DIGITAL TRANSFORMATION AND ADMINISTRATION INNOVATION

Citation: Seraj, N., Rousta, A., Asayesh, F., & Askari, A. (2025). Designing a Digital Marketing Model with an Emphasis on Artificial Intelligence in the Insurance Industry. *Digital Transformation and Administration Innovation*, 3(1), 1-12.

Received date: 2024-12-13 Revised date: 2025-02-13 Accepted date: 2025-02-24 Published date: 2025-03-01

Designing a Digital Marketing Model with an Emphasis on Artificial Intelligence in the Insurance Industry

Neda Seraj[1], Alireza Rousta[2*], Farzad Asayesh[2], Ahmad Askari[3]

1. Department of Business Management, Kish International Branch, Islamic Azad University, Kish Island, Iran
2. Department of Business Management, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran
3. Department of Business Management, Lamerd Branch, Islamic Azad University, Lamerd, Iran

*Correspondence: alirezarousta@yahoo.com

Abstract

The present study aims to design a digital marketing model with an emphasis on artificial intelligence in the insurance industry. This research falls within the category of mixed-methods studies (qualitative and quantitative). The qualitative strategy employed is the grounded theory method, and the quantitative strategy is survey-based. The qualitative population includes 20 experts and managers from the insurance industry, while the quantitative section encompasses all managers and employees in the insurance sector. In the quantitative part, a non-random convenience sampling method was used, and the Cochran formula was applied to determine the sample size, resulting in the collection and analysis of 384 completed questionnaires. To assess the validity of the questionnaire, confirmatory factor analysis (CFA) was employed, and structural equation modeling (SEM) was used to test the research questions. In the qualitative phase, the data were analyzed using MAXQDA software and categorized into causal conditions, core phenomena, intervening conditions, contextual conditions, strategies, and outcomes. In the quantitative phase, using SmartPLS 3 software, two models—standard and significance models—were constructed. The path coefficient between causal conditions and the core phenomenon was 0.598 with a significance value of 7.644. The path coefficient between the core phenomenon and strategic factors was 0.635 with a significance value of 7.640. Additionally, the path coefficient between contextual conditions and strategic factors was 0.651 with a significance value of 8.021, and the coefficient between intervening conditions and strategic factors was 0.721 with a significance value of 9.458. Finally, the path coefficient between strategic factors and outcomes was 0.624 with a significance value of 8.450. These findings indicate that the components of the proposed executive model significantly and positively influence one another, and the overall model demonstrates a desirable level of fit.

Keywords: Digital Marketing, Artificial Intelligence, Insurance Industry

1. Introduction

In an era increasingly characterized by hyperconnectivity, digital transformation, and data-driven decisions, the integration of artificial intelligence (AI) into marketing has transcended trend status to become a strategic necessity. Particularly in industries with highly regulated, customer-sensitive, and data-intensive structures such as insurance, AI-driven digital marketing offers transformative potential. The insurance industry, traditionally conservative and reliant on manual processes, is now confronted with mounting pressures to innovate, personalize customer experiences, and compete with agile tech-based entrants. In this context, the convergence of digital marketing strategies and artificial intelligence tools has emerged as a pivotal pathway to achieving competitive differentiation, operational efficiency, and customer-centric service design (Alizadeh & Jalali Filshour, 2023).

The adoption of AI within marketing is not simply about automation—it represents a fundamental reconfiguration of how organizations understand and interact with their customers. AI technologies enable businesses to analyze massive volumes of structured and unstructured data, deliver personalized content, predict customer behavior, and optimize campaign effectiveness in real-time (Basit et al., 2024; Gupta et al., 2025). In particular, digital marketing models embedded with AI capabilities can enhance customer segmentation, automate content creation, and support interactive platforms that foster customer engagement (Tran & Ho, 2024; Triteos et al., 2024). The insurance industry, with its large transactional datasets and frequent touchpoints, is well-positioned to leverage these capacities for both personalization and predictive analytics (Masoudi, 2024).

At the heart of this transformation lies the shift toward data-centricity. The insurance sector's historical reliance on actuarial models and risk pooling provides a fertile ground for AI-based algorithms to thrive, especially when integrated into customer-facing marketing systems (Kamkankaew, 2024; Kharis, 2024). AI can empower insurers to analyze behavioral, contextual, and transactional data in real time, thus enabling hyper-personalized marketing campaigns and dynamically priced offerings. This strategic alignment is not only an operational enhancement but also a response to rising customer expectations in the digital economy (Fallah Noushabadi et al., 2024; George et al., 2024).

Empirical studies emphasize that personalization is a dominant driver of customer satisfaction and brand loyalty in the digital domain (Behera, 2024; Eshiett & Eshiett, 2024). AI facilitates this by allowing firms to anticipate needs, recommend products, and engage customers through preferred channels with customized messages (Singh, 2024; Suryathi & Mariani, 2024). In the insurance industry, such capabilities can translate into offering policy recommendations, risk-based premium models, or automated claim support. These services enhance not only the customer experience but also the efficiency of marketing operations, contributing to sustained competitive advantage (Arumugam et al., 2024; Kotha, 2024).

Theoretical advancements in the field have evolved toward post-human-centered models that explore the implications of algorithmic governance, predictive control, and machine-mediated marketing decisions (Torabi et al., 2024). While digital marketing once revolved around content strategy and SEO, AI introduces capabilities for dynamic decision-making, real-time feedback loops, and campaign optimization that redefine the marketer's role and strategic focus (Talha, 2025). As such, the focus has moved from reactive to proactive engagement—driven by intelligent systems capable of learning, adapting, and evolving (Tauheed et al., 2024).

