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From Deplorability to ROI Evaluability: Expert Perceptions of AI-Enabled Capabilities in Digital Marketing, Armenia

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Abstract

Artificial intelligence (AI) is widely used in digital marketing and e-commerce, but its strategic value is often harder to prove than its operational usefulness. This tension is especially visible in small and emerging markets, where tool adoption may outpace measurement and governance capacity (Gama & Magistretti, 2023; Islam et al., 2024). The study adopts a capability-based and governance-oriented perspective on AI value in digital marketing management (Abrardi et al., 2021; Mariani et al., 2021). It examines how Armenian marketing experts evaluate four AI domains—predictive analytics, sentiment analysis, personalization, and programmatic advertising—and tests how these evaluations relate to perceived ROI-oriented impact, adoption outlook, and governance perceptions (Mariani et al., 2021; Haleem et al., 2022; Dumitriu & Popescu, 2020). A cross-sectional expert survey (N = 29) was used because objective performance data are limited and fragmented in this small-market context. The survey collected 5-point Likert ratings and one open-ended response on adoption barriers. Differences in perceived tool effectiveness were assessed using the Friedman test with Durbin–Conover post hoc comparisons. Hypothesized relationships were examined using Spearman correlations, supplemented by exploratory regression models. Personalization and programmatic advertising were rated highest in perceived day-to-day effectiveness, but only predictive analytics showed a clear positive association with perceived ROI-oriented impact. Perceived ROI-oriented impact was positively associated with adoption outlook. Governance perceptions were asymmetric: privacy concerns were negatively associated with adoption outlook, whereas bias/fairness concerns were positively associated with oversight/accountability expectations.

Open-ended responses identified weak measurement discipline, capability gaps, and poor strategic integration as the main barriers to realizing AI value. These findings imply that AI value realization in digital marketing depends not only on tool deplorability but also on measurement discipline, integration routines, and governance capacity. The study is limited by its small, non-probability, expert sample, perception-based measures, and cross-sectional design, so the findings should be interpreted as exploratory and context-bound. The study contributes to theory by distinguishing deplorability from ROI evaluability, and to practice by showing that AI value realization in small and emerging markets depends on measurement discipline, integration, and governance (Avram et al., 2020; Pop, 2020; Akter et al., 2023; Schmauder et al., 2023).

Keywords: *artificial intelligence; digital marketing management; e-commerce; consumer behavior analytics; Armenia; predictive analytics; personalization; programmatic advertising; perceived ROI impact; privacy; bias/fairness; AI governance; small and emerging markets context*

1. Introduction

Digital marketing increasingly relies on AI to support forecasting, targeting, personalization, and media optimization across the customer journey. In many firms, these tools are already part of everyday marketing work. Their presence, however, does not guarantee strategic value. AI becomes valuable when firms can connect its outputs to measurable decisions, integrate them into marketing routines, and govern their use effectively (Gama & Magistretti,2023; Islam et al., 2024). In strategic terms, AI-enabled marketing can be understood as a dynamic capability that helps firms sense consumer signals, seize market opportunities, and reconfigure marketing resources and decision routines. This matters because managers are not only deciding whether to use AI. They are also deciding where to invest, how to evaluate outcomes, and how to manage ethical risk.

In marketing and consumer behavior research, four application domains recur as core components of AI-enabled marketing: predictive analytics, sentiment analysis, personalization, and programmatic advertising (Mariani et al., 2021; Haleem et al., 2022; Dumitriu & Popescu, 2020). These capabilities are often associated with stronger engagement and improved conversion. However, their business impact depends on implementation maturity, especially the ability to connect AI outputs to observed outcomes through stable feedback loops, attribution routines, and lifecycle metrics (Nazir et al., 2022). Taken together, the literature suggests that AI tools may improve marketing execution, but their strategic value remains contingent on the quality of measurement, organizational integration, and responsible governance. This places the study at the intersection of consumer behavior analysis and digital marketing management. For practitioners, the problem is clear: AI tools may appear effective in day-to-day execution but remain difficult to validate as drivers of ROI when measurement discipline is weak.

This issue is especially relevant in small and emerging markets, where platform-driven adoption can outpace internal capability building. In such settings, fragmented data collection, uneven CRM integration, and limited analytics capacity may constrain ROI validation even when AI tools are actively used. This creates a distinction between deplorability—visible operational usefulness in execution—and ROI evaluability—the extent to which business impact can be credibly evidenced. From a process perspective, this reflects the difference between using AI for augmentation or automation and having the data and decision infrastructure required to make AI-supported choices auditable and performance-linked (Avram et al., 2020; Pop, 2020).

At the same time, wider AI use in marketing increases exposure to privacy, fairness, transparency, and accountability concerns. These concerns may shape trust and influence whether firms scale AI sustainably. In such contexts, expert perceptions become especially informative because objective firm-level evidence on AI-related performance is often fragmented, unevenly measured, or difficult to compare across organizations. Despite the growing literature on AI in marketing, empirical evidence remains limited on how practitioners in small or emerging markets evaluate the strategic value of AI across different application domains. Existing studies have focused mainly on technological possibilities and case-based success stories (Mariani et al., 2021; Haleem et al., 2022; Dumitriu & Popescu, 2020). Much less is known about how practitioners evaluate AI under constrained measurement conditions and how these evaluations relate to perceptions of adoption and governance. This gap matters because the link between perceived effectiveness and perceived business impact may vary across AI domains. It may also depend on whether firms have the measurement and governance conditions needed to validate AI-supported decisions in practice.

