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Unlocking the promise of AI in personalized marketing: mapping the hidden barriers to adoption

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Abstract

Purpose – This study aims to examine the interdependent barriers impeding the effective adoption of artificial intelligence (AI) in personalized marketing. By integrating the technology–organization–environment (TOE) framework, the theory of planned behavior (TPB) and institutional theory, it develops a systems-oriented understanding of how technological, organizational, behavioral and ethical factors interact to constrain AI's strategic potential in marketing contexts.

Design/methodology/approach – A mixed, two-stage design was used. Ten barriers were identified through a structured literature review and validated via a Delphi process involving 33 domain experts. Subsequently, data from 187 professionals engaged in AI-driven marketing were analyzed using interpretive structural modeling (ISM) and MICMAC analysis to determine hierarchical re lationships, driving–dependence power and systemic dynamics.

Findings – The ISM hierarchy revealed eight structural levels, positioning infrastructure and cost constraints as root drivers and ROI uncertainty and ethical concerns as dependent outcomes. MICMAC results confirmed data quality, system integration, awareness and infrastructure as high-driving factors, while resistance to change and privacy concerns functioned as volatile linkages. The results demonstrate that technological readiness and AI literacy form the foundation for overcoming downstream governance and performance uncertainties.

Research limitations/implications – Given its cross-sectional and expert-dependent design, the study captures a temporal snapshot of AI adoption. Longitudinal and cross-sector research could further test the stability and contextual variation of the identified hierarchies, especially under emerging generative AI conditions.

Practical implications – Managers and policymakers should prioritize interventions targeting high-driving enablers – particularly data quality, infrastructure and workforce capability – while evolving adaptive ethical and regulatory frameworks. Emphasizing these foundational levers can enhance scalability, mitigate ROI risk and build stakeholder trust in AI-enabled personalization.

Originality/value – This research advances AI adoption and service innovation theory by reconceptualizing adoption barriers as a hierarchically interdependent system rather than discrete determinants. The integrated TOE–TPB–institutional model and ISM–MICMAC framework together illuminate how structural, behavioral and legitimacy factors co-evolve to shape responsible and scalable AI implementation in marketing ecosystems.

Keywords Artificial intelligence, Personalized marketing, Technology adoption, TOE framework, Barriers, ROI, Data privacy

Paper type Research paper

1. Introduction

Artificial intelligence (AI) has evolved from a technological novelty to a central component of hyper-personalized marketing, defined as the algorithmic tailoring of content, offers and experiences to individual consumers based on real-time data (Rafieian and Yoganarasimhan, 2023; Mehmood *et al.*, 2024). Personalized marketing refers to the dynamic adaptation of marketing content and offers to individual consumers using AI-driven analytics and behavioral data. Through the application of machine learning, natural language processing

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and predictive analytics, AI empowers marketers to decipher complex consumer behaviors, deliver context-specific content and automate real-time decision-making on a large scale (Huang and Rust, 2022; Kaartemo and Helkkula, 2025). Prominent market leaders such as Amazon, Netflix and Spotify exemplify how AI integration can enhance consumer engagement and generate measurable business value (Chen *et al.*, 2025; Lee *et al.*, 2024; Liu *et al.*, 2024). Despite its potential, the adoption of AI across firms remains inconsistent, hindered by a complex network of technological, organizational, ethical and infrastructural barriers that impede scalability and accountability (Booyse and Scheepers, 2024; Walke and Winkler, 2024).

Existing research has identified many of these barriers, yet often examines them in isolation, neglecting their systemic interdependence (Gupta *et al.*, 2025a, 2025b; Chandra and Rahman, 2024). In practice, high implementation costs, privacy risks and integration failures frequently stem from underlying issues such as poor data quality, insufficient skills and limited awareness (Rafieian and Yoganarasimhan, 2023; Elhajjar, 2025; Iman, 2024). Furthermore, ambiguity in return on investment and opacity in algorithmic decision-making undermine organizational confidence, while developing markets face additional challenges due to infrastructural deficits and evolving regulatory frameworks (Alhitmi *et al.*, 2024; Khan and Mishra, 2024). This systemic fragility is more pronounced in developing economies, where fragmented data ecosystems, inconsistent broadband infrastructure and evolving data-protection regimes magnify adoption asymmetries between global and local firms (Greiner *et al.*, 2025). However, prior studies have typically portrayed these barriers as discrete antecedents rather than as interlocking drivers within a systemic architecture. Little is known about how technological, organizational and ethical constraints interact hierarchically to amplify or mitigate one another – an understanding essential for advancing service-system design and managerial decision-making (Ostrom *et al.*, 2015; Gupta *et al.*, 2025a, 2025b; Mulcahy *et al.*, 2024). Consequently, the barriers to AI adoption are not merely discrete technical or managerial constraints but are components of a hierarchically interdependent system.

Addressing this gap necessitates a service-systems perspective that integrates structural, behavioral, and institutional determinants of technology adoption (De Cicco *et al.*, 2025). This study extends the technology–organization–environment (TOE) framework, the theory of planned behavior (TPB) and institutional theory to develop a comprehensive model that captures the co-evolution of readiness, intention and legitimacy in shaping AI diffusion within marketing contexts. Guided by this tri-theoretic foundation, the research uses interpretive structural modeling (ISM) and MICMAC analysis to examine the relational hierarchy among ten fundamental obstacles synthesized from prior literature and validated through expert assessment (Singh and Singh, 2025; Hamdi and Toumi, 2025; Balasubramanian *et al.*, 2025; Alkire *et al.*, 2024). The ISM–MICMAC approach was selected because it uncovers structural hierarchies and inter-barrier causality that conventional variance-based methods (e.g. PLS-SEM, regression) cannot capture. Preliminary insights suggest counter-intuitive dependencies – such as cognitive awareness preceding infrastructural maturity – highlighting why a systems-oriented analysis is essential for theory building in service innovation (Gupta *et al.*, 2025a, 2025b; Rafdinal *et al.*, 2025). These ten barriers encompass technological (e.g. data quality, integration, infrastructure), organizational (e.g. cost, skill, change readiness) and institutional (e.g. ethics, privacy, ROI uncertainty) factors that collectively determine the success or failure of AI-enabled personalization. By mapping the driving and dependent relationships among these barriers, this study advances AI-adoption theory beyond linear predictor models toward a systemic understanding of hierarchical causality. It contributes to the service-innovation literature by demonstrating how foundational enablers such as infrastructure and awareness propagate upward to influence higher-order outcomes like ethical compliance and perceived ROI (Gupta *et al.*, 2025a, 2025b; Kim *et al.*, 2025; Castaneda *et al.*, 2025). This shift from an additive to a hierarchically dynamic conceptualization not only enriches the TOE–TPB–institutional synthesis but also provides actionable pathways for managers and policymakers to accelerate responsible AI integration in marketing ecosystems (Walke and Winkler, 2024; Iman, 2024).

Accordingly, this research investigates:

RQ1. What are the key organizational, technological, ethical and infrastructural barriers that constrain effective AI adoption in personalized marketing?

RQ2. How do these barriers interact within a structured system, and what hierarchies emerge in terms of their influence and dependence?

RQ3. Which barriers function as foundational drivers and which emerge as outcome variables within the AI-adoption ecosystem?

RQ4. What strategic implications can be drawn for marketers, technologists, and policymakers aiming to enable responsible and scalable AI integration?