Nevertheless, the integration of AI in marketing is not without its challenges. Issues related to algorithmic bias, customer data privacy, interpretability of models, and workforce displacement are significant concerns (Lyndyuk et al., 2024; Ponomarenko, 2024). In regulated sectors like insurance, compliance with data protection laws and ethical frameworks for automated decision-making must be carefully navigated. Moreover, the effectiveness of AI-based marketing strategies depends on the technological readiness, digital maturity, and cultural alignment within the organization (Alizadeh & Jalali Filshour, 2023; Jalali Filshour & Alizadeh, 2022).

One of the most transformative aspects of AI in marketing is the rise of intelligent automation, where cognitive technologies like natural language processing (NLP), computer vision, and machine learning converge with marketing platforms to create adaptive systems (Malenko, 2024; Ocak, 2024). These systems can autonomously adjust campaigns based on performance metrics, conduct A/B testing at scale, and manage cross-channel consistency in branding. In the insurance industry, such innovations are evident in AI-driven chatbots, automated onboarding processes, and smart policy recommendations based on real-time risk profiling (Nazari et al., 2024; Prameswaro et al., 2024).

Another critical dimension of AI-enhanced marketing is the integration of neuromarketing and affective computing techniques. By leveraging EEG-based analytics and emotion-detection algorithms, firms can refine their messaging and interface designs to optimize engagement and decision-making (Ghazvini et al., 2024). These capabilities are particularly relevant for insurance products, where trust, emotion, and perceived value significantly influence purchasing behavior. AI technologies allow marketers to simulate emotional resonance and align offerings with the customer's cognitive state, thereby increasing conversion rates (Kumar, 2025).

While the technological capabilities of AI are well-documented, their successful deployment in marketing requires a clear strategic framework, cross-functional collaboration, and continuous learning. Organizations must invest in upskilling teams, refining their data governance practices, and fostering a culture of experimentation and agility (Talha, 2025; Teng et al., 2025). In this regard, research highlights the importance of model calibration, iterative testing, and ethical foresight in developing sustainable AI-based marketing architectures (Arumugam et al., 2024; Ponomarenko, 2024).

In summary, the fusion of artificial intelligence and digital marketing has sparked a paradigmatic shift in how firms approach value creation, customer engagement, and operational agility. The insurance industry, long seen as conservative in its adoption of disruptive technologies, now stands at a critical juncture where AI-enabled digital marketing can serve as both a catalyst for transformation and a tool for resilience in volatile markets. Building on foundational studies and emerging empirical evidence, this research seeks to design a digital marketing model tailored to the structural, cultural, and technological contours of the insurance sector—guided by the strategic imperatives of personalization, automation, and intelligence

2. Methods and Materials

This study was conducted using a mixed-methods approach, incorporating both qualitative and quantitative methods. Initially, the research employed a qualitative method using interviews based on the grounded theory approach. The collected interview data were coded and analyzed to extract the research model. The grounded theory approach, as proposed by Strauss and Corbin, is one of the qualitative research methods used to analyze and interpret data. This approach enables researchers to generate new theories and concepts from collected data. In grounded theory, data collection and analysis occur simultaneously. Researchers may use interviews, observations, and documents, incrementally incorporating new data into their analyses. One of the central stages in this approach is data coding. Researchers divide the data into smaller segments, assign codes to each segment, and eventually use these codes to identify patterns and concepts.

The qualitative sample included academic experts, specialists, and managers actively engaged in the insurance and digital marketing industries. Data collection continued until theoretical saturation was reached. Gradually, the coding of interview transcripts and data analysis led to the categorization and synthesis of the findings. To ensure the validity and reliability of the research, the interview questions were validated by several experts. Lincoln and Guba emphasized the criteria of credibility, dependability, confirmability, transferability, and authenticity in evaluating qualitative studies. To achieve these standards, the following actions were taken: transcribing interviews, conducting continuous analysis alongside data collection, verifying the coding process by another expert to ensure its accuracy and to avoid subjective bias in the researcher's interpretation of grounded theory interviews. For qualitative analysis, MAXQDA 2020 software was used.

In the second phase, the extracted model was validated using the partial least squares (PLS) technique and based on the researcher-made questionnaire derived from the qualitative phase indicators. In the quantitative section, the statistical population consisted of all managers, employees, and staff in the insurance and digital marketing industries, with an unlimited population size. Using Cochran's formula, 384 questionnaires were distributed via convenience sampling. The collected data from the questionnaires were analyzed through exploratory factor analysis using SPSS 25 and SmartPLS software. The face validity of the questionnaire items was confirmed by a group of relevant experts. According to Table 1, the reliability of the items was calculated using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 1. Reliability and Validity of Research Variables

Construct	AVE	Cronbach's Alpha	Composite Reliability (CR)
Causal Conditions	0.609	0.894	0.895
Core Phenomenon	0.622	0.907	0.909
Contextual Conditions	0.611	0.723	0.725
Intervening Conditions	0.617	0.791	0.795
Strategic Factors	0.630	0.705	0.707
Outcomes	0.655	0.809	0.810

Cronbach's alpha and the composite reliability of all research variables were greater than 0.70, specifically exceeding 0.705, which indicates appropriate reliability for the study variables. Additionally, the results show that the AVE coefficients for all variables were above 0.50, suggesting acceptable convergent validity for the research constructs.