Accordingly, this study examines expert perceptions of AI-enabled marketing in Armenia. It assesses the perceived effectiveness of four AI domains and tests how these perceptions relate to (a) perceived ROI-oriented impact, (b) adoption outlook, and (c) governance perceptions, with particular attention to privacy concern, bias/fairness concern, and oversight/accountability expectations. Using a cross-sectional expert survey complemented by an open-ended barrier item, the study links tool-level judgments to the practical constraints that may prevent AI use from translating into measurable performance gains.

This study contributes to digital marketing management theory by clarifying how practitioners in a small-market context differentiate deplorability from ROI evaluability across AI domains under constrained measurement conditions. It contributes to practice by showing that governance concerns are not interpreted uniformly and that sustainable AI adoption depends on the strategic and organizational conditions needed for measurable, trusted value creation. These contributions are relevant to managers, agencies, and policy actors working in SME-dominant environments where AI adoption may advance faster than the organizational conditions required for accountable performance.

2. Literature Review

2.1 AI-enabled marketing as a capability value under small-market constraints

AI is increasingly embedded in consumer analytics and digital marketing as a set of capabilities that support insight generation, targeting, and personalization, and media and campaign optimization (Raji et al., 2024). In digital marketing management, AI is often described as a decision-support and decision-automation layer that turns consumer signals into marketing actions, sometimes at scale and in near real time (Mariani et al., 2021; Haleem et al., 2022; Dumitriu & Popescu, 2020). However, the presence of AI tools does not automatically create business value. Value depends on complementary organizational conditions, including measurement discipline, data quality, and routines that connect analytics outputs to KPI-linked decisions (Abrardi et al., 2021; Mariani et al., 2021; Gama & Magistretti, 2023; Islam et al., 2024).

From a capability perspective, AI-enabled marketing is better understood as an organizational capability bundle than as a standalone technology. Its performance depends on whether firms can maintain tracking and attribution routines, integrate CRM and analytics systems, and use experimentation and feedback loops to support learning over time (Abrardi et al., 2021; Mariani et al., 2021). This logic becomes even more important in small and emerging markets, where platform dependence is often high, analytics capacity is uneven, and governance routines are less standardized. In these settings, platform-provided AI features may spread faster than firms' ability to validate outcomes and manage risk (OECD, 2024; United Nations, 2025; World Bank, 2024).

As a result, AI adoption in small ecosystems may be driven more by access to deployable tools than by readiness for performance validation. This creates a practical distinction between deplorability and the evaluability of ROI. Deplorability refers to how easily AI functionality can be activated, used, and observed in daily marketing execution through platform features and automation. ROI evaluability refers to the extent to which business effects can be credibly attributed to AI use through stable measurement infrastructure, CRM linkage, and decision routines (Avram et al., 2020; Pop, 2020). When measurement maturity is limited, practitioners may judge a tool to be effective in execution while remaining uncertain about its incremental ROI, especially where attribution is opaque, and outcomes reflect multiple touchpoints and interacting factors (Abrardi et al., 2021; Mariani et al., 2021).

To examine these mechanisms empirically, this study focuses on four widely cited AI application domains in marketing and consumer analytics: predictive analytics, sentiment analysis, personalization, and programmatic advertising (Mariani et al., 2021; Haleem et al., 2022; Nazir et al., 2022; Davtyan, 2024). These domains provide the comparative structure for assessing perceived effectiveness at the tool-domain level and for testing how such perceptions relate to perceived ROI-oriented impact, adoption outlook, and governance perceptions in applied settings. The central premise is that domains closer to measurable decision outputs are more likely to show stronger ROI evaluability. By contrast, domains with high execution visibility but weaker attribution clarity may show stronger deplorability without an equally strong ROI link. This framing provides the basis for the domain-level hypotheses developed below.

2.1.1 AI value realization in SME-dominant markets: measurement maturity and integration routines

Building on the distinction between deplorability and ROI evaluability, this subsection explains how AI-enabled marketing creates value in SME-dominant markets through complementary routines and governance conditions. Prior research increasingly treats AI-enabled marketing not as a standalone technological asset, but as an organizational capability whose performance effects depend on such conditions (Mariani et al., 2021; Abrardi et al., 2021). In AI-enabled consumer analytics, value is realized when firms can translate signals into decisions and validate those decisions through credible feedback loops (Mariani et al., 2021). This dependency becomes more acute in SME-dominant ecosystems, where tool adoption can be rapid, but the systems required for data quality, experimentation, accountability, and cross-channel integration remain uneven (Abrardi et al., 2021). In this context, measurement maturity is treated as a central mechanism shaping the realization of AI value in small markets.