Collectively, these questions aim to reposition AI-adoption research within service-system theory by mapping the pathways through which technological readiness, behavioral intention and institutional legitimacy co-evolve. The paper proceeds by reviewing the theoretical underpinnings of AI adoption barriers, detailing the ISM–MICMAC methodology, presenting empirical results and discussing theoretical, managerial and policy implications. It concludes with limitations and directions for future research.

2. Theoretical background

This study uses an integrated theoretical framework that combines the TOE framework, TPB and institutional theory to elucidate the interdependent barriers impeding the adoption of AI in personalized marketing. Collectively, these perspectives elucidate how technological readiness, behavioral intention and legitimacy pressures collectively influence the dynamics of service innovation and organizational transformation (Booyse and Scheepers, 2024; Foroughi *et al.*, 2025; Alkire *et al.*, 2024). This integration advances extant adoption research by offering a cross-level explanatory framework that links structural readiness (TOE), behavioral intention (TPB) and institutional legitimacy (IT) within a single systemic model – a linkage rarely articulated in prior service-management literature (Walke and Winkler, 2024; Mehmood *et al.*, 2024).

The integration of these theories advances previous service-management research by conceptualizing AI not merely as a technological tool but as an enabler within a broader service ecosystem shaped by infrastructure, human cognition and institutional trust (Ostrom *et al.*, 2015; Lusch and Nambisan, 2015; Kaartemo and Helkkula, 2025; Chandra and Rahman, 2024).

The TOE model (Tornatzky and Fleischer, 1990) delineates technological, organizational, and environmental domains that affect innovation adoption. In this study, the technological context includes barriers such as data quality, system integration and infrastructure limitations that hinder scalability and personalization accuracy (Bauer *et al.*, 2024; Rafdinal *et al.*, 2025). Organizational constraints – such as resistance to change, skill deficiencies and high implementation costs – reflect internal capability gaps that obstruct AI assimilation (Chen *et al.*, 2025; Iman, 2024). The environmental dimension pertains to external ecosystem readiness and policy support that influence implementation success (Kumar *et al.*, 2025; Walke and Winkler, 2024). Thus, the TOE framework provides a structural lens for comprehending foundational enablers and system-level interdependencies that affect AI readiness in marketing services (Parasuraman *et al.*, 2021; De Cicco *et al.*, 2025).

Building upon this foundation, the TPB (Ajzen, 1991) elucidates the behavioral and cognitive precursors to technology utilization. Attitudes, perceived behavioral control and subjective norms are pivotal in determining whether individuals and teams convert awareness into an intention to adopt (Kim *et al.*, 2025). Resistance to change, limited awareness and concerns regarding ethics or privacy are indicative of negative attitudes or a diminished sense of control over AI outcomes (Teepapal, 2025; Greiner *et al.*, 2025). Within marketing organizations, collective perceptions of usefulness and risk not only influence employee intentions but also affect managerial endorsement of AI systems (Şenyapar, 2024; Castaneda *et al.*, 2025). Integrating TPB extends adoption theory beyond mere technical readiness to encompass behavioral readiness, which is essential for sustained AI utilization (Mehmood *et al.*, 2024).

Furthermore, institutional theory (DiMaggio and Powell, 1983) positions AI adoption within broader normative and regulatory contexts. Ethical and data-privacy challenges emerge from coercive and normative pressures – such as GDPR, CCPA and India's DPDPA – that necessitate compliance and transparency (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024; Khan and Mishra, 2024). Uncertainty regarding ROI further reflects institutional expectations for demonstrable, socially legitimate value generation (Torres *et al.*, 2025). Consequently, organizations must align internal capabilities with external legitimacy to maintain responsible AI practices in personalized marketing (Kabadayi *et al.*, 2023; Mulcahy *et al.*, 2024).

The convergence of these frameworks establishes a cascading logic: technological readiness (TOE) influences behavioral intention (TPB), which subsequently conditions institutional legitimacy pressures (IT). This tri-theoretic alignment facilitates a systemic understanding of how infrastructural deficits propagate into ethical and performance uncertainties, transforming independent barriers into hierarchical dependencies (Gupta *et al.*, 2025a, 2025b; Hamdi and Toumi, 2025; Liu *et al.*, 2024). Unlike earlier adoption models that treat factors as parallel antecedents, this study conceptualizes them as hierarchically interdependent, revealing how foundational enablers such as infrastructure, skills and awareness determine higher-order outcomes such as ethics and ROI (Rafieian and Yoganarasimhan, 2023; Masialeti *et al.*, 2024; Iman, 2024). By embedding AI adoption within a service-system perspective, the integrated TOE–TPB–institutional framework elucidates both the structural and behavioral mechanisms that govern the diffusion of AI-driven personalization in marketing. Table 1 below provides a clean conceptual crosswalk between constructs and theory, directly demonstrating how each barrier is theoretically grounded and will later be modelled in the ISM–MICMAC hierarchy.

By uniting these theoretical lenses, this study extends service innovation scholarship (Rodríguez *et al.*, 2025; Rabetino *et al.*, 2024) by shifting the analytical focus from variance to structure – from explaining how much barriers matter to how they propagate within the service system (Kaartemo and Helkkula, 2025; De Cicco *et al.*, 2025; Walke and Winkler, 2024). The following mapping reflects hypothesized causal direction, from foundational enablers to outcome-level constraints.

3. Literature review

AI has transformed marketing and service delivery by enabling hyper-personalized interactions and predictive engagement. Yet, its organizational diffusion remains fragmented, constrained by complex, interdependent barriers that span technological, behavioral and institutional domains (Booyse and Scheepers, 2024; Huang and Rust, 2022). The service-management literature stresses that technology adoption cannot be understood without considering its embeddedness

Table 1. Conceptual mapping of AI adoption barriers within TOE–TPB–institutional framework

Code	Barrier	Primary theoretical domain	Illustrative rationale
F1	Data quality issues	TOE – technological	Poor or biased data reduce personalization accuracy and system reliability, limiting technological readiness
F2	System integration issues	TOE – technological	Lack of interoperability between legacy and AI systems weakens infrastructure scalability
F3	Change resistance	TPB – behavioral	Negative attitudes and low perceived control impede behavioral intention to adopt AI
F4	Skill deficiency	TOE / TPB (organizational–behavioral)	Limited AI literacy constrains both organizational capability and user confidence
F5	Ethical concerns	Institutional – normative	Algorithmic bias and fairness concerns reflect external legitimacy and moral expectations
F6	ROI uncertainty	Institutional – cognitive/ coercive	Pressure for measurable outcomes creates institutionalized performance constraints
F7	Data privacy concerns	Institutional – regulative	Compliance with GDPR/DPDPA and societal trust requirements influences adoption legitimacy
F8	Limited awareness	TPB – cognitive	Lack of understanding lowers perceived usefulness and subjective norms supporting adoption
F9	High costs	TOE – organizational	Financial and resource constraints restrict innovation capacity and scalability
F10	Infrastructure limitations	TOE – technological	Inadequate computing power and connectivity inhibit AI deployment at scale

in service systems, value co-creation and customer-experience processes (Ostrom *et al.*, 2015; Lusch and Nambisan, 2015; Chandra and Rahman, 2024; Kaartemo and Helkkula, 2025). This section synthesizes prior research through the combined lenses of the TOE framework, TPB and institutional theory to provide a multilevel understanding of AI-adoption challenges in personalized marketing.

