday interactions. Before interpreting the results, standard regression diagnostics were checked. Residual normality held across all models (Kolmogorov-Smirnov, $p > 0.05$), homoscedasticity was confirmed through residual plot inspection, and VIF values ranging from 1.2 to 3.9 gave no cause for multicollinearity concern (Hair et al., 2019). Common method bias was assessed using Harman's single-factor test. An unrotated factor analysis extracted seven factors with eigenvalues >1.0; the first factor accounted for 28.4% of the total variance, below the 50% threshold, indicating no substantial common method bias (Podsakoff et al., 2003). Convergent validity was assessed via Average Variance Extracted (AVE) and Composite Reliability (CR). All constructs exceeded recommended thresholds (AVE > 0.50, CR > 0.70), as shown in Table 2. Discriminant validity was confirmed using the Fornell-Larcker criterion (Table 3), where the square root of AVE for each construct (diagonal) exceeded its correlations with other constructs (Fornell & Larcker,1981).

Table 2. Reliability and validity of constructs

Construct	**Items**	**α**	**AVE**	**CR**
AI Efficiency	3	0.81	0.54	0.83
Transparency & Security	4	0.81	0.57	0.84
Personalisation	3	0.84	0.62	0.86
Satisfaction	4	0.82	0.55	0.83
AI Acceptance	4	0.79	0.51	0.81
Loyalty	3	0.85	0.67	0.87
Absence of Human Support	2	0.76	0.51	0.77

Source: Authors' computation using SPSS (2025)

Table 3: Discriminant validity Fornell-Larcker criterion

Construct	1	2	3	4	5	6	7
1. AI Efficiency	0.73						
2. Transparency & Security	0.41	0.75					
3. Personalisation	0.38	0.44	0.79				
4. Satisfaction	0.52	0.48	0.51	0.74			
5. AI Acceptance	0.39	0.55	0.42	0.46	0.71		

Construct	1	2	3	4	5	6	7
6. Loyalty	0.44	0.47	0.61	0.53	0.49	0.82	
7. Absence of Human Support	-0.31	-0.28	-0.25	-0.39	-0.27	-0.33	0.71

Source: Authors' computation using SPSS (2025)

Chi-square tests were run alongside but carry no inferential weight: they served only as a descriptive cross-check on the directionality of associations.

Although structural equation modeling (SEM) could provide a more integrated assessment of the relationships among latent constructs, multiple linear regression was retained as the primary analytical approach for three reasons. First, each hypothesis examines a direct association between a specific AI-related predictor and a distinct customer outcome. Second, the study aims to prioritise interpretability and practical managerial implications across sectors. Third, the sample size, while adequate for regression analysis, remains relatively modest for estimating a more complex covariance-based SEM model with multiple latent constructs simultaneously. Nevertheless, SEM represents an important avenue for future research and would allow a more comprehensive assessment of mediating and moderating mechanisms.

Results:

This section reports findings from the 350 valid responses, organised around the four hypotheses. Multiple linear regression served as the primary analytical method, while chi-square tests were run as supplementary bivariate checks only.

Sample profile. The sample was slightly female-majority (52% women, 48% men), predominantly young (58% fell in the 25–34 age bracket) and well-educated, with 65% holding a higher education degree. A large majority (71%) reported using AI-powered services daily or weekly, which matches the user profile targeted in this study.

Descriptive statistics. Across all constructs, mean scores sat above the midpoint of the scale. Moroccan consumers, in other words, came into this study with broadly favorable views of AI in service contexts. Personalisation returned the highest average (M = 4.0, SD = 0.7), followed by loyalty (M = 3.9, SD = 0.8) and AI efficiency (M = 3.9, SD

= 0.8). Satisfaction (M = 3.8, SD = 0.8) and AI acceptance (M = 3.7, SD = 0.9) were also favorable, while transparency and security scored lowest among the constructs (M = 3.5, SD = 0.9). The absence of human support construct averaged 3.6 (SD = 1.0), with the highest dispersion in the dataset, suggesting that reactions to fully automated service vary considerably from one consumer to the next. Full descriptive statistics and intercorrelations are presented in Table 4.

Table 4. Descriptive Statistics and Intercorrelations

Construct	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. Satisfaction	3.80	0.80	—						
2. AI Acceptance	3.70	0.90	.41**	—					
3. Loyalty	3.90	0.80	.52**	.38**	—				
4. AI Efficiency	3.90	0.80	.52**	.31**	.44**	—			
5. Transparency & Security	3.50	0.90	.38**	.48**	.35**	.29**	—		
6. Personalisation	4.00	0.70	.45**	.36**	.61**	.48**	.33**	—	
7. Absence of Human Support	3.60	1.00	-.39**	-.22**	-.28**	-.19*	-.15*	-.21**	—

Note. N = 350. M = Mean; SD = Standard Deviation. *p < .05. **p < .01.