3. Findings and Results

The characteristics of the experts are presented in Table 2.

Table 2. Characteristics of the Experts

Variable	Variable Levels	Frequency	Percentage
Gender	Male	13	65.0%
	Female	7	35.0%
	Total	20	100.0%
Work Experience	Less than 10 years	2	10.0%
	11–15 years	2	10.0%
	16–20 years	2	10.0%
	21–25 years	5	25.0%
	26–30 years	7	35.0%
	Over 30 years	2	10.0%
	Total	20	100.0%
Age	31–40 years	2	10.0%
	41–50 years	11	55.0%
	51 years and above	7	35.0%
	Total	20	100.0%
Marital Status	Single	1	5.0%
	Married	19	95.0%
	Total	20	100.0%
Education	Master's degree and above	20	100.0%
	Total	20	100.0%

In this section, based on the interviews conducted with 20 experts, codes were identified through semantic and conceptual similarities. From the 20 conducted interviews, a total of 7,302 codes were extracted, as detailed in Table 3.

Table 3. Interview Code Frequencies

Number of Extracted Codes	Interviewee
324	Interview No. 1
347	Interview No. 2
383	Interview No. 3
324	Interview No. 4
412	Interview No. 5
436	Interview No. 6
390	Interview No. 7
328	Interview No. 8
409	Interview No. 9
388	Interview No. 10
371	Interview No. 11
372	Interview No. 12
52	Interview No. 13
304	Interview No. 14
409	Interview No. 15
304	Interview No. 16
353	Interview No. 17
347	Interview No. 18
307	Interview No. 19
342	Interview No. 20
7,302	Total

The extracted components from the qualitative phase used for developing the conceptual model are presented below.

Table 4. Extracted Codes from Interviews for Designing the Digital Marketing Model with Emphasis on Artificial Intelligence in the Insurance Industry

Paradigm	Selective Coding	Axial Coding	Open Coding
Causal Conditions	Technological Infrastructure	IT and digital infrastructure development	Access to cloud platforms, data security, information exchange speed
		Data processing capabilities	Server processing power, cloud computing, resource scalability
		Compatibility with emerging technologies	AI and IoT support, API compatibility
	Technological Innovation	AI tools implementation	Machine learning, NLP, recommender systems
		Integration of new technologies	CRM integration, systems convergence
		Big data utilization	Big data analysis, pattern extraction
	Digital Culture	Organizational digital mindset	Innovation tendency, openness to technology
		Continuous technological learning	Professional training, digital skills
		Employee participation in innovation	Technology suggestions, participation in projects
Core Phenomenon	Digital Transformation in Marketing	Optimization of the insurance user experience	UX design, service time reduction
		Designing digital insurance architecture	Integration of online insurance services
		Implementation of automation processes	Automated issuance, claims automation
	Artificial Intelligence in Marketing	Intelligent customer behavior analysis	Behavior prediction, segmentation
		Automated and smart content generation	NLP, personalized emails
		Insurance recommender systems	Smart suggestions based on data
	Digital Integration in Insurance	Convergence of marketing and CRM systems	Customer journey tracking
		Linking insurance data with AI	Machine learning + big data
		Organizational coordination in digital marketing implementation	Collaboration between tech and marketing teams
Contextual Conditions	Organizational Culture	Cultural alignment with digital transformation	Readiness for change, learning commitment
		Acceptance of innovative values	Positive attitude towards technology, digital creativity
		Organizational digital behavior	Inter-unit online interaction, system usage
	Managerial Structure	Senior management support	Budget allocation, leadership in digital transformation
		Facilitation of digital decision-making	Decision speed, policy transparency
		Training and empowerment	Training programs, digital literacy enhancement
	Legal and Economic Environment	Government incentive policies	Tech subsidies, legal support for InsurTech
		Data regulation and privacy	GDPR laws, data security
		Economic and digital stability	Investment security, sustainable digital growth
Intervening Conditions	Human Factors	Expertise in digital human resources	AI proficiency, expert recruitment, continuous training
		Behavioral readiness for digital transformation	Technology acceptance, tech motivation
		Technological cross-functional interaction	Team-based tech collaboration
	Customer Insight	Behavioral data analysis	Intelligent CRM systems, behavioral segmentation
		Trust in smart technologies	Trust in chatbots, use of automated systems
		Customer digital literacy level	App usage skills, familiarity with online services
	Environmental Challenges	Cybersecurity threats	Cyberattacks, data risks
		Macroeconomic fluctuations	Recession, inflation, exchange rate
		Legal and administrative barriers	Lack of tech guidelines, delay in permits
Strategies	Interactive Strategy	Content marketing and social media	Engagement rate, content sharing, personalized content
		Targeted digital advertising	Click-through rate, conversion rate, customer acquisition cost
		Direct interaction with customers	Chatbots, quick response, feedback forms
	Service Personalization	Customized insurance package design	Plan variety, data-based flexibility
		Data-based suggestions	Recommender algorithms, needs alignment
		Personalized digital experience	Flexible purchase journey, interactive product display
	Digital Brand Development	Branding through modern channels	Influencer marketing, creative campaigns