3.1 Technological and organizational barriers (TOE domain)

The TOE framework (Tornatzky and Fleischer, 1990) identifies the technological, organizational and environmental contexts shaping innovation adoption. Within personalized marketing, technological constraints – such as poor data quality, integration failures and inadequate infrastructure – impede scalability and personalization accuracy (Bauer *et al.*, 2024; Rafieian and Yoganarasimhan, 2023; Walke and Winkler, 2024). Fragmented databases and inconsistent metadata weaken AI learning models, limiting reliability in customer segmentation. Organizational barriers, including skill deficiencies, change resistance and high implementation costs, similarly hinder transformation (Chen *et al.*, 2025; Iman, 2024; Liu *et al.*, 2024). Limited AI literacy restricts experimentation and slows cross-functional coordination, while cost perceptions deter firms from moving beyond pilot projects (Elhajjar, 2025; Rafdinal *et al.*, 2025). These studies collectively indicate that technological readiness and resource adequacy form the structural foundation upon which higher-order behavioral and ethical concerns evolve. Recent works in service operations further highlight that such readiness directly influences perceived service quality and innovation effectiveness (Parasuraman *et al.*, 2021; Rodríguez *et al.*, 2025).

3.2 Behavioral and cognitive barriers (TPB domain)

Building on this structural base, the TPB (Ajzen, 1991) explains how attitudes, subjective norms and perceived behavioral control shape technology-use intention. In marketing contexts, resistance to change, limited awareness and risk aversion reflect negative attitudes toward automation and perceived loss of human judgment (Teepapal, 2025; Greiner *et al.*, 2025). Low confidence in data interpretation and fear of job displacement reduce behavioral intention to adopt AI solutions (Castaneda *et al.*, 2025). In emerging marketing environments, technological literacy – the cognitive understanding of AI's logic and interpretability – differs from operational confidence, which relates to the perceived ease of managing AI-enabled workflows. The latter often lags even among digitally skilled employees, amplifying the intention–behavior gap (Mehmood *et al.*, 2024). Studies in digital-service settings suggest that when employees and managers lack a sense of control or understanding, they underestimate AI's potential for improving service personalization (Şenyapar, 2024; Kim *et al.*, 2025). These findings reaffirm that cognitive misalignment mediates the link between organizational readiness and adoption behavior. Moreover, behavioral inertia often interacts with technological uncertainty: inadequate infrastructure amplifies skepticism about performance outcomes, thereby reinforcing TPB's premise that intention is bounded by perceived feasibility (De Cicco *et al.*, 2025).

3.3 Ethical, privacy and legitimacy barriers (institutional domain)

Institutional theory (DiMaggio and Powell, 1983) elucidates how organizations conform to coercive, normative and cognitive pressures to gain legitimacy. In AI-driven marketing, ethical concerns, data-privacy anxieties and ROI uncertainty mirror these external forces. Compliance with regulatory frameworks such as GDPR, CCPA and India's DPDPA compels firms to adopt conservative data-handling practices, sometimes constraining innovation (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024; Khan and Mishra, 2024). Simultaneously, societal expectations for transparency and algorithmic fairness create normative pressures for responsible AI (Kabadayi *et al.*, 2023; Mulcahy *et al.*, 2024). ROI ambiguity, frequently cited as an obstacle, reflects cognitive legitimacy demands from investors and top management who seek quantifiable, ethical returns on AI investment (Torres *et al.*, 2025; Alkire *et al.*, 2024). These institutional dynamics demonstrate that the barriers to AI adoption extend beyond technical feasibility to encompass moral, reputational and policy-driven constraints that condition organizational behavior (Gupta *et al.*, 2025a, 2025b; Rabetino *et al.*, 2024). These interlocking constraints illustrate the need for a systems approach that traces how technological deficits cascade into behavioral and institutional barriers.

3.4 Integrative insights and research gap

Across these domains, the literature converges on two key insights. First, barriers are not independent but sequentially connected: technological inadequacies foster behavioral hesitation, which amplifies ethical and ROI-related uncertainty (Gupta *et al.*, 2025a, 2025b; Huang and Rust, 2022). Second, extant research largely uses linear or additive models, overlooking the hierarchical interdependencies that characterize real-world adoption systems (Iman, 2024). Accordingly, a structural modeling approach such as ISM–MICMAC becomes essential for uncovering not merely correlation but the directional and hierarchical causality among interlinked barriers, offering a methodologically rigorous basis for intervention prioritization (Hamdi and Toumi, 2025; Balasubramanian *et al.*, 2025). Studies using PLS-SEM, TAM or TOE extensions capture variance but not causality among inter-barrier relationships (Masialeti *et al.*, 2024; Rodríguez *et al.*, 2025). As a result, managerial prescriptions often remain generic – calling for "training" or "investment" without identifying which levers yield the highest systemic impact. This conceptual fragmentation underscores the need for a structural modeling approach that reveals directional influence and dependency among barriers.

Accordingly, this study advances the literature by integrating TOE's structural readiness, TPB's behavioral intention, and Institutional Theory's legitimacy logic into a unified framework. Through interpretive structural modeling (ISM) and MICMAC analysis, it systematically maps ten validated barriers to uncover their hierarchical architecture and driving–dependence power (Singh and Singh, 2025; Hamdi and Toumi, 2025; Balasubramanian *et al.*, 2025). This integrative perspective extends service-innovation scholarship by reconceptualizing AI adoption as a co-evolutionary process linking infrastructure, cognition, and institutional alignment – offering a theoretically grounded and empirically transparent pathway for responsible, scalable AI implementation in marketing and service ecosystems (Rabetino *et al.*, 2024; Rodríguez *et al.*, 2025; Kaartemo and Helkkula, 2025).

4. Research methodology

4.1 Research design

This study employs a mixed exploratory–confirmatory design to systematically identify, validate, and structurally model the barriers impeding AI adoption in personalized marketing. A combination of ISM (Singh and Singh, 2025) and MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) (Hamdi and Toumi, 2025) was used to map interdependencies among ten critical barriers. ISM (Singh and Singh, 2025) was chosen for its ability to reveal multi-level, hierarchical relationships among complex variables, while MICMAC (Hamdi and Toumi, 2025) was applied to categorize these barriers according to their *driving* and *dependence* power. The ISM–MICMAC combination has been widely used in operations, service systems and digital transformation research (Singh and Singh, 2025; Hamdi and Toumi, 2025), but remains underutilized in AI-driven marketing contexts.

Ethical approval was granted by the Ethics Review Board of Amrita School of Business, Amaravati. All participants provided informed electronic consent, and the study adhered to the World Medical Association Declaration of Helsinki (2013) and standard ethical guidelines for research involving human participants.

4.2 Identification and validation of barriers

The research employed a dual-phase approach comprising a literature synthesis and expert validation. Initially, a systematic literature review was conducted to identify barriers frequently discussed in studies on AI marketing adoption, with a focus on service and technology contexts (e.g. *Journal of Service Research, Journal of Services Marketing*). Ten potential barriers were shortlisted based on their frequency, theoretical relevance (TOE, TPB, institutional theory) and empirical recurrence.

Subsequently, a Delphi-based expert validation was undertaken to confirm and contextualize these barriers. Thirty-three subject-matter experts were purposively selected from four regions in India (North, South, East and West) to ensure representational diversity. The panel consisted of marketing strategists, data scientists, digital consultants and AI solution architects, each possessing a minimum of five years of experience in implementing or evaluating AI systems in marketing.