In this study, measurement maturity refers to the extent to which marketing performance is tracked in ways that support attribution, comparability, and learning over time. This includes stable definitions, consistent tagging, and routine reporting. Integration routines refer to the organizational practices that connect AI-enabled actions to outcome data, such as linking platforms to web analytics and CRM systems and ensuring that leads and conversions remain traceable across touchpoints. Together, measurement maturity and integration routines define the conditions under which perceived operational effectiveness becomes ROI-evaluable.

Without them, AI may remain deployable but not credibly attributable to business outcomes. This distinction also clarifies how perceived ROI-oriented impact differs conceptually from perceived tool effectiveness, as each reflects a different layer of AI value realization.

Readiness is therefore specified as five operational foundations that form a minimal AI performance infrastructure in SME contexts: (i) measurement and attribution discipline, including consistent conversion definitions, tagging conventions, and reporting cadence; (ii) CRM and data integration, linking touchpoints, leads, and outcomes; (iii) analytics literacy, including the ability to interpret outputs, detect errors, and avoid automation bias; (iv) experimentation cadence, supported by structured testing routines and learning cycles; and (v) governance routines, including privacy-by-design, responsibility assignment, escalation rules, and oversight mechanisms (Mariani et al., 2021; Abrardi et al., 2021; Akter et al., 2023; Schmauder et al., 2023). These foundations do not replace AI tools. They determine whether AI-supported decisions can be evaluated, trusted, and scaled as ROI-relevant capabilities rather than used only as ad hoc productivity aids.

Country-level assessments in Armenia also highlight uneven firm capabilities, skills constraints, and the need for practical standards that move adoption beyond superficial tool use (OECD, 2024; World Bank, 2024; United Nations, 2025). Consistent with this logic, the present study treats perceived tool effectiveness and perceived ROI-oriented impact as analytically distinct outcomes shaped, directly or indirectly, by measurement maturity and integration routines. This framing prepares the construct logic in Section 2.2 and motivates the domain-level hypotheses by explaining why some AI applications may be highly deployable yet weakly ROI-evaluable in SME-dominant markets.

2.2 Construct logic and operational definitions

To avoid a descriptive catalog of AI tools, the study organizes four AI marketing application clusters through a customer-journey lens. This provides a parsimonious mapping between domain use cases and the expected evaluability of outcomes. Predictive analytics primarily supports anticipation and prioritization, such as propensity and churn-risk estimation, across consideration, conversion, and retention. Sentiment analysis supports the diagnosis of experience signals and service failures, particularly in service recovery and loyalty. Personalization operationalizes relevance and next-best-action logic across lifecycle interactions. Programmatic advertising optimizes reach, bidding, and allocation during acquisition and retargeting (Bag et al., 2021; Gao & Liu, 2022; Dumitriu & Popescu, 2020; Haleem et al., 2022). This mapping is not intended to be exhaustive of the literature. Rather, it clarifies why experts may judge effectiveness based on operational visibility or deplorability, whereas perceived ROI-oriented impact depends on attribution logic and feedback loops, or on ROI evaluability, as established in Sections 2.1–2.1.1.

The constructs are therefore specified as perceptions of capability value and governance readiness rather than as direct performance metrics (Mariani et al., 2021; Abrardi et al., 2021). This distinction sharpens the conceptual boundary between perceived tool effectiveness and perceived ROI-oriented impact and improves the interpretability of the later hypotheses and results.

2.2.1 Construct set and operational definitions

C1. Perceived effectiveness of AI applications (tool-domain level).
This construct captures experts’ judgments of the effectiveness of four AI capability domains in applied marketing practice: predictive analytics, sentiment analysis, personalization, and programmatic advertising (Haleem et al., 2022; Mariani et al., 2021). It reflects operational

utility and execution visibility, or deplorability, rather than financial attribution.

C2. Perceived ROI-oriented impact (performance evaluability level). This construct reflects experts' perceptions of AI-enabled marketing's contribution to ROI-relevant outcomes, including improvements in marketing performance, efficiency gains that translate into measurable returns, and decision-quality improvements that can be credibly linked to outcomes (Bag et al., 2021; Gao & Liu, 2022). It represents ROI evaluability, that is, the extent to which outcomes are seen as attributable through measurement and integration routines, as defined in Section 2.1.1.

C3. Adoption outlook and competitive pressure (perception of market diffusion). This construct captures perceived growth in AI adoption in marketing practice and the perceived competitive risk of non-adoption, reflecting diffusion pressure and strategic urgency (Abrardi et al., 2021; Mariani et al., 2021). It is treated as a forward-looking managerial expectation rather than as a measured adoption rate.

C4. Ethical risk perceptions (risk salience). This construct captures perceived privacy concern and bias/fairness concern related to AI-enabled marketing decisions and data use, representing two distinct risk pathways: individual-data harm and decision-integrity harm (Khrais, 2020; Akter et al., 2023; Fan & Liu, 2022). The distinction is theoretically important because privacy concerns may directly reduce willingness to adopt, whereas bias/fairness concerns may primarily increase demand for safeguards and oversight.

C5. Governance expectations (legitimacy and control requirements). This construct reflects the perceived need for oversight and accountability, including responsibility assignment, auditability, and escalation, as well as transparency in how AI influences marketing decisions (Schmauder et al., 2023; Mariani et al., 2021). It captures the legitimacy requirements that shape the scaling and institutionalization of AI use. Within this construct, oversight/accountability is treated as the primary hypothesized governance expectation, while transparency is examined as an exploratory variable.

