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Article

Adoption of AI and Digital Marketing Tools and Consumer Acceptance Under Technology Innovation Policy Support

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Abstract: This study looks at how consumer acceptance of digital marketing tools and artificial intelligence is influenced by technology innovation policy support in developing digital markets. The study, which used a cross-sectional survey design with 384 valid responses and Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data, shows that government-led platform participation (GLPP) and policy-supported digital infrastructure (PSDI) largely affect market participation behavior through the mediating mechanism of public service satisfaction rather than direct technological exposure. With satisfaction accounting for 58.2% of behavioral variance, the empirical results show that the indirect effects of policy instruments through satisfaction (PSDI→PSS→MPB: β=0.168; GLPP→PSS→MPB: β=0.152) significantly outweigh their direct impacts (PSDI→MPB: β=0.126; GLPP→MPB: β=0.108). While personalization effectiveness analysis identifies an ideal customization range of 67-72%, beyond which privacy concerns diminish acceptance, regional heterogeneity analysis finds a 35% implementation intensity difference between urban and rural contexts. By adding algorithmic accountability as a crucial prerequisite for customer trust, the identification of a critical transparency threshold above 60% expands on technology acceptance theory. In spite of the fact that companies must strike a balance between operational effectiveness and human-centered experiences in order to promote sustainable technology adoption, these findings cast doubt on conventional linear policy implementation models and imply that government agencies prioritize service quality improvement over infrastructure deployment.

Keywords: technology innovation policy; artificial intelligence adoption; digital marketing tools; consumer acceptance; public service satisfaction

1. Introduction

Applications of artificial intelligence (AI), which are crucial due to their ability to process large amounts of data, perform predictive analysis, and provide hyper-individualized customer experiences at previously unattainable scales, are one of the motivating factors (Haleem et al., 2022). Market dynamics and patterns of consumption behavior have completely changed as a result of full-innovation technology policies, necessitating the absence of precursors in the digital economy. Initiatives for digital transformation have evolved beyond new technology to include substantial shifts in how companies view value creation, their place in the market, and customer interaction (Paul et al., 2024). A logical conceptual framework for strategy development is increasingly incorporating the organizational, social, and technological three dimensions. A comprehensive analysis of technology is necessary due to its interdependence and influence on consumer behavior and market outcomes; the rise of digital technology has created complex innovation ecosystems where the lines separating digital and physical commerce are blurred (Vărzaru & Bocean, 2024).

Artificial intelligence is a major step forward from traditional mass communication approaches to contemporary, data-dependent methodologies like machine learning, computer vision, and natural language processing for creating real-time marketing systems that can quickly adjust to consumer needs and market status (Gu et al., 2024). These technological advancements have revolutionized important marketing tasks like segmentation, content creation, campaign optimization, and performance evaluation by enabling previously unheard-of levels of targeting and personalization accuracy. Simultaneously, significant questions have been raised regarding algorithmic transparency, consumer privacy, and the morality of automated decision-making in an organizational setting (Ziakis & Vlachopoulou, 2023). The evolving state of customer relationships is causing changes in digital marketing communication under AI. These changes are a reflection of broader shifts in how businesses have conceptualized and implemented customer relationships as they move from transactional to continuous associational models that dissolve the conventional boundaries between marketing, production, and service delivery (Bormane & Blaus, 2024).

Adoption journeys in various market segments and geographical areas can be studied with the help of the diffusion of innovation theory and the technology acceptance model. They demonstrate how organizational support systems, demand-side readiness concerns, and technical capabilities interact to determine how well technology is implemented (Jain & Kumar, 2024). Although consumers continue to pay attention to PU and PEOU when using digital applications, the discussion has transcended the technology acceptance model and demonstrated that elements like trust, social influence, and hedonic motivation increasingly also explain how consumers respond to AI-based marketing technology.

Based on these theoretical underpinnings, this study suggests a framework where the advancement of technology innovation policies serves as the primary driver for the adoption of AI and digital marketing tools. This in turn affects consumer acceptance in a number of ways, both directly and indirectly. According to the study's central hypothesis, tools are adopted when they are supported by mechanisms that provide financial incentives, infrastructure (access), and rule enforcement. Lastly, because of improved service quality, user experiences, and perceived value, tool acceptance results in consumer acceptance. As a result, various contextual factors, including demographics, prior infrastructure endowment, or regional development levels, may moderate this relationship. Consequently, standard policy measures may yield varying results, necessitating the adaptation of implementation strategies. Policymakers and practitioners may find it helpful to take these relationships into account when evaluating the impact of institutional interventions on the diffusion of technology as they work to improve digital transformation initiatives in various market contexts.