		Visual and communication identity development	Logo design, brand message consistency
		Creative digital campaigns	View rates, sales effectiveness
	Data Analytics	Smart analytics systems	Customer behavior dashboards, real-time data mining
		Predictive algorithms	Churn prediction, demand trends
		Data-driven decision-making	Using analytics in campaign design
Outcomes	Individual Outcomes	Positive customer experience	Satisfaction, loyalty, NPS
		Enhanced understanding of digital services	Use of online services, successful process completion
		Active customer engagement	Feedback rate, participation in channels
	Organizational Outcomes	Improved sales performance	Conversion rate, digital sales growth
		Sustainable competitive advantage	Market share, product differentiation
		Development of digital channels	Increase in online sales
	Cultural Outcomes	Increased trust in technology	Reduced resistance, information transparency
		Advancement of organizational digital culture	Employee participation, tech training
		Institutionalization of modern values	Adoption of new norms, digital decision-making
	Technological Outcomes	Innovation advancement in insurance	New AI-based products
		Use of intelligent systems	Error reduction, faster response
		Facilitation of futuristic technology development	Blockchain, insurance IoT

Following the expert interviews, the coding process was conducted. By the twentieth interview, no new codes were generated, and the extracted codes were repetitive.

Upon reaching theoretical saturation in the interviews, the qualitative data analysis was concluded. All processes and qualitative data analyses were performed using the MAXQDA 2020 qualitative data analysis software.

After developing the conceptual model, the quantitative section begins with an analysis of the demographic characteristics of the respondents who participated in the study and completed the questionnaire. The findings from the target group indicate that among the 384 participants, 56.3% (216 individuals) were male and 43.8% (168 individuals) were female. Of the respondents, 15.6% were under 30 years old, 40.9% were between 31 and 40 years old, and 30.5% were aged 41 to 50. Regarding educational attainment, 9.1% held a high school diploma, 29.2% had an associate degree, 38.3% a bachelor's degree, 21.9% a master's degree, and 1.6% held a doctoral degree. Additionally, 44.8% (172 individuals) were single, and 55.2% (212 individuals) were married. In terms of work experience, 27.6% had 11–15 years, and 10.9% had 1–5 years of experience.

To test the assumption of normality for the study variables, the one-sample Kolmogorov–Smirnov test was used. A significance level greater than 0.05 indicates a normally distributed variable; otherwise, the variable is non-normal. As shown in Table 5, all variables are non-normally distributed.

Table 5. Kolmogorov–Smirnov Test Results for Assessing Normality Assumption

Variables	Sample Size	Test Statistic	P-value	Result
Causal Conditions	384	0.103	0.000	Non-normal
Technological Infrastructure	384	0.113	0.000	Non-normal
Technological Innovation	384	0.111	0.000	Non-normal
Digital Culture	384	0.112	0.000	Non-normal
Core Phenomenon	384	0.162	0.001	Non-normal
Digital Transformation in Marketing	384	0.184	0.000	Non-normal
Artificial Intelligence in Marketing	384	0.139	0.000	Non-normal
Digital Integration in Insurance	384	0.118	0.000	Non-normal
Contextual Conditions	384	0.078	0.000	Non-normal
Organizational Culture	384	0.097	0.000	Non-normal
Managerial Structure	384	0.107	0.001	Non-normal
Legal and Economic Infrastructure	384	0.125	0.000	Non-normal
Intervening Conditions	384	0.186	0.000	Non-normal
Human Factors	384	0.114	0.000	Non-normal
Customer Insight	384	0.127	0.000	Non-normal
Environmental Challenges	384	0.202	0.000	Non-normal
Strategies	384	0.075	0.000	Non-normal
Interactive Strategy	384	0.084	0.000	Non-normal

Service Personalization	384	0.175	0.000	Non-normal
Digital Brand Development	384	0.192	0.000	Non-normal
Data Analytics	384	0.134	0.000	Non-normal
Outcomes	384	0.103	0.000	Non-normal
Individual Outcomes	384	0.150	0.000	Non-normal
Organizational Outcomes	384	0.116	0.000	Non-normal
Cultural Outcomes	384	0.176	0.000	Non-normal
Technological Outcomes	384	0.135	0.000	Non-normal

To evaluate the fit of the structural model, several criteria were employed. The first and most fundamental criterion is the significance of t-values. For a structural model to be valid, t-values must exceed 1.96 to be considered significant at the 95% confidence level. Standardized path coefficients were also used to assess model fit; these coefficients must be greater than 0.30 to be deemed acceptable at the 95% confidence level.

Another critical criterion involves discriminant validity, which assesses whether a construct shares more variance with its own indicators than with other constructs. Discriminant validity is considered acceptable when the AVE for each construct is greater than the squared correlations with other constructs. This is evaluated through a matrix containing both the square roots of AVE on the diagonal and inter-construct correlations in the lower left triangle. Discriminant validity is confirmed when diagonal values exceed those below them. The diagonal values are then replaced with the square roots of AVE, resulting in Table 6.