Together, these constructs reflect the premise that AI can improve marketing performance, while adoption and scaling depend on the interaction between perceived capability value, reflected in effectiveness and ROI-oriented impact, and governance legitimacy, reflected in risk perceptions and governance expectations (Mariani et al., 2021; Khrais, 2020). This structure also operationalizes the distinction between deplorability and ROI evaluability under SME measurement constraints and motivates the domain and association hypotheses developed in the following subsections. These relationships are integrated in the conceptual model shown in Figure 1.

2.3 Perceived tool effectiveness and perceived ROI-oriented impact

AI marketing applications differ not only in function but also in how confidently their effects can be linked to business outcomes under real-world measurement constraints. As discussed in Sections 2.1–2.1.1, this study refers to that condition as ROI evaluability. In SME-dominant and platform-dependent settings, ROI evaluability becomes a key differentiator because some capabilities can be highly deployable in execution while remaining weakly attributable in performance terms. This section, therefore, explains why perceived tool-domain effectiveness (C1) may translate unevenly into perceived ROI-oriented impact (C2) across AI application domains.

Predictive analytics is typically more closely linked to decision outputs because it converts consumer and transactional signals into forecasts or propensities, such as purchase likelihood, churn risk, and response probability. These outputs map more directly onto measurable indicators and can be validated through structured testing and downstream behavioral outcomes when basic feedback loops are in place (Bag et al., 2021; Khrais, 2020). In capability terms, predictive analytics can strengthen targeting and resource-allocation decisions in ways that are comparatively easier to connect to performance improvements. Sentiment analysis, by contrast, functions primarily as a diagnostic capability. It can surface experience signals, emerging dissatisfaction, and service failures, but its ROI contribution is often mediated by managerial response and operational follow-through. As a result, attribution may be weaker in multi-touch environments where several actions, channels, and operational constraints intervene between signal detection and outcome (Bag et al., 2021; Haleem et al., 2022).

Personalization and programmatic advertising are often embedded in platform ecosystems that optimize delivery at scale through recommendation logic, automated bidding, and audience expansion. Their operational value is highly visible in execution, but ROI evaluability may be lower when attribution is opaque, outcomes are multi-touch, and platform optimization reduces transparency about which specific AI-driven actions produced incremental impact (Dumitriu & Popescu, 2020; Gao & Liu, 2022; Haleem et al., 2022). Under these conditions, strong deplorability does not necessarily translate into equally strong ROI confidence.

Despite these evaluability differences, perceived ROI-oriented impact should increase when experts believe that AI improves decision quality and resource allocation in ROI-relevant ways, such as who to target, what to offer, when to intervene, and how to allocate budget. It should also increase when efficiency gains are seen as contributing to measurable outcomes rather than solely for operational convenience (Mariani et al., 2021; Haleem et al., 2022). Accordingly, the study tests whether higher perceived effectiveness in each AI domain (C1) is associated with stronger perceived ROI-oriented impact (C2), while recognizing that the strength of this association may vary across domains.

H1: Perceived effectiveness of AI-driven personalization is positively associated with perceived ROI-oriented impact.

H2: Perceived effectiveness of AI-driven predictive analytics is positively associated with perceived ROI-oriented impact.

H3: Perceived effectiveness of AI-driven sentiment analysis is positively associated with perceived ROI-oriented impact.

H4: Perceived effectiveness of AI-driven programmatic advertising is positively associated with perceived ROI-oriented impact.

In Figure 1, this logic is represented as the pathway from perceived effectiveness of AI domains (C1) to perceived ROI-oriented impact (C2).

2.4 Perceived ROI-oriented impact and adoption outlook

Technology diffusion in marketing is shaped by perceived relative advantage and strategic necessity, not only by tool availability. When practitioners perceive AI as improving ROI-relevant outcomes (C2), adoption expectations tend to increase because AI is framed as a capability that strengthens competitiveness through faster decisions, better resource allocation, and improved targeting precision (Abrardi et al., 2021; Mariani et al., 2021). Perceived ROI-oriented impact also supports internal justification for investment in data infrastructure, skills, and integration routines, which are necessary for scaling AI use beyond isolated experiments (Mariani et al., 2021; Abrardi et al., 2021). Therefore, the study tests whether a stronger perceived ROI-oriented impact is associated with a more optimistic market outlook for AI adoption (C3).

H5: Perceived ROI-oriented impact is positively associated with a more optimistic AI adoption outlook.

2.5 Ethical risk perceptions as constraints on adoption optimism

AI-enabled marketing depends on extensive data capture, profiling, and automated targeting decisions. These features elevate governance legitimacy risks that can reduce acceptance when AI use is perceived as intrusive, unfair, or insufficiently controlled (Khrais, 2020; Mariani et al., 2021; Fan & Liu, 2022; Akter et al., 2023). In this study, ethical risk perceptions (C4) are operationalized as two salient, conceptually distinct dimensions: privacy concern (risk of inappropriate data use, surveillance-like targeting, and loss of consumer control) and bias/fairness concern (risk of discriminatory or systematically skewed decision outcomes). These dimensions are particularly relevant for AI-mediated targeting and personalization and are amplified when governance routines are perceived as underdeveloped—an issue frequently noted in policy and development assessments in small and emerging ecosystems (OECD, 2024; United Nations, 2025; World Bank, 2024; Schmauder et al., 2023; Davtyan, 2024).