The experts participated in two iterative Delphi rounds. In Round 1, participants refined and ranked the barriers; in Round 2, they reassessed their interrelationships and relevance after reviewing aggregated feedback. Kendall's coefficient of concordance ($W = 0.71$) indicated substantial agreement across rounds, demonstrating the reliability of expert consensus (Kumar *et al.*, 2025). The validated barriers are presented in Table 2.

Table 2. Description of barriers

Code	Barrier	Description
F1	Data quality issues	Incomplete, inconsistent, or biased data undermining personalization accuracy
F2	System integration issues	Lack of interoperability between AI systems and legacy infrastructure
F3	Change resistance	Organizational reluctance to adopt or trust AI systems
F4	Skill deficiency	Shortage of AI-literate marketing professionals
F5	Ethical concerns	Algorithmic bias, fairness, and manipulation concerns
F6	ROI uncertainty	Difficulty in quantifying AI's financial impact
F7	Data privacy concerns	Legal and consumer mistrust regarding personal data use
F8	Limited awareness	Low perceived relevance or understanding of AI benefits
F9	High costs	Significant implementation and maintenance expenditure
F10	Infrastructure limitations	Insufficient computing, storage, and connectivity resources

4.3 Delphi-based scoring and descriptive analysis

Experts assessed the perceived significance of each barrier using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). These assessments were used to calculate the mean, standard deviation, skewness and kurtosis, as summarized in Table 3. The rankings

Table 3. Summary statistics of identified barriers (Delphi stage)

No.	List of factors	Average score	Ranking	SD	Skewness	Kurtosis
F1	Poor data quality limits the effectiveness of AI in delivering personalized marketing	3.450	2	1.954	0.300	−1.168
F2	Incompatible systems disrupt the integration of AI into personalized marketing tools	4.390	8	1.903	−0.203	−0.939
F3	Resistance to change slows the adoption of AI in personalized marketing strategies	3.880	4	1.654	−0.192	−0.966
F4	Lack of skilled professionals hampers the use of AI in personalized marketing	4.300	7	2.201	−0.243	−1.434
F5	Ethical concerns reduce trust in using AI for personalized customer engagement	3.700	3	2.128	0.051	−1.471
F6	Uncertain return on investment discourages the use of AI in personalized marketing	4.670	10	1.708	−0.524	−0.370
F7	Privacy concerns restrict the use of personal data for AI-driven marketing	4.520	9	2.138	−0.339	−1.323
F8	Limited awareness about AI reduces its adoption in personalized marketing	3.940	5	1.853	0.000	−1.002
F9	High costs make it difficult to implement AI for personalized marketing	3.240	1	1.601	0.695	0.181
F10	Inadequate infrastructure limits the scalability of AI in personalized marketing	4.150	6	1.460	−0.664	0.089

indicate relative importance, thereby establishing a preliminary prioritization for ISM analysis. In addition, Table 4 presents the final sample profile for the study.

To test intra-panel reliability, ten experts re-evaluated their ratings after a two-week interval. An 89% consistency rate was achieved, confirming stable prioritization. Experts emphasized that the interaction between technological and behavioral barriers (e.g. F1–F3–F4) was especially critical to AI adoption success.

4.4 ISM methodology and process steps

Table 4. Final sample profile

Age range	Frequency	%	Cumulative (%)
25–35	91	48.7	48.7
35–45	56	29.9	78.6
45–55	36	19.3	97.9
55–65	3	1.6	99.5
65+	1	0.5	100
Total	187	100	
Do you currently work in an organization that utilizes AI-powered personalized marketing tools?			
AI tool usage	Frequency	%	Cumulative (%)
No	53	28.3	28.3
Yes	134	71.7	100
Total	187	100	
Are you involved in decision-making related to AI adoption in your organization?			
AI decision involvement	Frequency	%	Cumulative (%)
No	54	28.9	28.9
Yes	133	71.1	100
Total	187	100	
Your organization actively considering or has already adopted AI technologies in its marketing strategies?			
AI adoption status	Frequency	%	Cumulative (%)
No	46	24.6	24.6
Yes	141	75.4	100
Total	187	100	
Geographical region			
Region	Frequency	%	Cumulative (%)
East	51	27.3	27.3
North	27	14.4	41.7
South	95	50.8	92.5
West	14	7.5	100
Total	187	100	
Sector representation			
Sector	Frequency	%	Cumulative (%)
Banking	28	15	15
E-commerce	27	14.4	29.4
FMCG	13	7	36.4
Healthcare	34	18.2	54.5
Other	32	17.1	71.7
Retail	22	11.8	83.4
Technology	31	16.6	100
Total	187	100	

The ISM approach was implemented following the six-stage process developed by Warfield (1974) and subsequently refined for service and digital transformation research (Singh and Singh, 2025). Each step was adapted to the marketing technology context as follows:

(1) Variable identification: The ten validated barriers (F1–F10) served as system elements.

(2) Establishing contextual relationships: Experts defined pairwise relationships using the prompt: "Does barrier *i* significantly influence barrier *j* in the context of AI adoption for personalized marketing?"

(3) Structural self-interaction matrix (SSIM): Responses were translated into directional symbols – V (*i* influences j), A (*j* influences *i*), X (both influence each other), O (no relation). A minimum of 70% consensus determined directional coding. For instance, when 26 of 33 experts agreed that *Data Quality (F1)* influences *ROI Uncertainty (F6)*, the cell (F1, F6) was marked "V."

(4) Initial and final reachability matrices: The SSIM was converted into a binary matrix (1 = relationship exists, 0 = none). Transitivity was enforced using logical inference: if F1 → F2 and F2 → F6, then F1 → F6.

(5) Level partitioning: Barriers were grouped into hierarchical levels through iterative comparison of *reachability* and *antecedent* sets.

(6) Model formation: The final hierarchy was visualized as an ISM digraph, depicting directional flows of influence among barriers.

Pairwise comparisons obtained on a seven-point scale were converted into ISM directional symbols (V, A, X, O) following expert consensus thresholds (≥70% agreement). The SSIM table, Conversion process are shown in Appendix 1 Table A1. Appendix 2 Table A2 further shows the final reachability matrix.

4.5 Survey for cross-validation

To enhance generalizability and mitigate expert bias, a survey was conducted involving 187 marketing professionals across India, who were screened using two filter questions: (1) "Are you familiar with AI applications in personalized marketing?" and (2) "Have you implemented or been directly influenced by AI-based personalization in your professional role?"

The respondents represented sectors such as retail, IT, BFSI, manufacturing, and media, with 72% occupying managerial or technical positions. Approximately 28% of the initial respondents, who lacked direct AI experience, were excluded. Their responses were used to validate directional relationships from the ISM phase and to confirm the practical plausibility of each linkage. The cross-validation confirmed over 85% directional consistency, thereby strengthening the structural robustness of the ISM model.

4.6 Derivation of hierarchical levels

The final reachability matrix yielded eight hierarchical levels (Table 5). Foundational drivers such as *High Costs (F9)* and *Infrastructure Limitations (F10)* occupy the base, while *ROI Uncertainty (F6)* and *Ethical Concerns (F5)* appear as top-level dependent outcomes. This structure clarifies that financial, infrastructural, and data-related deficiencies propagate upward to affect organizational behavior, ethics and performance evaluation.