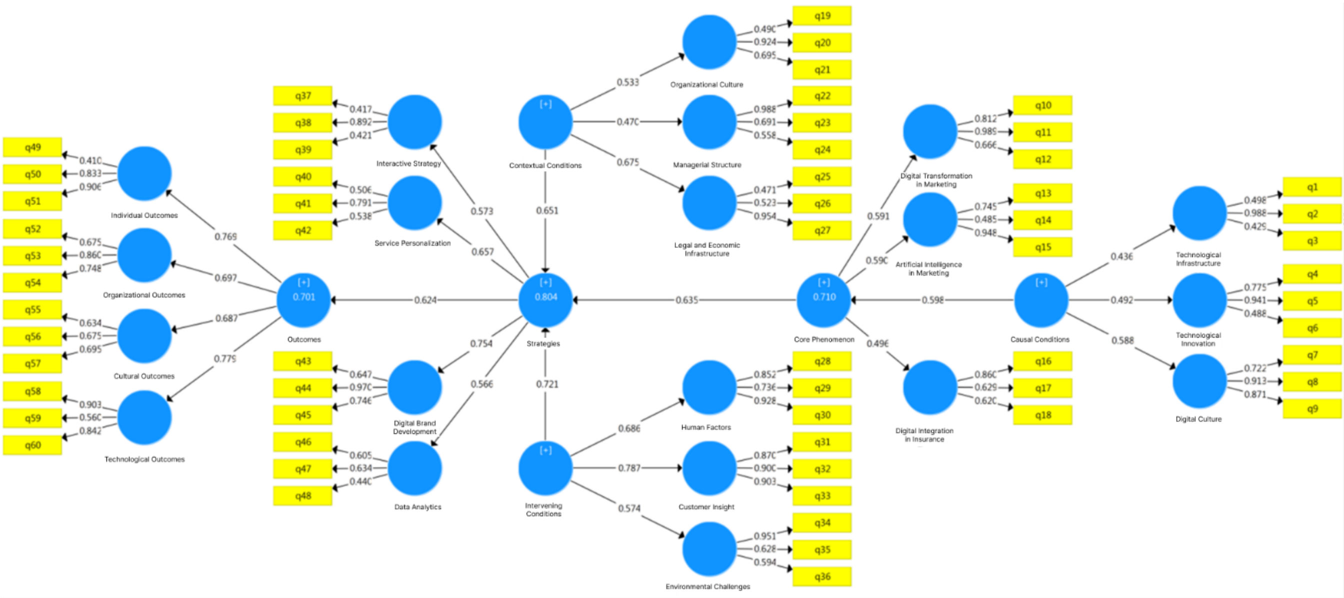
Table 6. Fornell and Larcker Method

Variables	1	2	3	4	5	6
Causal Conditions	0.563					
Core Phenomenon	0.544	0.559				
Intervening	0.539	0.533	0.543			
Contextual	0.518	0.525	0.511	0.526		
Strategies	0.512	0.520	0.509	0.503	0.511	
Outcomes	0.510	0.515	0.503	0.499	0.498	0.504

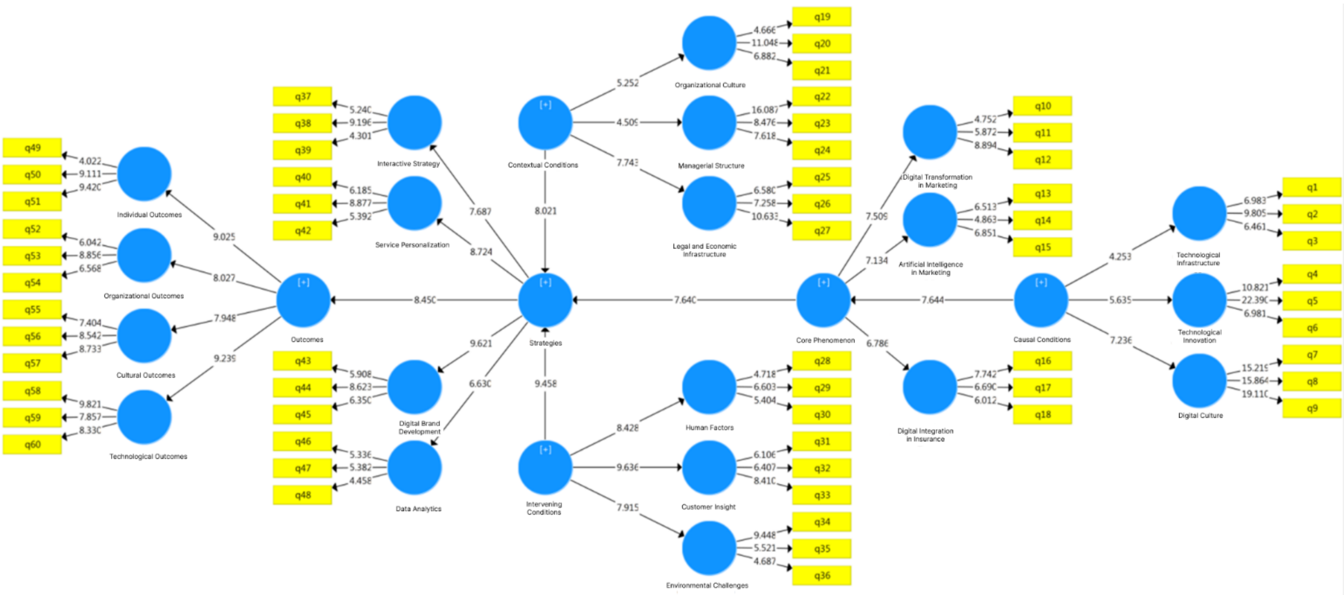
As shown in Table 6, based on the Fornell and Larcker (1981) method, the square roots of AVE values for latent variables, which appear on the diagonal, are greater than the inter-construct correlations below them. This indicates that the latent variables interact more strongly with their respective indicators than with other constructs, confirming acceptable discriminant validity.

Figure 1 illustrates the conceptual model of the study with path coefficients and outer loadings. This figure is the output of the PLS algorithm command, which is used to extract outer loadings and path coefficients. As shown, all items have outer loadings above 0.4, and therefore, no items were removed.

