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ORIGINAL

Leveraging Digital Marketing and Artificial Intelligence to Assess Enhanced Customer Experiences

Aprovechando el marketing digital y la inteligencia artificial para evaluar la mejora de la experiencia del cliente

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ABSTRACT

Introduction: incorporation of Artificial Intelligence (AI) into Digital Marketing (DM) has changed customer engagement by providing a personalized and efficient way to give service and interact with customers. For all of these advancements, there is limited empirical research that has explored how AI-driven personalization, convenience, and service quality impact customer experience through trust.
Objective: this research uses a quantitative, survey-based research design to investigate how AI and DM influence customer experience.
Method: data is collected from 350 respondents that currently engage with an AI-enabled platform. Key constructs Perceived Personalization (PP), Perceived Convenience (PC), Customer Trust (CT), Customer Experience (CE) and AI-Enabled Service Quality (AESQ) were analyzed in this research.
Result: outcomes expose that PP (β = 0,34), PC (β = 0,28), and AESQ (β = 0,31) significantly influence CT, which in turn has a strong effect on CE (β = 0,62). The model explained that CT was 62 % and CE was 56 % variance, with statistical support of all hypothesis.
Conclusion: this analysis concludes that AI-integrated DM strategies provide a better customer experience primarily because of developing trust. There are implications that marketers find practical in designing trust-centered AI interactions to enhance overall satisfaction and loyalty.

Keywords: Artificial Intelligence; Digital Marketing; Customer Experience; Personalization; Customer Trust.

RESUMEN

Introducción: la incorporación de la Inteligencia Artificial (IA) al Marketing Digital (DM) ha cambiado el compromiso con el cliente al proporcionar una forma personalizada y eficiente de dar servicio e interactuar con los clientes. A pesar de todos estos avances, la investigación empírica que ha explorado cómo la

personalización impulsada por la IA, la conveniencia y la calidad del servicio afectan a la experiencia del cliente a través de la confianza es limitada.
Objetivo: esta investigación utiliza un diseño de investigación cuantitativo basado en encuestas para investigar cómo influyen la IA y la DM en la experiencia del cliente.
Método: se recogen datos de 350 encuestados que actualmente utilizan una plataforma basada en IA. En esta investigación se analizaron los constructos clave Personalización percibida (PP), Conveniencia percibida (PC), Confianza del cliente (CT), Experiencia del cliente (CE) y Calidad del servicio posibilitada por la IA (AESQ).
Resultado: los resultados exponen que PP (β = 0,34), PC (β = 0,28) y AESQ (β = 0,31) influyen significativamente en CT, que a su vez tiene un fuerte efecto en CE (β = 0,62). El modelo explicó que CT fue 62 % y CE fue 56 % varianza, con apoyo estadístico de todas las hipótesis.
Conclusión: este análisis concluye que las estrategias de DM integradas en IA proporcionan una mejor experiencia al cliente principalmente debido al desarrollo de la confianza. Existen implicaciones que los profesionales del marketing encuentran prácticas a la hora de diseñar interacciones de IA centradas en la confianza para mejorar la satisfacción general y la lealtad.

Palabras clave: Inteligencia Artificial; Marketing Digital; Experiencia del Cliente; Personalización; Confianza del Cliente.

INTRODUCTION

In today's hyper connected digital ecosystem, Customer Experience (CE) has become a key driver of business success.[1] With a growing number of competitors, and consumers becoming more selective, organizations are being asked to provide seamless, personalized, and captivating experiences across multiple digital channels.[2] Digital Marketing (DM) is the most comprehensive and versatile means of communicating with potential customers and influencing the development of consumer connections and how consumers can make sense of and understand brands.[3] Applications like Artificial Intelligence (AI) powered recommendations systems, chatbots, and sentiment analysis give businesses the ability to personalize experiences at scale, predict customer needs, and proactively triage and resolve problems, which in turn increases the customer experience.[4] AI and DM are coming together to shift CE from reactive to predictive and generic to hyper-personalized.[5] This shift is helping to improve customer satisfaction, as well as customer retention, operational efficiencies, and revenue creation. However, many organizations continue to have challenges measuring the impact of AI-enabled customer experiences and tying investments in technology to tangible outcomes.[6]