Table 5. Hierarchical levels of AI adoption barriers (ISM results)

Level	Barrier(s)	Functional category
I	ROI uncertainty (F6)	Outcome
II	Data privacy concerns (F7)	Compliance outcome
III	Ethical concerns (F5)	Governance outcome
IV	Limited awareness (F8)	Cognitive driver
V	Data quality issues (F1)	Technical foundation
VI	System integration (F2), change resistance (F3)	Structural/behavioral drivers
VII	Skill deficiency (F4)	Human resource constraint
VIII	High costs (F9), infrastructure limitations (F10)	Foundational enablers

This hierarchical formation reveals cascading influence – where infrastructural investments and workforce readiness enable better data systems, which in turn mitigate ethical, privacy and ROI challenges.

4.7 MICMAC analysis: driving–dependence classification

MICMAC analysis quantifies the driving power (how many variables a factor influences) and dependence power (how many variables influence it) of each barrier. These metrics categorize barriers into four quadrants: *autonomous*, *dependent*, *linkage* and *independent* factors. Table 6 shows the driver-dependence classification.

No autonomous barriers were identified, indicating that each variable actively contributes to the system's dynamics. The independent factors (F1, F2, F4, F8, F10) exert the most significant systemic influence and thus represent the most strategic points for intervention. Linkage factors (F3, F7, F9) exhibit both high driving and dependence power, indicating instability and necessitating continuous managerial oversight. Dependent factors (F5, F6) are symptomatic outcomes influenced by upstream deficiencies in data, skills and infrastructure.

4.8 Robustness, stability and validation

To evaluate the reliability of the ISM hierarchy, two validation methodologies were employed. Initially, a sensitivity analysis was performed by randomly modifying 10% of the pairwise relationships within the reachability matrix. The resulting hierarchy remained consistent, thereby affirming the model's stability. Subsequently, temporal reliability was assessed by requesting 12 experts to re-evaluate the SSIM after a two-week interval, which resulted in a 91% consistency in directional judgments. These procedures collectively

Table 6. Driving and dependence power of barriers (MICMAC results)

Code	Driving power	Dependence power	Zone	Managerial interpretation
F1	8	2	Independent	Foundational technical enabler
F2	7	3	Independent	Integration and compatibility driver
F3	6	6	Linkage	Volatile cultural friction point
F4	5	4	Independent	Human capital and competency base
F5	2	8	Dependent	Ethical and normative consequence
F6	1	9	Dependent	Performance uncertainty outcome
F7	6	6	Linkage	Privacy and compliance instability
F8	7	3	Independent	Awareness and attitude driver
F9	4	5	Linkage	Financial and scalability feedback
F10	8	2	Independent	Core infrastructural determinant

indicate that the model's structure is not a product of sampling bias but rather a stable representation of systemic barrier relationships.

4.9 Analytical tools and data handling

All descriptive analyses were executed utilizing SPSS 28, whereas the ISM and MICMAC computations were conducted in Microsoft Excel, following manual verification of transitivity and consistency rules. Figures were produced in MS Word to ensure visual clarity and adherence to standard journal graphical standards. Data from both the Delphi and survey phases were stored on encrypted institutional drives, accessible solely to the research team. Only aggregated, de-identified statistics were reported. This rigorous data management ensures methodological transparency, reproducibility and compliance with standard research integrity guidelines. The analytical outcomes of ISM and MICMAC collectively illustrate how foundational enablers cascade into outcome barriers. These visualizations (Figures 1 and 2) encapsulate the emergent system structure and managerial priorities.

Figure 1 presents the driver–dependence matrix, while Figure 2 visualizes the ISM hierarchy illustrating these interactions.

Arrows indicate directional influence (from driving to dependent barrier); arrow placement is purely illustrative and has no additional semantic meaning.

5. Discussion

This study investigated the complex barriers impeding the adoption of AI in personalized marketing. Utilizing ISM–MICMAC analysis, ten interdependent constraints were identified and modeled to elucidate their hierarchical interactions within the AI adoption ecosystem. The findings highlight that AI barriers function as a dynamic and cascading system, rather

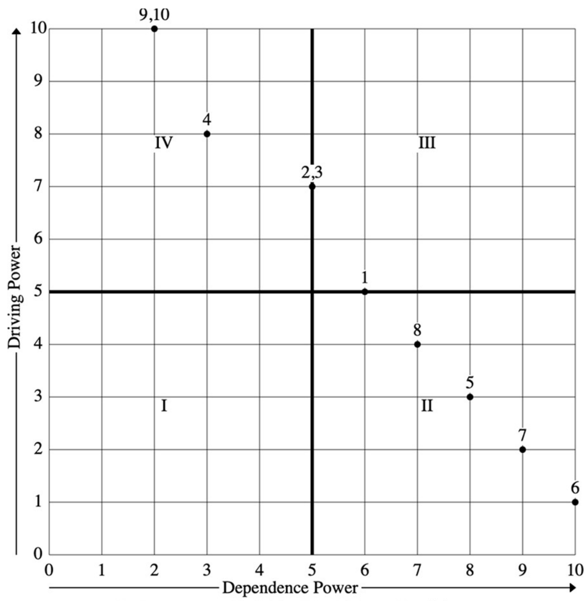

Figure 1. Driver–dependence matrix of AI adoption barriers (MICMAC output)

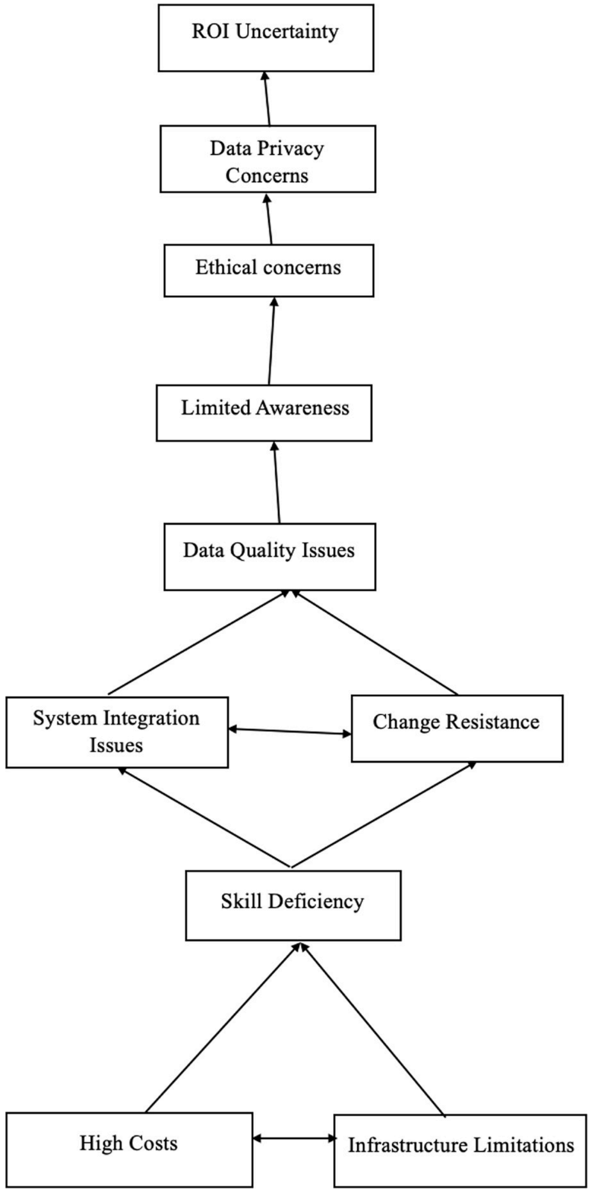

Figure 2. Hierarchical ISM model depicting multi-level interactions among barriers

than as isolated challenges, emphasizing the necessity for systemic rather than fragmented interventions.