Figure 2 presents the conceptual model with t-values.



Figre 1. Model with Beta Coefficients



Figre 2. Model with T-Values

Moreover, the GOF (Goodness of Fit) index for the overall model is 0.50, which is greater than the threshold value of 0.53, indicating a strong model fit.

Table 7. Summary of Hypothesis Testing Results

Path	Path Coefficient	Standard Error	T Statistic	P-value	Test Result
Strategies → Outcomes	0.624	0.022	8.450	0.000	Accepted
Contextual Conditions → Strategies	0.651	0.062	8.021	0.005	Accepted
Causal Conditions → Core Phenomenon	0.598	0.014	7.644	0.000	Accepted
Intervening Conditions → Strategies	0.721	0.053	9.458	0.000	Accepted
Core Phenomenon → Strategies	0.635	0.053	7.640	0.000	Accepted

4. Discussion and Conclusion

The findings of this study confirm the significance and relevance of integrating artificial intelligence into digital marketing strategies within the insurance industry. In the structural model, all hypothesized paths were supported with high t-values and standardized path coefficients, indicating strong relationships among key constructs. Specifically, the path from causal conditions to the core phenomenon (digital transformation and AI integration in marketing) was both statistically significant and conceptually coherent, with a path coefficient of 0.598 and a t-value of 7.644. This suggests that elements such as technological infrastructure, innovation capacity, and digital culture are foundational in enabling AI-driven marketing transformation. These findings are in line with prior studies that emphasized the role of robust IT systems, adaptability to emerging technologies, and organizational digital maturity as enablers of AI adoption in marketing functions (George et al., 2024; Kamkankaew, 2024; Kharis, 2024).

The core phenomenon, defined as digital transformation in marketing through AI, was significantly influenced by strategic and operational elements. The relationship between the core phenomenon and strategic factors showed a high path coefficient of 0.635 (t = 7.640), indicating that effective implementation of AI in marketing directly contributes to the formation and success of personalized, interactive, and data-driven marketing strategies. This is strongly supported by previous studies highlighting that AI enables marketing departments to predict customer behavior, tailor messaging, and optimize campaign outcomes dynamically (Behera, 2024; Singh, 2024; Tran & Ho, 2024). These strategies, in turn, had a direct effect on outcomes such as customer engagement, organizational performance, and cultural readiness for AI integration. The empirical results resonate with the findings of (Fallah Noushabadi et al., 2024), who assert that the use of AI in marketing fosters personalization, improves brand trust, and accelerates service efficiency, particularly in customer-sensitive sectors like insurance.

Further, the influence of contextual conditions on strategic actions was also significant ($\beta = 0.651$, $t = 8.021$), reinforcing the role of organizational culture, management structure, and regulatory and economic environments in shaping AI-driven marketing frameworks. These contextual enablers act as both catalysts and constraints. For example, the commitment of top management and the provision of digital literacy programs serve to reinforce AI adoption, while regulatory limitations or economic instability might delay or distort its implementation. These observations confirm what (Torabi et al., 2024) described as the “post-human-centered marketing structure,” wherein organizational ecosystems must be agile and resilient to fully leverage the capabilities of AI. Similarly, (Masoudi, 2024) emphasized that for personalized strategies to be successful, cultural and leadership alignment is essential.

Intervening conditions also showed a strong and positive relationship with strategic factors ($\beta = 0.721$, $t = 9.458$), highlighting the moderating role of human factors, customer insight, and environmental threats. Digital competencies among employees, behavioral readiness for change, and customers' trust in AI-enabled systems appeared to be essential enablers. These findings align with research by (Eshiett & Eshiett, 2024) and (Teng et al., 2025), who pointed out that employee resilience and digital literacy are key determinants of successful AI integration in marketing practices. Moreover, the presence of environmental challenges such as cybersecurity threats or legal bottlenecks also affected the dynamics of strategy formulation, as reflected in the literature by (Ocak, 2024) and (Lyndyuk et al., 2024), who highlighted the dual role of external volatility as both a motivator for AI-based solutions and a barrier to their effective application.

The final link in the structural model between strategic factors and outcomes ($\beta = 0.624$, $t = 8.450$) was statistically significant and underscored the practical implications of the research model. Digital marketing strategies that included interactive campaigns, service personalization, and data analytics were shown to significantly enhance individual, organizational, cultural, and technological outcomes. This supports the argument made by (Gupta et al., 2025) that AI and IoT integration in retail and insurance not only improves service delivery but also elevates the entire customer experience. Similarly, (Basit et al., 2024) emphasized that AI-based product offerings promote sustainable marketing by responding to real-time data and shifting customer needs. Outcomes such as increased customer satisfaction, brand loyalty, innovation in product offerings, and greater efficiency in service channels validated the operational effectiveness of the proposed model.

The use of the Fornell and Larcker criterion to verify discriminant validity further validated the robustness of the research model. The square root of AVE values in the diagonal of the correlation matrix exceeded inter-construct correlations, confirming that each construct exhibited greater interaction with its own indicators than with others. This is consistent with standard model validation procedures recommended by (Ponomarenko, 2024) and implemented in similar empirical studies across financial and service sectors (Arumugam et al., 2024; Talha, 2025). Additionally, the model's GOF value of 0.53 surpasses the threshold for good model fit, corroborating its structural integrity.