AI is being used in DM to improve client experiences. To identify issues and their effects on engagement and performance, the author of [7] examines the literature on the application of AI to improve customer experiences. Recommendation engines driven by AI have been effectively deployed by companies such as Amazon, Netflix, and Spotify, increasing engagement and conversion rates.[8] This forecast customer behavior and preferences to provide customized, personalized experiences that build loyalty and strike an equilibrium between mechanization and human communication, opening the entrance to a hyper-personalized future.[9] Predictive analytics and ML are important technologies that increase retention and engagement. New developments show that AI-driven marketing tactics have the potential to help SMEs increase sales and return on investment.[10]

According to the [11], the study investigates the connection between the use of AI and consumer pleasure while buying digitally. The data suggest that satisfied customers are driven by a renewed purpose, and that AI implementation improves customer loyalty and conversions. AI and digital advertising are transforming the consumer's experiences. Companies can improve customer happiness and loyalty by leveraging targeted advertising, interactive materials, and AI.[12] AI and ML are transforming advertising by facilitating the development of advanced algorithms and information management.[13,14,15,16]

In an era here AI is reshaping digital engagement, this research examines the ways in which AI-powered personalization, convenience, and service quality affect customer experience. This research creates and validates an empirical model that demonstrates the significant effect of the margin of AI-integrated marketing strategies on consumer loyalty and satisfaction.[17,18]

DEVELOPMENT

The integration of AI with DM strategies has transformed how brands interact with consumers, particularly in shaping meaningful customer experiences. The following illustrates the research hypothesis.

Personalization illustrates how digital content, recommendations, and services are personalized to individual users. AI technologies used in marketing use predictive algorithms and behavioral data analysis to deliver personalization. It has been suggested that increased personalization can enhance customer trust as it reinforces brand relevance and value.

H1: Perceived Personalization positively influences Customer Trust

Convenience refers to the ease, speed, and efficiency of interacting with AI-powered digital interfaces such as chatbots and automated support. Making access easier and less effortful adds to the user's comfort and perceived value of the brand experience. In this way, convenience reinforces trust in that brand and its supporting identity.

H2: Perceived Convenience positively influences Customer Trust

This construct captures the reliability, responsiveness, and effectiveness of AI-rich services. Users are reassured of their brand's competence and care from high service quality from AI tools, with reliability helping to establish trust through consistency and performance.

H3: AI-Enabled Service Quality positively influences Customer Trust

Trust relates to customers' willingness to rely on AI-enabled digital platforms with assurance and less uncertainty. Trust is like a psychological bridge from the functional performance of marketing tools to the emotional effect of the experience. A higher sense of trust increases total customer satisfaction and loyalty.

H4: Customer Trust positively influences Customer Experience

Customer trust is mediating the relationship between personalization and overall customer experience. Trust is a cognitive construct that is used to interpret and incorporate personalized experiences. The indirect effect indicates the process by which personalized experiences enhance experience via tailored moments that build trust.

H5: Customer Trust mediates the relationship between Perceived Personalization and

Customer Experience

AI-enabled service quality is perceived as trustworthiness, responsiveness, and performance from AI-driven digital services such as chatbots, recommendation systems, or assistants. This mediated pathway suggests a functional and psychological effect of perceived service quality on experience that relies upon trust to convert technical efficiency into positive emotional engagement.

H6: Customer Trust mediates the relationship between AI-Enabled Service Quality and Customer Experience

METHOD

Grounded in a data-driven approach, this research employed a structured, quantitative design to investigate the relationship between AI-integrated marketing strategies and customer experience.

Research Design

This analysis adopts a quantitative, cross-sectional research proposal to examine the relationships between DM constructs, AI-driven service dimensions, and customer experience. A theory-driven conceptual framework underpins the development of hypothesis, guiding empirical analysis. The design is structured to support hypothesis testing through astructural model, ensuring both causal inference and model validity.