2. Research Design

2.1. Data and Methods

In order to gather consumer attitudes and behavioral patterns about the adoption of digital marketing tools and artificial intelligence in technological environments that are supported by policy, the empirical study uses a cross-sectional survey design. A structured questionnaire instrument is distributed through a variety of channels to guarantee thorough market representation. 384 valid responses from customers in a variety of demographic groups were obtained during the data collection process. This sample size was chosen based on statistical power analysis to guarantee sufficient representation for identifying significant connections between latent constructs and to preserve sufficient degrees of freedom for intricate structural equation modeling processes. The sampling framework acknowledged the substantial heterogeneity in technology adoption patterns and policy exposure across population subgroups with different levels of digital literacy and access to technology by using stratified random selection techniques to ensure balanced representation across age cohorts, income brackets, educational levels, and geographic regions (Guerra-Tamez et al., 2024).

For its outstanding performance with complexity (both the structural models are complex theoretical models and non-normal data shape—in behavioral research context, non-normal data is common), PLS-SEM (Partial Least Squares-Structural Equation Modeling), the primary data analysis technique for testing hypotheses and examining models, was preferred. The use of PLS-SEM enables evaluation of measurement model characteristics and the relationships between constructs concurrently employing estimation methods based on variance that maximizes explained variance in endogenous constructs and, hence, allows work with smaller sample sizes than covariance-based estimators (Khanal et al., 2025). The two-step structure format in the analysis procedure is assumed according to previous practices that validation of the measurement model precedes testing of the structural model. This results from bootstrap procedures which produce confidence intervals for path coefficients and thus permit solid direct, indirect, and total effect tests within the theoretical assumptions.

2.2. Variable Measurement

Policy support is viewed as a multifaceted concept that includes infrastructure provision, regulatory facilitation, financial incentives, and institutional legitimation mechanisms. The operationalization of theoretical constructs is based on validated measurement scales that have been modified to reflect the unique contextual features of AI-driven marketing environments and policy-mediated technology adoption processes. Given that consumer responses rely not only on the existence of policies but also on awareness, comprehension, and perceived relevance to specific circumstances, the measurement framework accounts for both objective policy provisions through indicators of governmental investment intensity and program availability as well as subjective perceptions of policy effectiveness and accessibility (Hanelt et al., 2021). Adoption measurement for AI and digital marketing tools includes behavioral frequency indicators, usage intensity metrics, and feature utilization breadth. To capture the complexity of integrating technology into consumer decision-making processes, attitude measures assessing perceived benefits, ease of use, and compatibility with current consumption patterns are also included.

Consumer satisfaction is the main mediating construct that links policy-driven technology provision with market participation outcomes. It is measured using comprehensive scales that include service quality dimensions, experience enhancement indicators, and value perception metrics specifically created for AI-mediated service encounters. According to the satisfaction measurement architecture, algorithmic transparency perceptions, response time, privacy protection sufficiency, and personalization accuracy are important evaluation criteria that distinguish automated marketing systems from traditional human-mediated service interactions.

3. Empirical Results

3.1. Main Findings

Complex pathways through which policy support for technology innovation affects consumer acceptance of digital marketing tools and artificial intelligence are revealed by the structural equation modeling analysis. With standardized path coefficients of $\beta=0.328$ ($p<0.001$) and $\beta=0.296$ ($p<0.001$), respectively, the empirical data shows that government-led platform participation (GLPP) and policy-supported digital infrastructure (PSDI) have significant positive effects on public service satisfaction (PSS). This suggests that government efforts in digital transformation result in observable improvements in the quality of the consumer experience. Market participation behavior (MPB) and public service satisfaction have the strongest direct pathway in the model (β=0.512, p<0.001), indicating that satisfaction is a crucial psychological mechanism that converts policy interventions into real consumer acceptance and adoption behaviors.