Source: Authors' computation using SPSS (2025)

Sectoral comparisons: To assess whether the observed associations varied across service contexts, we compared mean scores for e-commerce (n = 118), banking (n = 114), and telecommunications (n = 118) using one-way ANOVA. Table 5 presents the results. No significant differences emerged across sectors for any construct (all $F < 1.50$, $p > 0.20$), indicating that the patterns observed in the pooled sample are stable across the three sectors.

All regression coefficients had 95% confidence intervals: H1 [0.41, 0.63]; H2 [0.36, 0.60]; H3 [0.49, 0.73]; H4 [-0.63, -0.15]

Table 5. Mean scores by sector (N = 350)

Construct	**E-commerce (n = 118)**	**Banking (n = 114)**	**Telecommunications (n = 118)**	**F**	**p**
Satisfaction	3.82 (0.79)	3.75 (0.81)	3.83 (0.78)	0.48	0.62
AI Acceptance	3.73 (0.88)	3.65 (0.91)	3.72 (0.89)	0.34	0.71
Loyalty	3.92 (0.80)	3.85 (0.82)	3.93 (0.78)	0.55	0.58
AI Efficiency	3.88 (0.81)	3.86 (0.79)	3.96 (0.80)	0.72	0.49
Personalisation	4.02 (0.69)	3.95 (0.72)	4.03 (0.68)	0.61	0.54
Transparency & Security	3.52 (0.91)	3.48 (0.89)	3.50 (0.90)	0.08	0.92
Absence of Human Support	3.58 (1.02)	3.62 (0.99)	3.60 (1.01)	0.05	0.95

Note. Values are means with standard deviations in parentheses. No significant sector differences were found; pooled analysis is therefore appropriate.

Source: Authors' computation using SPSS (2025)

H1: AI efficiency and customer satisfaction

The satisfaction finding is the most straightforward of the four. Seventy-two percent of respondents perceived that AI is associated with faster service and an improved overall experience. The regression confirmed this: AI efficiency associated positively with satisfaction ($\beta = 0.52$, $p < 0.001$), supporting H1.This finding reinforces SERVQUAL-based arguments that responsiveness and operational reliability remain central determinants of satisfaction, even in AI-mediated service environments. The supplementary bivariate check pointed in the same direction ($\chi^2 = 24.56$, $p = 0.001$). These results indicate that perceived AI efficiency is strongly associated with higher customer satisfaction in AI-enabled service environments.

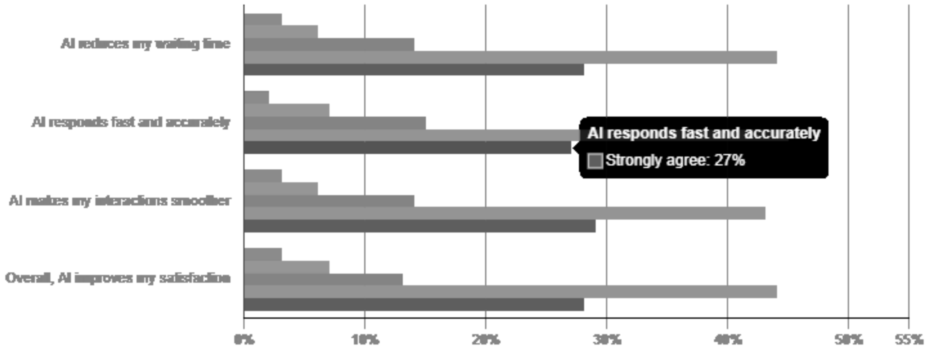

Figure 2: Perceptions of AI efficiency and customer satisfaction in customer Service. N = 350. Source: Authors' computation using SPSS (2025)

H2: Transparency, data security, and AI acceptance

Figure 3 reports perceptions of transparency and data security. Respondents were most confident about data protection and clarity around data use, though trust in AI with personal information showed more variation. The regression confirmed what the descriptive pattern suggested: perceived transparency and security associated positively with AI acceptance ($\beta = 0.48$, $p < 0.001$), supporting H2. The result aligns with TAM and trust-based frameworks, which suggest that mitigating uncertainty enhances consumer willingness to adopt AI-enabled services. The bivariate check pointed in the same direction ($\chi^2 = 18.91$, $p = 0.004$). These findings suggest that transparency and perceived security are positively associated with AI acceptance through reduced perceived uncertainty.