Overall, the results demonstrate that AI-powered digital marketing strategies in the insurance industry are multidimensional and context-dependent. They rely on foundational technological and cultural factors, interact with dynamic human and environmental conditions, and translate into effective outcomes through strategically designed initiatives. The alignment of these findings with the extensive body of literature (Fallah Noushabadi et al., 2024; Ghazvini et al., 2024; Jalali Filshour & Alizadeh, 2022; Triteos et al., 2024) supports the theoretical and practical relevance of the model developed in this study. Importantly, the proposed model encapsulates a systemic understanding of how digital infrastructure, AI capabilities, organizational readiness, and market engagement mechanisms collectively enable a transformative shift in insurance marketing.

While the study presents a comprehensive framework for integrating AI into digital marketing strategies in the insurance sector, it has several limitations. First, the generalizability of the findings may be constrained due to the reliance on non-probability sampling and a sample restricted to specific segments within the insurance industry. The insights obtained from a single regional or national context might not fully reflect the diversity of regulatory environments, consumer behaviors, and technological infrastructure across international markets. Second, the research primarily employed cross-sectional data, which limits causal inferences. The dynamic nature of AI adoption and digital transformation requires longitudinal designs to capture evolving patterns. Third, although structural equation modeling (SEM) was used to test relationships among latent constructs, the study did not include multigroup analyses, which could have provided insights into moderating variables such as firm size, digital maturity, or customer segments.

Future studies could expand upon this work in several meaningful ways. Longitudinal research designs should be utilized to observe how AI adoption in digital marketing evolves over time and responds to shifting organizational and market contexts. Additionally, comparative studies across industries such as healthcare, banking, and education could validate or refine the model by accounting for sector-specific dynamics. It would also be valuable to incorporate behavioral experiments or field interventions that test the efficacy of specific AI-driven marketing tactics. Researchers are encouraged to explore ethical dimensions such as algorithmic bias, customer consent in data use, and AI transparency, especially in sensitive industries like insurance. Finally, integration of hybrid technologies—such as blockchain, IoT, and Web3—with AI-powered marketing could form an advanced line of inquiry in the future.

Organizations, particularly within the insurance industry, should prioritize foundational investments in digital infrastructure and cultivate a culture open to technological change. Executive leadership must champion AI integration as a strategic imperative rather than a technical upgrade, aligning cross-functional teams around a unified digital vision. Training programs to enhance digital literacy, customer insight analysis, and agile marketing methods are vital. Moreover, companies should adopt flexible and modular AI tools that can adapt to changing regulatory and market environments. Ultimately, success in AI-driven marketing lies in designing customer-centric, ethically sound, and data-informed strategies that enhance trust, improve service personalization, and support sustainable growth.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all who helped us through this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

Alizadeh, H., & Jalali Filshour, M. (2023). Proposing a Mixed Model of a Digital Marketing in the Financial Services Sector with an Emphasis on Artificial Intelligence Tools. *30th National and 11th International Conference on Insurance and Development*. https://www.sid.ir/paper/1086101/fa

Arumugam, T., Arun, R., Natarajan, S., Thoti, K. K., Shanthi, P., & Kommuri, U. K. (2024). *Unlocking the Power of Artificial Intelligence and Machine Learning in Transforming Marketing as We Know It*. IGI Global. https://doi.org/10.4018/979-8-3693-0049-7.ch005

Basit, S. A., Gharleghi, B., Rehman, A. U., Tee, P. K., Batool, K., & Nawaser, K. (2024). The Impact of Digital Products and Artificial Intelligence on Sustainable Marketing Methods. 1-24. https://doi.org/10.4018/979-8-3693-5668-5.ch001

Behera, R. K. (2024). Empowering Co-Creation of Services With Artificial Intelligence: An Empirical Analysis to Examine Adoption Intention. *Marketing Intelligence & Planning*, *42*(6), 941-975. https://doi.org/10.1108/mip-08-2023-0412

Eshiett, I. O., & Eshiett, O. E. (2024). Artificial Intelligence Marketing and Customer Satisfaction: An Employee Job Security Threat Review. *World Journal of Advanced Research and Reviews*, *21*(1), 446-456. https://doi.org/10.30574/wjarr.2024.21.1.2655

Fallah Noushabadi, M., Kazemi, V., Farahi, F., Raheb, A., & Mazouchi, M. (2024). The Role of Artificial Intelligence in Personalizing Marketing Efforts. *Strategic Research in Education and Training*, *28*, 361-369. https://en.civilica.com/doc/2153195/

George, W., Oliver, J., William, L., & Brown. (2024). *Exploring the Use of Artificial Intelligence in Personalizing Marketing Campaigns*.

Ghazvini, N. S., Nazari, E., Salleh, N. Z. M., & Baharun, R. (2024). The Role and Application of Artificial Intelligence in Neuromarketing Research Based on Electroencephalography (EEG). *International Journal of Academic Research in Business and Social Sciences*, *14*(12), 1556-1567. https://doi.org/http://dx.doi.org/10.6007/IJARBSS/v14-i12/24111

Gupta, R., Usman, M., Kashid, P. V., Mohan, M. L., Gaidhani, V. A., & Ghuge, M. A. R. (2025). Artificial Intelligence and IoT in Retail Marketing: Innovations in Smart Stores and Personalized Shopping. *Artificial Intelligence*, *5*(2). https://www.researchgate.net/profile/Mohammed-Usman-30/publication/390740662