5.1 RQ1 – identifying key barriers

Ten interdependent barriers were identified across four domains: technological (e.g. data quality, system integration), organizational (e.g. skill deficiency, change resistance), ethical (e.g. data privacy, algorithmic bias) and infrastructural (e.g. legacy systems, high costs). These findings align with previous studies (Booyse and Scheepers, 2024; Chen *et al.*, 2025) and corroborate the TOE framework, which posits that technological readiness and organizational capability collectively influence adoption (Tornatzky and Fleischer, 1990). Notably, the interactions between domains were critical: poor data quality exacerbated privacy and bias risks, while inadequate skills and resistance to change heightened concerns regarding cost and return on investment. This interdependence transcends the linear assumptions of the TOE framework, demonstrating that barriers evolve through reinforcing loops within a shared system of influence:

P1. Technological readiness – in the form of high-quality data and seamless system integration – acts as the foundational driver of AI adoption effectiveness in personalized marketing.

5.2 RQ2 – hierarchical interactions and structural dynamics

The ISM hierarchy delineated eight interconnected levels. Foundational constraints, such as high costs (F9) and infrastructure limitations (F10), constituted the base, while skill deficiency (F4) and system integration (F2) served as a bridge between operational capacity and behavioral adoption. At the apex, ethical concerns (F5) and ROI uncertainty (F6) emerged as dependent outcomes. This pattern corroborates institutional theory (DiMaggio and Powell, 1983): when infrastructural or technical readiness is deficient, external pressures – whether regulatory or societal – intensify internal uncertainty, thereby exacerbating ethical apprehensions and financial hesitancy. These cascading relationships demonstrate that infrastructural weaknesses and cost rigidity propagate upward, resulting in governance and perception issues rather than originating from them:

P2. Infrastructure limitations should be reframed as internal structural barriers – rather than external environmental factors – that critically constrain AI scalability and performance in marketing contexts.

5.3 RQ3 – foundational drivers versus outcome barriers

MICMAC analysis indicates that data quality (F1), system integration (F2) and limited awareness (F8) exhibit high driving power and low dependence, whereas ethical concerns (F5) and ROI uncertainty (F6) are characterized by high dependence. This suggests that technological and cognitive preparedness are pivotal in driving the entire adoption process. The identification of limited awareness as a primary driver supports the TPB, which posits that attitude formation and perceived control influence behavioral intention (Ajzen, 1991). Consequently, organizational transformation is contingent upon fostering AI literacy, which serves as the cognitive foundation preceding technical readiness (Teepapal, 2025; Şenyapar, 2024):

P3. Awareness of AI capabilities and implications functions as a primary antecedent that shapes both adoption intent and implementation effectiveness.

At the behavioral level, resistance to change and deficiencies in skills have emerged as intermediate constraints that diminish perceived behavioral control, in accordance with the attitudinal dimension of the TPB (Chakraborty *et al.*, 2025). The persistence of these factors generates organizational inertia, thereby impeding transformation despite investments in technology:

P4. Organizational inertia – manifested through change resistance and skill deficiency – negatively moderates the behavioral intention to adopt AI in marketing settings.

5.4 RQ4 – strategic and policy implications

In a strategic context, addressing significant barriers must take precedence over ethical considerations and return on investment (ROI) assessments. Organizations should prioritize investments in data governance, interoperable systems and workforce upskilling before anticipating measurable returns (Rafieian and Yoganarasimhan, 2023). Concurrently, policymakers are tasked with formulating balanced regulatory frameworks that foster innovation while ensuring accountability (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024). The prioritization hierarchy also varies according to firm size and data maturity. Small and medium-sized enterprises (SMEs), often limited by financial constraints and awareness, necessitate shared digital infrastructure and government-supported capacity-building initiatives. In contrast, large enterprises, which are typically technologically advanced, should focus on ethical AI design, algorithmic transparency, and cross-departmental governance. These hierarchical dependencies may vary by firm size – data-rich platforms face normative scrutiny earlier, whereas SMEs encounter infrastructural and cost bottlenecks.

Ultimately, the uncertainty surrounding ROI, frequently perceived as a primary deterrent, is revealed to be a dependent outcome rather than a fundamental cause. Deficiencies in infrastructure, data and skills contribute to financial ambiguity, which is further exacerbated by institutional demands for short-term returns (Torres *et al.*, 2025; Lee *et al.*, 2022):

P5. Perceived ROI uncertainty is an outcome barrier driven by technological and organizational deficits rather than an inherent flaw of AI itself.

By integrating the TOE, TPB and institutional perspectives, this study reconceptualizes AI adoption as a socio-technical-regulatory system wherein technological infrastructure (TOE), behavioral readiness (TPB) and legitimacy pressures (institutional theory) dynamically co-evolve. Ethical and privacy concerns are not external disruptions but rather endogenous outcomes exacerbated by internal governance deficiencies (Alhitmi *et al.*, 2024). This tri-theoretic synthesis advances previous models by revealing hierarchical interdependencies among barriers, drivers, linkages and outcomes, which form feedback loops that perpetuate adoption inertia (Hamdi and Toumi, 2025; Singh and Singh, 2025):

P6. AI adoption theory should evolve toward a systems-oriented model that acknowledges the hierarchical interdependence and dynamic role-switching among barriers across technological, organizational and institutional domains.

The findings and embedded propositions collectively affirm that the successful adoption of artificial intelligence in personalized marketing necessitates more than mere technical investment; it requires multi-level coordination encompassing infrastructure, cognition, behavior and governance. Addressing foundational drivers produces ripple effects that alleviate ethical and return on investment-related uncertainties. Consequently, this study provides both a conceptual bridge between fragmented adoption theories and a strategic roadmap for practice, demonstrating that responsible and scalable AI integration is contingent upon synchronized advancement across technological, human and institutional dimensions. These hierarchical dependencies may vary by firm size – data-rich platforms face normative scrutiny earlier, whereas SMEs encounter infrastructural and cost bottlenecks.

6. Implications for theory

This research contributes to the theoretical understanding of technology adoption and service innovation by reconceptualizing AI adoption in personalized marketing as a hierarchical, interdependent system, rather than a linear sequence of distinct determinants (Booyse and Scheepers, 2024; Gupta *et al.*, 2025a, 2025b). By integrating the TOE framework (Tornatzky and Fleischer, 1990), TPB (Ajzen, 1991) and institutional theory (DiMaggio and Powell, 1983), the study illustrates how technological infrastructure, behavioral readiness and institutional legitimacy co-evolve to influence the trajectory of AI integration. The resultant ISM–MICMAC framework shifts the focus from identifying barriers to understanding their interactions, thereby elucidating the causal architecture that either sustains or mitigates adoption inertia (Chadha *et al.*, 2023; Hamdi and Toumi, 2025).