Sampling and Data Collection

Data were collected through an online structured questionnaire distributed over four weeks via digital platforms, targeting consumers who had engaged with AI-enabled DM services in the past six months. A non-probability purposive sample system was used to ensure participants had relevant experience, resulting in 350 valid responses from a diverse pool including e-commerce and service app users. Inclusion criteria were applied to the selection process, which included respondents beingover 18 years of age and havinginteracted at least once with an AI-based feature such as a chatbot or recommendation system. Eligibility criteria were applied to exclude individuals if they did not have experience with AI, or were incomplete in their responses for data quality and construct relevance. The survey instrument was developed using validated scale items adapted from existing literature grounded in the Technology Acceptance Model (TAM), trust-commitment theory, and service quality frameworks. Constructs were measured using 5-point Likert scales.

Key Variables and Conceptual Frameworks

As AI continues to redefine the DM landscape, understanding the psychological and experiential responses of consumers becomes increasingly vital. This researchconceptual framework (figure 1) in which Perceived Convenience (PC), Perceived Personalization (PP), and AI-Enabled Service Quality (AESQ) act as core independent variables influencing Customer Trust (CT), the central mediating construct. CT is positioned as a relational mechanism that bridges service performance and emotional engagement, ultimately shaping the Customer Experience (CE), which serves as the dependent variable. The hypothesis (H1–H6) reflect both direct and indirect effects, allowing for the examination of mediating pathways that convert operational value into customer-centric outcomes.

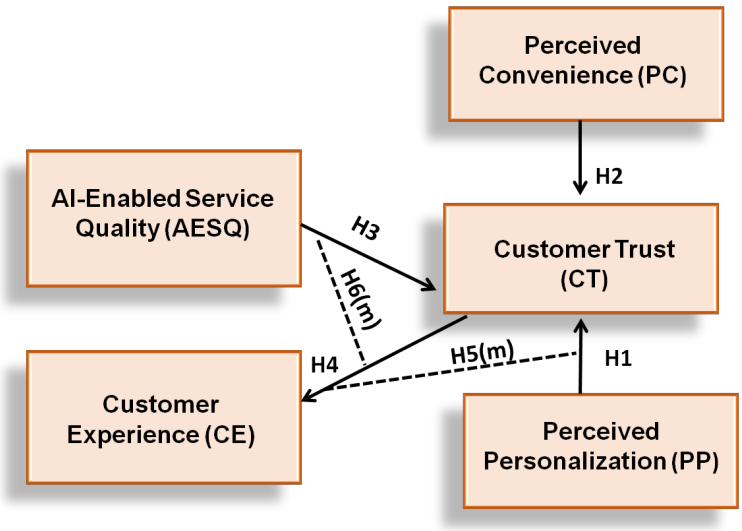

Figure 1. Conceptual Framework

Data Analysis

Data were initially cleaned and coded using IBM SPSS 26,0 to ensure accuracy and remove incomplete responses. Descriptive statistics were used to summarize demographic variables, while Smart Partial Least Squares (SmartPLS) 4.0 was employed for measurement and structural model analysis. Reliability, validity, and hypothesis testing were conducted through PLS-SEM using bootstrapping techniques. This combination ensured both statistical rigor and model validation.

RESULTS

Table 1. Demographic Characteristics of Participants (n = 350)

Characteristics	Category	Frequency (n)	Percentage (%)
Gender	Female	166	47,4 %
	Male	182	52,0 %
	Prefernottosay	2	0,6 %
Age Group (years)	18-24	102	29,1 %
	25-34	148	42,3 %
	35-44	65	18,6 %
	45 and above	35	10,0 %
EducationLevel	Undergraduate	112	32,0 %
	Postgraduate	178	50,9 %
	Doctorate	34	9,7 %
	Others	26	7,4 %
Occupation	Student	84	24,0 %
	Working Professional	206	58,9 %
	Self-employed	38	10,9 %
	Unemployed	22	6,2 %
FrequencyofAI-BasedInteraction	Occasionally	86	24,6 %
	Regularly	162	46,3 %
	Frequently	102	29,1 %
PlatformType	E-commercewebsites (Amazon, Flipkart)	138	39,4 %
	Mobile apps (fooddelivery, banking)	114	32,6 %
	Social media platforms (Instagram, WhatsApp bots)	68	19,4 %
	Others (companywebsites, kiosks)	30	8,6 %