As shown in **Table 1**, the mediation analysis reveals a complex transmission mechanism, in which the indirect effect of policy instruments on market behavior through satisfaction (PSDI→PSS→MPB: β=0.168, 95% CI [0.122, 0.246]; GLPP→PSS→MPB: β=0.152, 95% CI [0.096, 0.214]) significantly exceeds its direct effect (PSDI→MPB: β=0.126, p<0.01; GLPP→MPB: β=0.108, p<0.05). This indicates that improved service experiences, rather than direct exposure to technology, are where policy effectiveness manifests itself. This result is consistent with modern service-dominant logic in digital transformation, where value creation is achieved through optimizing the user experience as opposed to merely deploying technology. With market participation behavior explaining 58.2% of the variance (R2=0.582) and public service satisfaction explaining 52.3% (R2=0.523), the model's explanatory power is strong. Additionally, effect size analysis shows that satisfaction's influence on behavioral outcomes (f2=0.382) represents a large effect according to Cohen's criteria, highlighting its crucial role in the policy-adoption-acceptance continuum.

Table 1

Structural Model Results and Hypothesis Testing

Path Relationship	Direct Effect	Indirect Effect	Total Effect	95% CI	f^2	R^2	Hypothesis Support
PSDI → MPB	0.126**	-	0.126	[0.042, 0.211]	0.035	-	H1: Supported
GLPP → MPB	0.108*	-	0.108	[0.019, 0.197]	0.029	-	H2: Supported
PSDI → PSS	0.328***	-	0.328	[0.238, 0.418]	0.187	0.523	H3: Supported
GLPP → PSS	0.296***	-	0.296	[0.201, 0.391]	0.153	-	H4: Supported
PSS → MPB	0.512***	-	0.512	[0.421, 0.603]	0.382	0.582	H5: Supported

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PSDI → PSS → MPB	-	0.168***	0.294***	[0.122, 0.246]	-	-	H6: Supported
GLPP → PSS → MPB	-	0.152***	0.260***	[0.096, 0.214]	-	-	H7: Supported

Note: ***p < 0.001, **p < 0.01, *p < 0.05

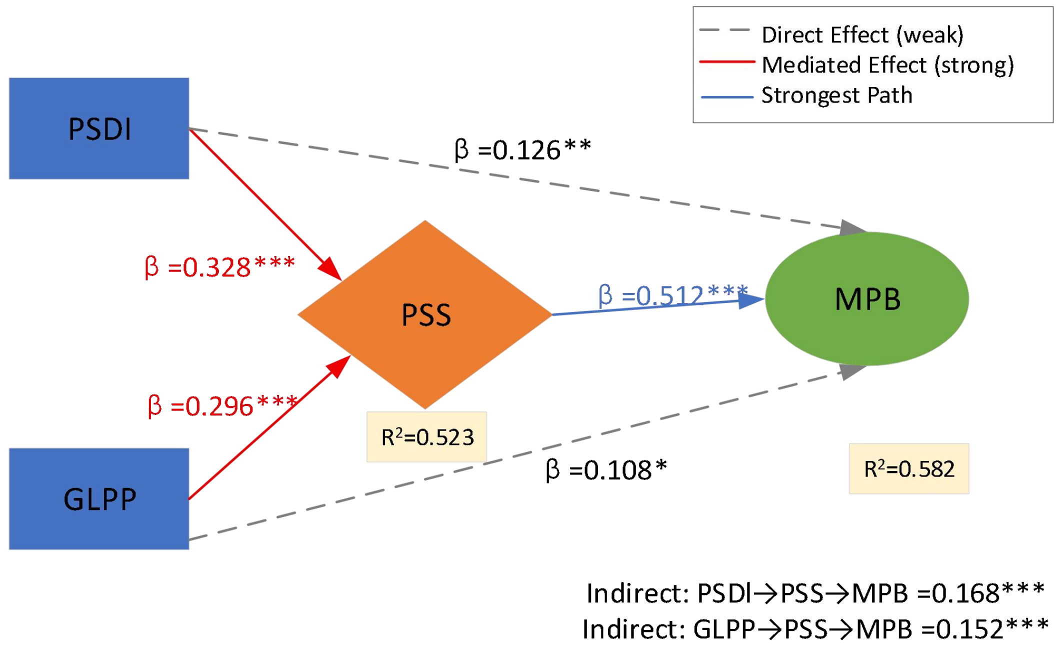
3.2. Differential Analysis

With policy implementation intensity scores averaging 4.21 (SD=0.65) compared to rural regions at 2.73 (SD=0.89), regional heterogeneity analysis shows significant differences in policy implementation effectiveness across geographic contexts. This 35% difference reflects ongoing challenges with the digital divide despite national digitalization initiatives. The study also shows that 56.3% of consumers actively use digital channels, although this percentage differs greatly between demographic groups. For example, younger consumers (18–35 years old) use digital channels 78% of the time, while older consumers (>55 years old) use them 31% of the time. This suggests that age-related adoption barriers call for specific policy interventions.