The theoretical expectation for privacy is comparatively straightforward: when privacy risk is salient, adoption optimism can decline because firms anticipate consumer distrust, reputational harm, and regulatory uncertainty, thereby increasing the perceived cost of AI use (Khrais, 2020; Mariani et al., 2021). For bias/fairness, the relationship can be more conditional: in some contexts, fairness concern may reduce adoption optimism by lowering trust in AI-driven decisions; in other contexts, it may instead heighten the demand for safeguards and oversight without reducing adoption expectations, especially when competitive pressure remains high (Akter et al., 2023; Schmauder et al., 2023). Given the study's perception-based design, we test whether higher ethical risk salience is associated with a less optimistic adoption outlook, while recognizing that bias/fairness may operate through governance expectations examined in Section 2.6.

H6: Privacy concerns are negatively associated with AI adoption outlook.

H7: Bias/fairness concern is negatively associated with AI adoption outlook.

Figure 1 reflects this distinction by modeling ethical risk perceptions (C4) as potential constraints on adoption outlook (C3).

2.6 Ethical risk perceptions and governance expectations (oversight/accountability)

Ethical risk perceptions can suppress adoption optimism (Section 2.5), but they can also increase demand for safeguards when practitioners anticipate reputational, consumer trust, or compliance exposure. In the AI governance literature, oversight and accountability mechanisms—such as responsibility assignment, human-in-the-loop review, audit routines, documentation standards, escalation rules, and post-deployment monitoring—are treated as essential for managing harms associated with automated or semi-automated decision systems (Akter et al., 2023; Schmauder et al., 2023). In marketing applications, this logic is particularly salient because AI-mediated targeting and personalization can lead to perceived privacy violations (intrusive data use) and fairness violations (biased audience inclusion/exclusion), undermining legitimacy and triggering managerial risk-control responses (Akter et al., 2023; Mariani et al., 2021).

Accordingly, when privacy concern or bias/fairness concern increases, practitioners are expected to demand stronger oversight/accountability arrangements. This expectation is theoretically consistent with a "governance response" pathway: even if competitive pressure sustains the adoption outlook, higher perceived salience of ethical risk can still elevate expectations for controls and accountability structures (Akter et al., 2023; Schmauder et al., 2023). Therefore, the study tests whether privacy and bias/fairness concerns (C4) are positively associated with oversight/accountability expectations (C5).

H8a: Privacy concern is positively associated with stronger oversight/accountability expectations.

H8b: Bias/fairness concern is positively associated with stronger oversight/accountability expectations.

In addition, transparency expectations are examined as an exploratory outcome because empirical evidence on whether disclosure consistently increases trust remains mixed. Some studies suggest transparency cues can strengthen perceived legitimacy, while other evidence indicates that disclosure effects depend on cue strength, framing, and audience perceptions of manipulation, which can trigger resistance to algorithmic influence (de Jong et al., 2025; Koning & Voorveld, 2025). Therefore, transparency is retained as exploratory rather than hypothesized directionally. Figure 1 integrates the full conceptual model across capability value, ROI evaluability, adoption outlook, and governance expectations, while

Table 1 summarizes the corresponding hypotheses and expected directions.

Figure 1. Conceptual model of perceived AI capability value, ROI evaluability, adoption outlook, and governance expectations