By identifying key findings through empirical analysis, the results will first profile participants' demographics

and their experience with AI-enabled platforms. Strong reliability and validity scores supported the measurement model, while Heterotrait–Monotrait Ratio (HTMT) analysis confirmed distinct differences between constructs. The PLS-SEM approach identified structural paths, which indicated statistically significant relationships and confirmed all hypothesis with strong explanatory power.

Demographic analysis (table 1) is used to understand the composition of the respondents based on variables like age, gender, education, occupation, and AI interaction habits. This helps establish the representativeness and contextual relevance of the sample. The findings show that most participants are working professionals (58,9 %) aged 25–34, and the majority interacts regularly with AI-based platforms such as e-commerce websites and mobile apps. This indicates that the sample is well-aligned with digitally active consumers who are familiar with AI technologies, validating their suitability for this study's objective on AI and customer experience.

This analysis examined each construct's internal consistency (reliability) and convergent validity in terms of factor loading, Composite Reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Kaiser-Meyer-Olkin Measure (KMO). The factor loadings were above 0,80, CR and CA were above 0,70, and the AVE values were > 0,65 (table 2). This suggests that internal consistency and convergent validity were observed across constructs. The results simply indicate this model is statistically significant, again that all constructs are reasonably calculated reliably under the reliability of the model.

Table 2. Reliability and Validity of the Measurement Model

Construct	Item	Loading	VIF	Mean	CR	CA	KMO	AVE
PP	PP1	0,84	2,13	3,92	0,89	0,84	0,81	0,68
	PP2	0,85	2,25	3,87				
	PP3	0,81	2,08	3,95				
	PP4	0,82	2,12	3,88				
PC	PC1	0,83	1,95	4,01	0,88	0,81	0,79	0,65
	PC2	0,80	1,88	3,97				
	PC3	0,81	1,92	3,89				
AESQ	AESQ1	0,86	2,22	3,78	0,90	0,85	0,83	0,69
	AESQ2	0,85	2,30	3,74				
	AESQ3	0,84	2,27	3,80				
CT	CT1	0,87	2,15	3,91	0,91	0,86	0,84	0,72
	CT2	0,86	2,10	3,85				
	CT3	0,85	2,12	3,90				
CE	CE1	0,83	2,08	4,05	0,88	0,83	0,82	0,66
	CE2	0,82	2,04	3,98				
	CE3	0,81	2,01	4,02				

Note*:* All factor loadings exceeded 0,80, with CR > 0,88 and AVE > 0,65 for all constructs

Discriminant validity (table 3) ensures that each construct measures a concept distinct from the others. HTMT is a robust method for assessing this, with values < 0,85 indicating acceptable separation. All HTMT values in this table are below 0,70, confirming that constructs like PC, CT, and AESQ are not statistically overlapping. This assures that each construct in your model captures unique aspects of the AI-enhanced customer experience, reinforcing the model's structural integrity.

Table 3. Discriminant Validity (HTMT Analysis)

Constructs	PP	PC	AESQ	CT	CE
PP					
PC	0,63				
AESQ	0,58	0,61			
CT	0,66	0,62	0,68		
CE	0,61	0,59	0,64	0,70	

Note: All HTMT standards are under the threshold of 0,85. Grey cells indicate construct self-comparisons, which are not reported in HTMT values.

The PLS-SEM (figure 2) visually represents the hypothesized relations between key constructs in the research. Arrows indicate the directional paths tested using SmartPLS, highlighting the influence of PP, OC, and AESQ on CT and CE.