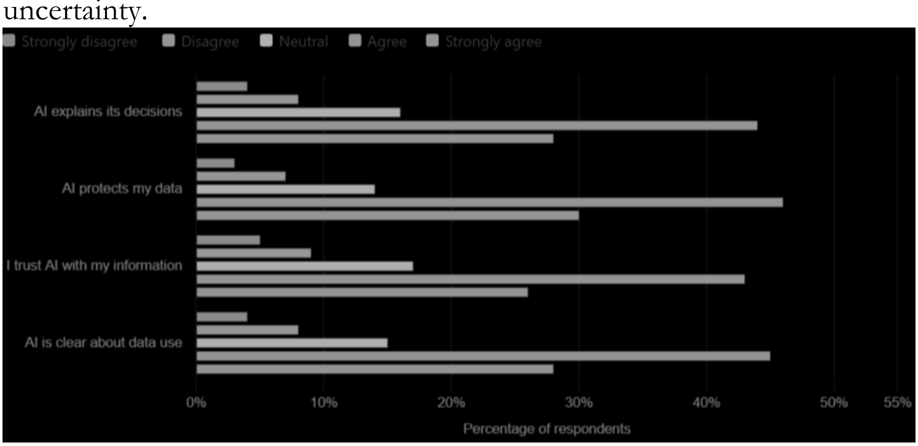

Figure 3: Perceptions of AI transparency and data security in customer services. N = 350. Source: Authors' computation using SPSS (2025)

H3: AI personalisation and customer loyalty

Figure 4 stands out from the other three: agreement was strong and remarkably consistent across all personalisation items, with very little neutral or negative response. Eighty percent of respondents valued AI-generated recommendations, and 55% said they are more likely to stay loyal to companies that adapt their services to individual needs. The regression returned the strongest coefficient of the four models ($\beta = 0.61$, $p < 0.001$), supporting H3. The finding also reinforces trust-based perspectives according to which individualised relevance is associated with both emotional attachment and behavioural loyalty. The bivariate check confirmed the same direction ($\chi^2 = 29.43$, $p < 0.001$). These results highlight personalisation as a key factor associated with customer loyalty in AI-enabled service contexts.

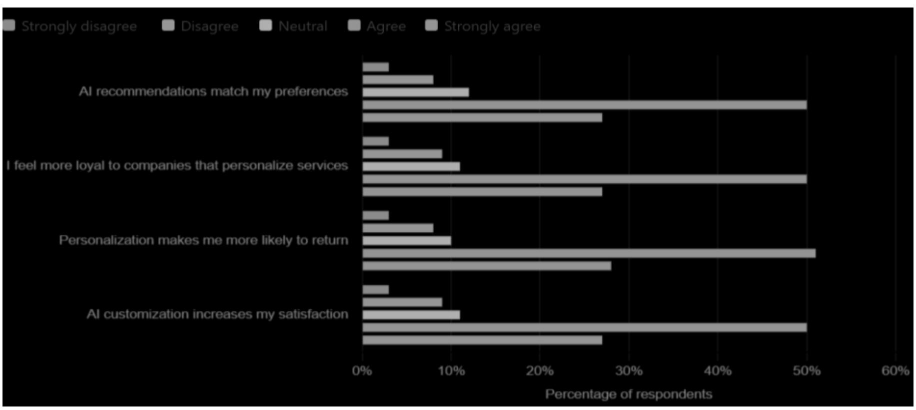

Figure 4: Relationship between AI personalisation and customer loyalty. N = 350. Source: Authors' computation using SPSS (2025)

H4: Absence of human support and customer satisfaction

The picture gets more complicated in Figure 5. Thirty-eight per cent said they get frustrated when no human agent is available. Half felt that AI regularly misreads their requests. And 62% would prefer a hybrid model over full automation. The regression confirmed it: absence of human support associated negatively with satisfaction ($\beta = -0.39$, $p = 0.002$), supporting H4. The negative relationship indicates that automation by itself cannot completely replace the perceived empathy and reassurance required during emotionally sensitive interactions. The bivariate check pointed the same way ($\chi^2 = 16.87$, $p = 0.007$). These findings suggest that the absence of human support is associated with lower customer satisfaction, particularly in emotionally sensitive service interactions.