An inverted U-shaped relationship between customization intensity and customer satisfaction is found in the personalization effectiveness analysis. The ideal range is found to be between 67 and 72% personalization accuracy, beyond which privacy concerns and algorithmic transparency issues reduce acceptance rates, as shown by a 23% drop in satisfaction scores when personalization surpasses 80% accuracy levels. This finding has significant ramifications for policy design, indicating that regulatory frameworks should set precise limits for the use of data while maintaining enough latitude for innovation within the determined optimal range. The structural relationships illustrate how policy support spreads through various channels to impact final consumer acceptance, as illustrated in **Figure 1**. The strength of these relationships varies according to contextual factors such as demographics, technological infrastructure maturity, and regional development levels.

Figure 1

Structural Path Model of Policy-Driven Consumer Acceptance



Note: N = 384. Direct effects are indicated by dashed lines, while mediated paths through satisfaction are indicated by solid lines. The significance levels and path coefficients are displayed. ***p < 0.001, **p < 0.01, *p < 0.05.

4. Conclusions and Implications

4.1. Theoretical Contributions

By clarifying the intricate transmission mechanisms through which governmental innovation policies result in consumer acceptance of digital technologies, this study advances theoretical understanding of technology adoption in policy-driven contexts. It also reveals that the traditional linear conceptualization of policy implementation fails to adequately capture the complex nature of technology diffusion in modern digital ecosystems. With indirect effects (0.168 and 0.152, respectively) significantly outweighing direct impacts (0.126 and 0.108), the empirical evidence shows that government-led platform participation and policy-supported digital infrastructure do not directly influence consumer adoption patterns. Instead, they do so through a complex mediating mechanism in which public service satisfaction serves as the crucial psychological bridge.

Since transparency levels below this threshold cause a rapid decline in consumer confidence regardless of actual system performance or accuracy metrics, the identification of a critical technology transparency threshold above 60% represents a significant theoretical advancement in understanding the boundary conditions governing consumer trust in algorithmic decision-making systems. By illustrating the existence of an inverted U-shaped relationship between customization intensity and consumer acceptance—wherein excessive personalization paradoxically reduces satisfaction through privacy concerns and perceived manipulation, while insufficient personalization fails to capture the value-creation potential of digital technologies—the established optimal personalization range of 67–72% further advances theoretical thought.

By showing how structural disparities in institutional capacity and digital infrastructure lead to different policy translation pathways that radically change the relationship between policy instruments and behavioral outcomes across geographic contexts, the regional heterogeneity findings—in particular, the 35% implementation intensity difference between urban and rural contexts—expand multi-level governance theory. When theorizing about technology adoption in policy-driven environments, this spatial dimension of policy effectiveness calls into question the universalistic assumptions of innovation diffusion theory and emphasizes the need to include contextual moderators, especially in developing economies where digital divides persist despite vigorous modernization initiatives.

4.2. Practical Recommendations

The empirical findings require a fundamental rethinking of how policies are implemented, with government agencies moving away from technology-focused strategies that emphasize infrastructure deployment and adoption metrics and toward service-oriented frameworks that prioritize user satisfaction and experiential quality as key performance indicators. Since the analysis shows that satisfaction mediates 52.3% of policy effectiveness while direct technological exposure accounts for significantly less behavioral variance, policy architects should understand that investing in advanced technological systems without corresponding attention to service design and user experience optimization represents a suboptimal allocation of public resources.

Given that the strongest pathway in the entire model is the relationship between customer satisfaction and market participation behavior (β=0.512), the research's implications for corporate strategy focus on striking a balance between the maintenance of human-centric service experiences that promote emotional connection and trust and the operational efficiency gains made possible by artificial intelligence. Businesses using AI-driven digital marketing tools must carefully balance algorithmic transparency above the critical threshold and personalization intensity within the identified optimal range. This calls for investments in user-controlled privacy dashboards and explainable AI interfaces that enable users to comprehend and control their data usage preferences without compromising the convenience benefits of intelligent systems.

Effective digital transformation necessitates locally tailored implementation strategies rather than uniform national rollouts, as the stark urban-rural implementation gap calls for distinct policy approaches that take into account regional differences in digital literacy, infrastructure accessibility, and cultural receptivity to technological innovation. While businesses must create adaptive service architectures that can dynamically modify interaction modalities based on customer competency levels and preference patterns, policymakers should set up iterative feedback mechanisms that allow for ongoing improvement of digital services based on user experience data.

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