6.1 Extending TOE with structural hierarchy

The findings extend the TOE framework by introducing a multi-level structural hierarchy of barriers (Gupta *et al.*, 2025a, 2025b; Masialeti *et al.*, 2024). Traditional TOE models treat technological, organizational and environmental domains as parallel antecedents of adoption; this study reveals their vertical ordering – where infrastructural and cost constraints trigger data and integration deficiencies, which in turn amplify ethical and ROI concerns (Rafieian and Yoganarasimhan, 2023). This reconceptualization positions TOE not as a static tripartite structure but as a dynamic cascade, in which lower-level enablers (infrastructure, data quality, skills) condition higher-order behavioral and institutional outcomes (Chen *et al.*, 2025; Lee *et al.*, 2022). The theoretical advancement lies in explaining why technology readiness failures propagate upward to normative and financial uncertainty, offering a processual lens to TOE theory (Bulchand-Gidumal *et al.*, 2024).

6.2 Enriching TPB with organizational behavioral loops

From a behavioral perspective, this study enhances the TPB by incorporating organizational inertia and AI literacy as structural moderators of perceived behavioral control (Chakraborty *et al.*, 2025; Teepapal, 2025). While TPB is traditionally applied to individual decision-making, the current model illustrates that collective perceptions – stemming from resistance to change, skill deficiencies and levels of awareness – shape firm-level behavioral intention (Şenyapar, 2024). In this context, adoption intention is reconceptualized as a distributed cognitive construct, mediated by competence networks rather than individual actors (Gupta *et al.*, 2025a, 2025b). This insight extends TPB's applicability from consumer or employee contexts to organizational technology adoption systems (Booyse and Scheepers, 2024).

6.3 Reinterpreting institutional theory within AI contexts

The findings further develop institutional theory by demonstrating that ethical and ROI considerations – typically perceived as externally imposed legitimacy pressures – are actually endogenous outcomes resulting from internal capability deficiencies (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024). Inadequate governance and substandard data infrastructure exacerbate vulnerability to normative scrutiny and societal mistrust, thereby illustrating a reverse-causality loop wherein internal preparedness influences external legitimacy demands

(Torres *et al.*, 2025). This challenges the conventional top-down institutional assumption and introduces a bidirectional interpretation of isomorphic pressure within emerging digital ecosystems (Singh and Singh, 2025).

6.4 Toward a systems-oriented model of AI adoption

Collectively, these insights advocate for a systems-oriented model of AI adoption in marketing, wherein barriers demonstrate hierarchical interdependence and alternate roles between drivers, linkages, and outcomes (Hamdi and Toumi, 2025). The ISM–MICMAC framework thus serves as a theoretical bridge between diffusion-of-innovation logic and complexity theory (Rafieian and Yoganarasimhan, 2023), elucidating why piecemeal interventions frequently fail in AI projects (Chadha *et al.*, 2023). It encourages future research to empirically test these hierarchical pathways using longitudinal and configurational methods (e.g. fsQCA, dynamic SEM), investigate sector-specific feedback loops and explore threshold conditions under which ethical or ROI concerns transition from dependent to independent roles (Lee *et al.*, 2022). In summary, this study's theoretical contribution lies in redefining AI adoption as a cascading socio-technical-institutional process (Booyse and Scheepers, 2024). It extends the TOE framework by incorporating structural sequencing, enriches the TPB through collective cognition, and reinterprets institutional theory as a reciprocal governance mechanism (DiMaggio and Powell, 1983). Collectively, these advancements provide a foundation for a next-generation theory of responsible and scalable AI adoption in marketing systems – one that encapsulates interdependence, feedback and hierarchy within an integrated systems framework (Gupta *et al.*, 2025a, 2025b; Masialeti *et al.*, 2024).

7. Implications for policy and practice

The findings of this study have substantial implications for policymakers, business strategists and marketing executives who aim to facilitate the responsible and scalable integration of AI in personalized marketing. The ISM–MICMAC framework reveals that foundational barriers, such as infrastructure limitations, data quality and high implementation costs, function as primary drivers, whereas outcome-level constraints – such as uncertainty in ROI, ethical risks and organizational reluctance – manifest as dependent consequences. Implementing this hierarchical understanding in practice necessitates systemic, anticipatory and multi-stakeholder interventions (Huang and Rust, 2022; Gupta *et al.*, 2025a, 2025b).

7.1 Digital infrastructure and ecosystem investment

To effectively address foundational barriers, it is imperative to implement a proactive digital infrastructure policy agenda. Collaborative investment by governments, industry consortia and development agencies in scalable, cloud-based AI infrastructure is essential to ensure accessibility for SMEs and firms in resource-constrained regions (Walke and Winkler, 2024; Rabetino *et al.*, 2024). Incentives such as AI-ready data centers, tax rebates for algorithmic innovation and public-private partnerships for computing resources can significantly lower initial entry barriers (Booyse and Scheepers, 2024; Chen *et al.*, 2025). The establishment of interoperable data-sharing standards, akin to open-banking frameworks, will improve data quality and facilitate secure cross-platform personalization (Gupta *et al.*, 2025a, 2025b; Rodríguez *et al.*, 2025). Furthermore, public grants aimed at ecosystem-level data curation and the development of shared model repositories can democratize access to high-quality, representative data sets (Iman, 2024).

7.2 Human capital and organizational capacity building

Mid-level linkage barriers, such as skill deficiencies and resistance to change, highlight the necessity for human-centric AI governance (Castaneda *et al.*, 2025). Capacity building should encompass more than just coding or analytics; it should incorporate algorithmic literacy, explainable AI (XAI) and ethical reasoning into business education and marketing curricula (Chandra and Rahman, 2024; Liu *et al.*, 2024). Policymakers, universities and industry alliances can collaboratively develop micro-credential programs and short-cycle certification pathways specifically designed for marketing and IT roles that require AI proficiency (Chakraborty *et al.*, 2025; Teepapal, 2025; Mehmood *et al.*, 2024). Organizations should implement AI-awareness workshops and cross-functional innovation labs to mitigate resistance, enhance trust and promote a collaborative mindset between data scientists and marketers (Kaartemo and Helkkula, 2025; De Cicco *et al.*, 2025).

7.3 Adaptive ethical and regulatory governance

Ethical and privacy-related challenges, identified as volatile linkage factors within the ISM model, necessitate the development of adaptive, sector-specific regulations (Mulcahy *et al.*, 2024; Khan and Mishra, 2024). Policymakers are encouraged to implement ethical AI standards that institutionalize transparency, conduct bias audits and establish consumer-consent protocols (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024). However, these regulations must remain flexible to adapt to advancements in generative AI, balancing the incentives for innovation with the need for accountability. Regulators might consider the establishment of "regulatory sandboxes," which would permit firms to test AI personalization under supervised ethical review prior to large-scale implementation. Such dynamic oversight would enhance consumer trust while mitigating the risk of stifling innovation (Kabadayi *et al.*, 2023).

7.4 Financial innovation and ROI risk mitigation

Given the emergence of ROI uncertainty as a significant outcome, it is imperative for economic policies to prioritize risk-sharing mechanisms to facilitate adoption. Governments and financial institutions might consider implementing performance-linked subsidies, AI deployment vouchers or outcome-based financing models to mitigate perceived investment risks (Torres *et al.*, 2025; Lee *et al.*, 2022; Rafdinal *et al.*, 2025). For private enterprises, integrating responsible-innovation metrics – such as compliance with ethical audits or transparency indices – into funding and procurement criteria can align financial incentives with accountability (Huang and Rust, 2022). Incorporating ROI evaluation frameworks within national digital-marketing strategies will assist firms in transitioning from pilot projects to sustained, value-driven adoption (Walke and Winkler, 2024).