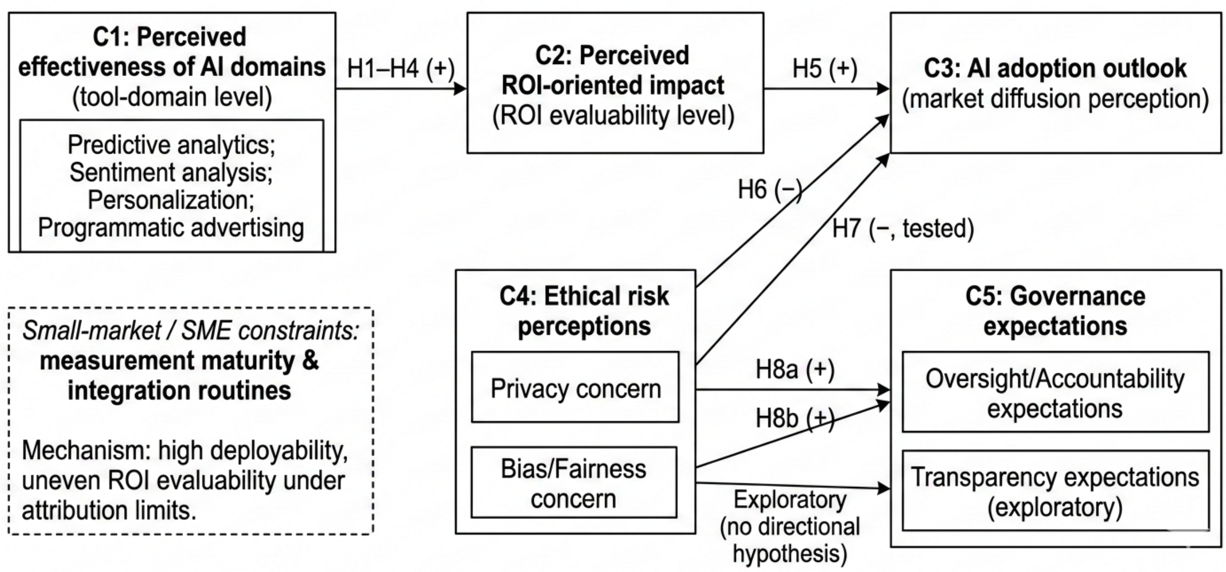

Table 1. Summary of hypotheses

Hypothesis	Predictor (X)	Outcome (Y)	Expected direction	Notes (construct logic / test type)
H1	Perceived effectiveness: AI-driven personalization (C1)	Perceived ROI-oriented impact (C2)	+	Association test (domain-level effectiveness → ROI evaluability)
H2	Perceived effectiveness: AI-driven predictive analytics (C1)	Perceived ROI-oriented impact (C2)	+	More decision-output-linked domain; expected stronger ROI evaluability linkage

Hypothesis	Predictor (X)	Outcome (Y)	Expected direction	Notes (construct logic / test type)
H3	Perceived effectiveness: AI-driven sentiment analysis (C1)	Perceived ROI-oriented impact (C2)	+	Diagnostic domain; ROI linkage mediated by managerial follow-through
H4	Perceived effectiveness: AI-driven programmatic advertising (C1)	Perceived ROI-oriented impact (C2)	+	Platform-embedded; high deplorability, potentially weaker ROI evaluability linkage
H5	Perceived ROI-oriented impact (C2)	AI adoption outlook (C3)	+	Perceived advantage → diffusion expectation
H6	Privacy concern (C4)	AI adoption outlook (C3)	–	Legitimacy/compliance concern expected to dampen optimism
H7	Bias/fairness concern (C4)	AI adoption outlook (C3)	–	May be conditional; also expected to elevate governance demands (see H8b)
H8a	Privacy concern (C4)	Oversight/accountability expectations (C5)	+	Governance response pathway (risk → control demand)
H8b	Bias/fairness concern (C4)	Oversight/accountability expectations (C5)	+	Governance response pathway (risk → control demand)
Exploratory	Privacy concern; bias/fairness concern (C4)	Transparency expectations (C5)	—	Exploratory association; no directional hypothesis due to mixed evidence

3. Methodology

3.1 Research design

This study employed an expert-based, cross-sectional survey design to examine how marketing and digital professionals serving the Armenian market evaluate the perceived effectiveness of core AI-enabled marketing capabilities and how these perceptions relate to perceived ROI-oriented impact, adoption outlook, and governance perceptions. Expert judgments were captured at a single point in time and treated as capability-level assessments, consistent with digital marketing management research in which practitioners and managers serve as valid informants of organizational routines, technology value realization, and governance readiness—dimensions that are often not observable through secondary performance data in SME-dominant contexts. This design is appropriate for exploratory inquiry where objective ROI and attribution data are fragmented, non-standardized, or inaccessible, and where the research objective is to identify patterned perceptions that indicate how AI value is interpreted under constrained measurement conditions (OECD, 2024; World Bank, 2024; United Nations, 2025).

The unit of analysis is therefore expert perception rather than audited performance outcomes. This choice aligns with the study's conceptual lens: AI-enabled marketing value depends on whether capabilities are (i) deployable in daily execution and (ii) ROI-evaluable through measurement discipline and integration routines. Expert perceptions are used to capture these distinctions at the level of applied decision-making, where strategic judgments about "what works" and "what can be justified" shape adoption and scaling behavior.

3.2 Context and study focus

The empirical setting was Armenia's marketing and digital ecosystem, characterized by a high share of SMEs, increasing platform-driven digitalization, and uneven maturity in analytics capacity and governance routines. In this environment, AI features embedded in platforms and marketing tools can diffuse rapidly, while attribution discipline, CRM linkage, and standardized governance practices may lag (OECD, 2024; World Bank, 2024; United Nations, 2025).

The study focused on four widely recognized AI-enabled marketing capability clusters that practitioners commonly encounter through platforms, tools, and agency practice: predictive analytics, sentiment analysis, personalization, and programmatic advertising (Mariani et al., 2021; Haleem et al., 2022; Dumitriu & Popescu, 2020). In addition, the study measured perceived outcomes (perceived ROI-oriented impact; adoption outlook/competitive pressure) and governance perceptions (privacy concern, bias/fairness concern, transparency expectations, and oversight/accountability expectations). This construct operationalizes the paper's central premise that perceived tool effectiveness (deplorability) and perceived ROI-oriented impact (ROI evaluability) represent distinct layers of AI value realization.