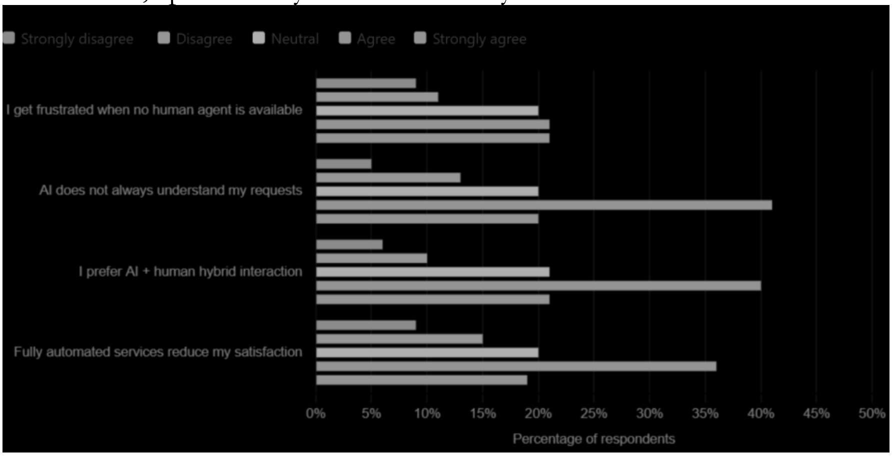

Figure 5: Association between absence of human support and customer satisfaction. N = 350.
Source: Authors' computation using SPSS (2025)

Control variables (age, gender, digital literacy, and sector) were included in all regression models. None of the control variables substantially altered the direction or significance of the hypothesised relationships. While digital literacy exhibited a weak positive association with AI acceptance, age was marginally negatively associated with both acceptance and satisfaction. Furthermore, gender and sector effects were non-significant across models.

Table 6 : Multiple linear regression results

Hypothesis	Independent variable	Dependent variable	β	t	p	R^2	Adjusted R^2	Supported
H1	AI efficiency	Satisfaction	0.52	6.81	<0.001	0.27	0.26	Yes
H2	Transparency & security	AI acceptance	0.48	5.94	<0.001	0.23	0.22	Yes
H3	Personalisation	Loyalty	0.61	8.20	<0.001	0.37	0.36	Yes
H4	Absence of human support	Satisfaction	-0.39	-3.12	0.002	0.15	0.14	Yes

Source: Authors' computation using SPSS (2025)

This is not a case against AI; it is a case for designing AI systems that know when to step aside. Together, these findings suggest that optimizing the AI-mediated customer experience requires more than transactional efficiency gains; firms must systematically maintain trust, transparency, and human reassurance within critical interactions.

Discussion of Findings:

Four patterns stand out from the data, each worth unpacking on its own terms. The satisfaction result is the least surprising, but also the most practically important: 72% of respondents believe that AI is associated with faster speed and better quality of customer service. Chen & Prentice, (2024) suggest a similar point: in high-volume sectors like e-commerce and telecommunications, speed and availability are no longer differentiators, but expectations. AI-mediated services are perceived as meeting those expectations more consistently in this sample, and consumers notice.

The transparency finding is where things get more interesting: 60% of respondents believe algorithmic transparency is important when using AI software, and 48% are concerned about the privacy of their personal data. This is consistent with Siau & Wang (2018), who argued that technical performance is not enough – the system also needs a transparent, accountable and ethical framework to build trust.

The personalisation result was the strongest in the model, and arguably the most actionable: 80% liked receiving personalised recommendations from AI, and 55% said they would be more loyal to businesses that customise services to their needs. Lemon & Verhoef (2016) argued that personalisation appears to function not only through convenience but by creating emotional relevance. The data here supports that reading: consumers who feel recognised, stay.

The fourth finding is the one that should give practitioners the most pause. When asked about their biggest frustrations while interacting with AI-based services: 38% were frustrated because a human was not available, 50% said that AI does not always understand requests, and 62% would prefer a combination of AI and human support. These findings are consistent with Ameen et al. (2021) and Tussyadiah (2020) , who found that although AI is capable of performing repetitive tasks, it fails in many complex or emotionally charged environments. The message is not that AI fails; it is that AI alone is not enough. Consumers want the efficiency of automation and the reassurance of a human backup. Organisations that offer both are the ones most likely to retain them.Theoretically, the study extends existing AI customer experience literature in two ways. First, it demonstrates that frameworks traditionally developed in Western and East Asian contexts, particularly SERVQUAL, TAM/UTAUT, and trust theory, remain applicable within an emerging digital economy. Second, the findings suggest that human co-presence functions as a boundary condition of satisfaction in AI-mediated contexts. Although previous studies have highlighted the benefits of efficiency and personalisation, the present results demonstrate that the absence of human reassurance reduces satisfaction, even when AI performance is otherwise well-regarded. This highlights the need to conceptualise customer experience in AI environments not only as a technological outcome, but also as a relational and socio-emotional process.