Jalali Filshour, M., & Alizadeh, H. (2022). Presenting a digital marketing model based on artificial intelligence in the field of financial services with a data foundation approach. The First National Conference on Digital Transformation, Banking and Insurance, https://civilica.com/doc/1578810/

Kamkankaew, P. (2024). How Artificial Intelligence Is Helping Businesses Grow and Thrive: The Transformative Role of Artificial Intelligence in Thai B2C Digital Marketing. *Ijsasr*, *4*(1), 137-164. https://doi.org/10.60027/ijsasr.2024.3651

Kharis, S. A. A. (2024). Unveiling the Potential of Artificial Intelligence in Digital Marketing for Universitas Terbuka. *E3s Web of Conferences*, *483*, 03014. https://doi.org/10.1051/e3sconf/202448303014

Kotha, S. K. (2024). The Transformative Impact of Artificial Intelligence and Machine Learning on Marketing Operations. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, *10*(6), 176-182. https://doi.org/10.32628/cseit24106166

Kumar, P. (2025). Impact of (AI) Artificial Intelligence on Traditional Marketing. *Jier*, *5*(1). https://doi.org/10.52783/jier.v5i1.2286

Lyndyuk, A., Havrylyuk, I., Tomashevskii, Y., Khirivskyi, R., & Kohut, M. (2024). The Impact of Artificial Intelligence on Marketing Communications: New Business Opportunities and Challenges. *Economics of Development*, *23*(4), 60-71. https://doi.org/10.57111/econ/4.2024.60

Malenko, M. (2024). Integration of Artificial Intelligence With Web3 Technologies for Affiliate Marketing: Review and Analysis. *Pidvodni Tehnologii*, *1*(14), 62-70. https://doi.org/10.32347/uwt.2024.14.1205

Masoudi, M. (2024). Understanding the Role of Artificial Intelligence in Personalized Marketing Strategies. The 2nd International Conference on Sociology, Social Sciences and Education with a Future-Oriented Approach, Bushehr. https://civilica.com/doc/2037913/

Nazari, M., Heydarzadeh, A., & Mostasharnezami, I. (2024). Investigating the Acceptance of Marketing with Artificial Intelligence in the Hotel Industry (Kish Island Hotels). The 2nd National Conference on Marketing (New Approach), Mashhad. https://civilica.com/doc/2131597/

Ocak, A. (2024). Integration of Generative Artificial Intelligence With Emotional Artificial Intelligence in Marketing. 235-261. https://doi.org/10.4018/979-8-3693-6145-0.ch010

Ponomarenko, I. (2024). Artificial Intelligence in Digital Marketing. *Sf*, *155*(3), 58-70. https://doi.org/10.31617/1.2024(155)04

Pramesworo, I. S., Alijoyo, F. A., Judijanto, L., Setianti, Y., & Susanto, H. (2024). Analysis Of The Interaction Between Marketing Communication Strategies And Economic Factors In Consumer Decision Making: Integrating Microeconomic Perspective And Communication Theory. *International Journal of Artificial Intelligence Research*, *8*(1.1). http://ijair.id/index.php/ijair/rt/captureCite/1145/527

Singh, A. (2024). The AI Revolution: How Artificial Intelligence Is Reshaping Marketing Strategies. *Interantional Journal of Scientific Research in Engineering and Management*, *08*(04), 1-5. https://doi.org/10.55041/ijsrem31793

Suryathi, W., & Mariani, N. W. R. (2024). Revitalizing Marketing Strategies Through the Use of Artificial Intelligence: Analysis of the Effect of Personalization, Market Data Analysis, and Campaign Automation on Sales Conversions. *Escalate*, *1*(02), 101-108. https://doi.org/10.61536/escalate.v1i02.25

Talha, M. (2025). Optimizing Digital Marketing Campaigns Using Artificial Intelligence (AI) and Social Media Analytics: A Comparative Study of Machine Learning Algorithms. *Interantional Journal of Scientific Research in Engineering and Management*, *09*(03), 1-9. https://doi.org/10.55041/ijsrem42691

Tauheed, J., Shabbir, A., & Pervez, M. S. (2024). Exploring the Role of Artificial Intelligence in Digital Marketing Strategies. *Journal of Business Communication & Technology*, 54-65. https://doi.org/10.56632/bct.2024.3105

Teng, H. Y., Li, M. W., & Chen, C. Y. (2025). Does smart technology, artificial intelligence, robotics, and algorithm (STARA) awareness have a double-edged-sword influence on proactive customer service performance? Effects of work engagement and employee resilience. *Journal of Hospitality Marketing & Management*, 1-24. https://doi.org/10.1080/19368623.2025.2449853

Torabi, M. A., Milani, S. M. S., & Abbasian, E. (2024). A Critical Review of Post-Human-Centered Marketing Structures: Beyond Digital Marketing and Artificial Intelligence. *Intelligent Marketing Management*, *5*(3), 2-10. https://www.magiran.com/paper/2774350/a-critical-review-of-post-human-centric-marketing-structures-beyond-digital-marketing-and-artificial-intelligence?lang=en

Tran, M. T., & Ho, R. C. (2024). Utilization of Artificial Intelligence in the Digital Marketing Industry. 195-222. https://doi.org/10.4018/979-8-3693-5668-5.ch008

Triteos, C., Halkiopoulos, C., & Antonopoulou, H. (2024). The Influence of Artificial Intelligence on Social Media Marketing - A Conceptual Review. *ICCMI E-Proceedings*. https://doi.org/10.12681/iccmi.7590