3.3 Sampling strategy and participants

3.3.1 Sampling approach

A purposive expert sampling strategy complemented by snowball sampling was used to identify respondents with informed professional exposure to marketing decision-making and AI-enabled tools in the Armenian market. This approach was appropriate because professionals with sustained exposure to AI and analytics in Armenia constitute a small, hard-to-reach expert pool, and peer referrals increase access to eligible respondents. The aim was to collect practice-informed judgments rather than estimate population parameters through probability sampling.

To mitigate the homophily risk inherent in snowball recruitment, sampling was deliberately diversified by initiating recruitment through multiple entry points and targeting heterogeneous role categories rather than relying on a single referral chain. Recruitment targeted professionals across (i) agency and service-provider roles, (ii) in-house marketing roles, (iii) e-commerce and analytics functions, and (iv) managerial or team-lead functions. Invitations were distributed through professional associations, business and marketing networks in Armenia, and partner organizations. Data collection was conducted in 2025. Given the study's exploratory objective and the ordinal nature of the perception measures, the resulting sample size was evaluated primarily for pattern identification rather than for statistical generalization. Accordingly, the analysis relies on nonparametric techniques suited to small samples and ordinal indicators, including Friedman tests for within-respondent comparisons across the four AI domains and Spearman correlations for monotonic associations among perception constructs (Sullivan & Artino, 2013; Mircioiu & Atkinson, 2017).

3.3.2 Inclusion criteria

Participants were eligible if they met all the following criteria:

1. Professional role relevance: actively engaged in marketing, digital promotion, analytics, consulting, e-commerce, communications, or closely related functions with decision or implementation responsibility.
2. Armenia-market exposure: direct professional experience with the Armenian market (based in Armenia and/or working primarily with Armenian clients, brands, campaigns, or audiences).
3. Applied AI exposure in digital commerce contexts: relevant hands-on exposure at the intersection of AI-enabled tools and e-commerce/digital commerce marketing (e.g., using, evaluating, configuring, or managing AI-supported tools/processes in digital commerce-oriented marketing practice).

Eligibility was verified using a two-stage screening protocol. First, potential respondents were pre-screened before receiving the survey link to confirm alignment with the focal context (AI-enabled tools in digital commerce marketing) and to reduce the likelihood of non-expert responses. Second, the survey instrument included two screening items at the start requiring self-confirmation of (i) role alignment and (ii) Armenia-market exposure. Duplicate submissions were checked manually (e.g., repeated entries and inconsistent metadata). No ineligible or incomplete responses were retained in the final dataset.

3.3.3 Sample characteristics

The final sample comprised n = 29 experts. In total, 56 professionals passed initial outreach and were screened for relevance. Prior to survey access, 27 were excluded for failing to meet the combined expertise requirement. Exclusions primarily reflected two patterns: (i) AI-related experience without sufficient applied exposure to e-commerce and digital commerce marketing contexts, and (ii) e-commerce marketing experience without applied AI exposure in that context. The remaining 29 eligible experts completed the anonymous instrument and were retained for analysis, with no exclusions after completion.

Participation was voluntary, and no incentives were offered. The instrument captured professional role category, experience bands, and current professional use of AI-enabled tools. Respondents represented a broad mix of agency and service roles, in-house marketing roles, e-commerce and analytics functions, managerial or team-lead positions, communications roles, and business leadership functions. Experience was also diverse, with the largest concentrations in the 4–7 years and 10+ years bands. In this sample, 28 of 29 respondents reported current professional AI use, indicating high practical exposure relevant to the study's measurement design.

Given the limited pool of professionals with sustained exposure to AI and analytics in Armenia, the sample size was treated as appropriate for exploratory pattern identification rather than for statistical generalization. Accordingly, the results are interpreted as exploratory and were analyzed using nonparametric techniques suitable for ordinal indicators and small samples.

3.4 Instrument and measures

3.4.1 Instrument development and questionnaire structure

Data were collected via a structured questionnaire designed to capture (a) respondents' professional context, (b) perceived effectiveness of core AI-enabled marketing capability domains, (c) perceived ROI-oriented impact and adoption outlook, and (d) governance-related perceptions relevant to responsible AI use. The instrument was designed to operationalize the study's conceptual distinction between deplorability (execution-visible effectiveness) and ROI evaluability (perceived ability to attribute performance impact), both of which are central to the paper's theoretical framing.

Item content was developed through a theory-to-measure mapping approach based on the construct logic specified in Sections 2.1–2.6 (Appendix B). Items were formulated to reflect expert perceptions of capability value and governance readiness, consistent with prior work framing AI value realization as contingent on complementary routines and governance conditions (Mariani et al., 2021; Abrardi et al., 2021). The questionnaire assessed four AI application clusters commonly encountered by practitioners through platforms, tools, and agency practice—predictive analytics, sentiment analysis, personalization, and programmatic advertising—alongside perceptions of outcomes and governance.

The instrument combined theory-derived items informed by prior literature on AI-enabled marketing, technology adoption, and governance with wording adapted to the applied context of digital commerce marketing in Armenia. Accordingly, the questionnaire was not intended to reproduce previously validated multi-item scales in full, but to capture focused expert judgments aligned with the study's exploratory objectives and conceptual model. No formal pilot study or cognitive pretest was conducted. The instrument should therefore be interpreted as exploratory, and future research should further validate and expand the measures through pretesting and multi-item scale development.