Conclusion

The question driving this study was simple: when is AI associated with better service for customers in Morocco, and when does it fall short? Four constructs structured the inquiry: satisfaction, acceptance, loyalty, and transparency. Drawing on 350 valid responses, what emerged was less a verdict on AI than a set of conditions. It works when consumers can understand it, when it recognises them as individuals, and when a human remains within reach.

Every hypothesis found support in the data. Efficiency was positively associated with satisfaction, and transparency was positively associated with acceptance. Personalisation, which yielded the highest coefficient of the four variables, was positively associated with consumer loyalty. Stripping out human support, though, was negatively associated with satisfaction, and that result matters. It highlights the specific capabilities that full automation cannot yet deliver. What the findings point to is not a case for or against AI, but for a specific kind of AI: one that is honest about how it works, attentive to who it is serving, and smart enough to hand off when the situation calls for it. For Moroccan firms navigating a fast-moving digital landscape, that distinction has practical consequences. Hybrid models, not full automation, appear to be where customer experience holds up.

There are, however, specific questions that this study cannot address. The sample leans young, educated, and digitally confident, so the results probably say less about rural consumers, older age groups, or those with limited exposure to AI-powered services. A single survey also freezes perceptions at one moment in time; it cannot track how attitudes shift as AI systems improve or as consumers accumulate more experience with them. Although the two-item scale measuring the absence of human support is functional, a more fully developed instrument would offer the construct greater psychometric precision.

What comes next should involve probability-based samples, repeated measures, and a sharper focus on sector-level differences between e-commerce, banking, and telecoms. Structural equation modelling would also allow researchers to probe the mechanisms more carefully, particularly how digital literacy and prior AI experience shape the relationships observed here.

References

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548.

ANRT. (2024). Tableau de bord des indicateurs de l'internet au Maroc. Agence Nationale de Réglementation des Télécommunications. https://www.anrt.ma

Bahangulu, J. K., & Owusu Berko, L. (2025). Algorithmic bias, data ethics, and governance : Ensuring fairness, transparency and compliance in AI-powered business analytics applications. World Journal of Advanced Research and Reviews, 25(2), 1746–1763. https://doi.org/10.30574/wjarr.2025.25.2.0571.

Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185–216

Chen, Y., & Prentice, C. (2024). Integrating artificial intelligence and customer experience. Australasian Marketing Journal.https://doi.org/10.1177/14413582241252904

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

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping : An integrated model. MIS Quarterly, 27(1), 51–90.

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing : A multidisciplinary perspective. Journal of the Academy of Marketing Science, 48, 1–8. https://doi.org/10.1007/s11747-019-00711-4.

Haenlein, M., & Kaplan, A. (2021). Artificial intelligence and robotics : Shaking up the business world and society at large. Journal of Business Research, 124, 405–407. https://doi.org/10.1016/j.jbusres.2020.10.042.

Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Ivanov, S., & Webster, C. (2019). Economic fundamentals of the use of robots, Artificial Intelligence, and Service Automation in Travel, Tourism, and Hospitality. Robots, Artificial Intelligence, and Service

Automation in Travel, Tourism and Hospitality (pp. 39–55). Emerald Publishing. https://doi.org/10.1108/978-1-78756-687-320191002.

Kumar, B. R., Madhuri, A., & Shireesha, M. (2024). Digital marketing in the age of personalization : Strategies, trends, and ethical considerations. In Shodhcholistan : A multidisciplinary framework for sustainable development modeling (pp. 61–65). Multi Spectrum International Publications.

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

Mariani, M. M., Dwivedi, Y. K., Baabdullah, A. M., Haag, M., & Yan, G. (2024). Applications of generative AI and future organizational performance : The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. Technovation, 133, 103021. https://doi.org/10.1016/j.technovation.2024.103021.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. Journal of Retailing, 64(1), 12–40.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research : A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Prentice, C., Lopes, S. D., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty Journal of Hospitality Marketing & Management, 29(7), 739–756. https://doi.org/10.1080/19368623.2020.1722304.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. Cutter Business Technology Journal, 31(2), 47–53.

Sulastri, L. (2023). The role of artificial intelligence in enhancing customer experience : A case study of global e-commerce platforms. International Journal of Science and Society, 5(3), 451–457. https://doi.org/10.54783/ijsoc.v5i3.1257.

Tussyadiah, I. P. (2020). A review of research into automation in tourism : Launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism. Annals of Tourism Research, 81, 102883.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology : Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world : Service robots in the frontline. Journal of Service Management, 29(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119.