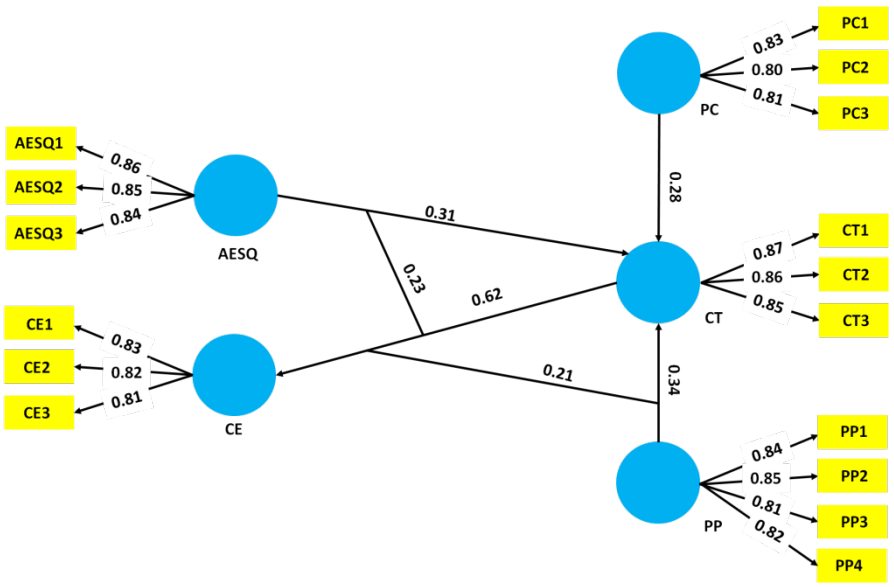

Figure 2. Structural Model

Structural model analysis tests (table 4) the hypothesized relationships between constructs, using path coefficients (β), t-values, p-values, R^2 (variance explained), and f^2 (effect size) to evaluate strength and significance. The findings show that all six hypothesis are supported with strong β values (e.g., CT → CE = 0,62), high t-values (> 4,8), and significant p-values (< 0,001). R^2 values for CT (0,62) and CE (0,56) are strong. These results indicate that PP, PC, and AESQ significantly influence CT, which in turn strongly drives CE, validating the model's theoretical and practical relevance.

Table 4. Structural Model Results with Hypothesis Testing

Hypothesis	PathRelationship	β	p-value	t-value	R^2	f^2	Result
H1	PP → CT	0,34	< 0,001	6,82	CT = 0,62	0,18	Supported
H2	PC → CT	0,28	< 0,001	5,97		0,15	Supported
H3	AESQ → CT	0,31	< 0,001	6,45		0,17	Supported
H4	CT → CE	0,62	< 0,001	9,88	CE = 0,56	0,34	Supported
H5	PE → CE (via CT)	0,21	< 0,001	4,89		-	Supported
H6	AESQ → CE (via CT)	0,23	< 0,001	5,32		-	Supported

Note: All hypothesis were statistically supported (p < 0,001). R^2 values indicate strong explanatory power, while f^2 values show medium to large effect sizes.

DISCUSSION

Previous research has explored the function of AI and DM in improving CE. Research [19] emphasized AI-driven content personalization in DM, demonstrating its impact on user engagement but without addressing trust as a mediating factor. Research [20] focused on AI-powered automation tools for SMEs, highlighting improvements in sales and retention, yet overlooked service quality and customer perception. Similarly, Author of [21] investigated DM strategies to improve engagement, but lacked focus on AI-enabled service constructs and behavioral drivers such as convenience and personalization.[22,23,24,25,26,27,28]

In contrast, this research integrates key experiential and trust-based variables, offering a more comprehensive framework. It identifies customer trust as a central mediator, linking AESQ features to enhanced CE. The use of PLS-SEM provides strong empirical support for the model.

CONCLUSION

As digital landscapes evolve, the synergy between AI and marketing strategies is redefining CE standards. This research uncovered how PP, PC, and AESQ influence CT, which in turn shapes overall CE. Using PLS-SEM, the model demonstrated strong explanatory power with 62 % variance in CT and 56 % in CE explained. All hypothesized relationships were statistically validated. While the findings offer meaningful insights, the research is limited to

a single-phase, self-reported dataset. Future research may explore cross-industry comparisons or incorporate emotional, ethical, or longitudinal variables to enrich the framework further and enhance generalizability.

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