7.5 Multi-stakeholder collaboration and knowledge governance

A robust AI ecosystem necessitates ongoing collaboration among technology vendors, marketing agencies, researchers and civil society actors. Multi-stakeholder forums should facilitate the co-development of context-aware AI solutions, the standardization of ethical personalization practices and cross-industry benchmarking of best practices (Masialeti *et al.*, 2024; Greiner *et al.*, 2025; Mehmood *et al.*, 2024). Shared learning platforms can disseminate successful use cases and reduce integration complexity. Such collective governance will enhance institutional legitimacy, minimize duplication of effort and sustain public confidence in AI-enabled personalization (Kaartemo and Helkkula, 2025; Rodríguez *et al.*, 2025).

7.6 Toward systemic and sustainable transformation

Adopting AI in marketing represents not merely a technical enhancement but a comprehensive transformation encompassing organizational, operational and institutional dimensions (Rabetino *et al.*, 2024). Policymakers are required to integrate these interventions – comprising digital infrastructure, human capability, ethical regulation, financial innovation and collaborative governance – within a systems-based policy framework (Gupta *et al.*, 2025a, 2025b). For firms, prioritizing investments according to a hierarchy of barriers – initially fortifying infrastructure and skills, followed by addressing ethical and financial outcomes – can optimize scalability and returns (Walke and Winkler, 2024). For governments, embedding these components within broader national AI initiatives will ensure that the advantages of AI-driven personalization are equitably distributed across sectors and regions (Iman, 2024). Collectively, these implications underscore that realizing the transformative potential of AI for value creation necessitates coordinated, multi-dimensional and sustained interventions across technological, human and policy domains (Rafdinal *et al.*, 2025; Kaartemo and Helkkula, 2025).

8. Limitations and future research

While this study provides significant insights into the hierarchical and systemic nature of barriers to AI adoption in personalized marketing, it is not devoid of limitations. Firstly, the employment of expert-based ISM and MICMAC inherently involves subjective interpretation, despite the mitigation of this risk through the Delphi procedure and subsequent survey validation ($n = 187$). Although the panel was diverse, encompassing domains such as retail, IT, BFSI and manufacturing, future research could benefit from expanding samples to include cross-country and cross-sector participants. This would enhance generalizability and capture variations in infrastructural maturity and regulatory environments (Singh and Singh, 2025; Hamdi and Toumi, 2025; Walke and Winkler, 2024). Comparative studies across developed and emerging markets could elucidate whether the same hierarchical configuration of barriers is globally persistent or varies with contextual maturity (Rabetino *et al.*, 2024; Rodríguez *et al.*, 2025).

Secondly, the study's cross-sectional design offers a static perspective on perceptions during a rapidly evolving technological cycle. Given the accelerated diffusion of generative and explainable AI (XAI), longitudinal studies could provide insights into the evolution of driving and dependent barriers – whether issues such as cost, data quality or ethical concerns stabilize or reverse over time (Booyse and Scheepers, 2024; Gupta *et al.*, 2025a, 2025b; Chandra and Rahman, 2024). Monitoring barrier transitions could also facilitate testing the temporal sequencing proposed in this study's hierarchical framework.

Thirdly, the model's causal assumptions remain theoretical rather than empirically validated. Future research could also triangulate ISM-MICMAC with configurational or longitudinal methods (e.g. fsQCA, dynamic SEM) to test hierarchical causality empirically (Torres *et al.*, 2025; Lee *et al.*, 2022; Liu *et al.*, 2024). Integrating ISM's structural mapping with predictive modeling would enhance both explanatory and confirmatory validity (Kaartemo and Helkkula, 2025). Fourth, while the current focus is on personalized marketing, expanding this systems-based approach to other AI-intensive domains – such as predictive customer analytics, conversational commerce, service robotics or dynamic pricing – could elucidate context-specific hierarchies of drivers and dependent constraints (Chen *et al.*, 2025; Masialeti *et al.*, 2024; Mehmood *et al.*, 2024). Future research could also investigate sectoral boundary conditions, particularly how SMEs, platform-based firms or data-scarce industries differ in overcoming foundational enablers such as skills and infrastructure (Iman, 2024; Rafdinal *et al.*, 2025). In addition, the rapid advancement of generative AI and XAI presents new challenges related to transparency, interpretability and bias mitigation that extend beyond conventional ethical frameworks (Alhitmi *et al.*, 2024; Kumar and Suthar, 2024; Khan and Mishra, 2024). Future studies should incorporate these emerging dimensions into updated barrier taxonomies and structural models, examining how algorithmic explainability, cognitive trust and regulatory agility interact as next-generation determinants of AI acceptance (Mulcahy *et al.*, 2024).

In summary, this study establishes a baseline model for understanding the hierarchical interdependence of AI adoption barriers in marketing. Future research should validate and extend this systems framework across time, context, and technology, integrating both quantitative rigor and ethical foresight to advance responsible, evidence-based adoption of AI in service and marketing ecosystems (De Cicco *et al.*, 2025; Kaartemo and Helkkula, 2025).

AI-assisted tools disclosure

This manuscript was checked for language clarity using *Paperpal*, an AI-assisted tool, limited to grammar and flow improvements in accordance with *Emerald Publishing's AI policy*.

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Appendix 1

Table A1. SSIM and conversion process

Structural self-interaction matrix (SSIM) Variables	1	2	3	4	5	6	7	8	9	10
Data quality issues		A	A	O	O	O	O	V	O	O
System integration issues			X	A	O	O	O	O	O	O
Change resistance				A	O	O	O	O	O	O
Skill deficiency					O	O	O	O	A	A
Ethical concerns						O	V	A	O	O
ROI uncertainty							A	O	O	O
Data privacy concerns								O	O	O
Limited awareness									O	O
High costs										X
Infrastructure limitations										

Mean/Consensus	*Symbol*	*Interpretation*
≥0.70 (*i* influences *j*)	V	Barrier *i* drives *j*
≥0.70 (*j* influences *i*)	A	Barrier *j* drives *i*
≥0.70 (mutual influence)	X	Both influence each other
<0.70	O	No direct relationship

Appendix 2

Table A2. Final reachability matrix

Variables	Final reachability matrix (FRM) 1	2	3	4	5	6	7	8	9	10	Driving power
Data quality issues	1	0	0	0	1*	1*	1*	1	0	0	5
System integration issues	1	1	1	0	1*	1*	1*	1*	0	0	7
Change resistance	1	1	1	0	1*	1*	1*	1*	0	0	7
Skill deficiency	1*	1	1	1	1*	1*	1*	1*	0	0	8
Ethical concerns	0	0	0	0	1	1*	1	0	0	0	3
ROI uncertainty	0	0	0	0	0	1	0	0	0	0	1
Data privacy concerns	0	0	0	0	0	1	1	0	0	0	2
Limited awareness	0	0	0	0	1	1*	1*	1	0	0	4
High costs	1*	1*	1*	1	1*	1*	1*	1*	1	1	10
Infrastructure limitations	1*	1*	1*	1	1*	1*	1*	1*	1	1	10
Dependence power	6	5	5	3	8	10	9	7	2	2	

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