The questionnaire included the following components:

- professional profile items (current role; years-of-experience band);
- AI exposure (current professional use of AI tools: yes/no);
- perception indicators capturing domain-level tool effectiveness, perceived ROI-oriented impact, adoption outlook, ethical risk perceptions, and governance expectations; and
- one open-ended item eliciting the primary perceived constraint to AI adoption in Armenian marketing practice, used for contextual triangulation of quantitative patterns.

The exact wording of all items is provided in Appendix A, and the construct-to-item mapping is summarized in Appendix B (Table A1). Single-item measurement rationale. Given the expert-based design and the intentionally compact instrument used to maximize completion quality in a small expert pool, the core constructs were measured using single-item Likert indicators. Single-item operationalization was selected to minimize respondent burden, reduce attrition, and preserve response quality for domain-level judgments. This choice is consistent with the study's exploratory objective (pattern identification rather than population estimation) and is treated as a measurement limitation motivating future research to validate multi-item scales for each construct.

3.4.2 Response format

All perception items used a 5-point Likert-type response scale anchored from 1 = strongly disagree to 5 = strongly agree. Given the ordinal nature of Likert-type responses and the small expert sample (N = 29), indicators were treated as ordinal for hypothesis testing, and nonparametric procedures were designated as the primary inferential approach (see Section 3.7 Data Analysis Plan). This decision supports defensible inference under small-sample conditions and prevents overinterpretation of interval-scale assumptions.

3.4.3 Operationalization of core constructs

Measures were aligned with the hypotheses and structured to distinguish (i) domain-level perceived tool effectiveness, (ii) perceived ROI-oriented impact, (iii) adoption outlook/competitive pressure, and (iv) ethical risk perceptions and governance expectations. Variable names are provided to ensure traceability across Appendices, Results tables, and the analysis plan.

A. Perceived tool effectiveness (domain-level indicators; C1).

Respondents rated the perceived effectiveness of four AI capability domains widely discussed in digital marketing and e-commerce practice:

- AI-driven personalization (ai_personalization)
- AI-driven predictive analytics (ai_predictive)
- AI-driven sentiment analysis (ai_sentiment)
- AI-driven programmatic advertising (ai_programmatic)

Two representations were used to support hypothesis testing while retaining domain specificity:

1. Domain-level indicators (each domain analyzed separately for H1–H4).
2. Composite index (ai_tools_mean), computed as the mean of the four domain ratings, representing overall perceived AI tool effectiveness across the capability set.

Reliability of the composite index (ai_tools_mean). Internal consistency for ai_tools_mean was moderate (Cronbach's α = .647; McDonald's ω = .666). Item–rest correlations ranged from .314 to .523, and deletion of any single domain rating did not improve α, supporting retention of the composite as a parsimonious summary indicator for exploratory association testing. To avoid over-aggregation, domain-level results are reported alongside the composite to preserve interpretability of evaluability differences across domains (consistent with the paper's deplorability vs ROI evaluability framing).

B. Perceived ROI-oriented impact (C2).

Perceived ROI-oriented impact (ai_roi) captured respondents' assessment of AI's contribution to marketing performance in an ROI-relevant sense (e.g., improvements in results and/or efficiency gains believed to translate into measurable returns). This variable operationalizes the "ROI evaluability" layer in the conceptual model and serves as the key outcome in H1–H4 and predictor in H5.

C. Adoption outlook / competitive pressure (C3).

Adoption outlook (adopt_growth) captured respondents' expectations that AI use in marketing will increase in the near term and that non-adoption may create a competitive disadvantage. This construct reflects perceived diffusion pressure rather than measured adoption intensity.

D. Ethical risk perceptions (C4).

Two indicators captured perceived ethical risk salience associated with AI-enabled marketing decision-making:

- Privacy-related concern (eth_privacy)

- Bias/fairness-related concern (eth_bias)

E. Governance expectations (C5).

Two indicators captured perceived expectations for governance mechanisms to ensure responsible AI use:

- Transparency expectations (gov_transparency)
- Oversight/accountability expectations (eth_oversight)

F. Open-ended adoption barrier item (qualitative triangulation).

A single open-ended item asked respondents to identify the primary constraint limiting AI adoption in Armenian marketing practice. Qualitative responses were used to contextualize quantitative patterns and support the interpretation of constraints in a small-market environment.

3.4.4 Measurement and inference note

The instrument employs multiple single-item Likert indicators for perceived outcomes, adoption outlook, and governance perceptions. Accordingly, the study does not interpret these measures as definitive estimates of latent psychological constructs; instead, it treats them as markers of expert perception appropriate for exploratory pattern identification in a small-market context. Inference is therefore framed as perception-based and associational, with emphasis on convergent evidence across complementary analytic components.

Specifically, inference prioritizes:

1. Convergent evidence across methods, including descriptive patterns, within-respondent domain comparisons (Friedman tests with post-hoc comparisons), and monotonic associations among constructs (Spearman correlations);
2. Tool-domain specificity alongside a composite representation (ai_tools_mean) to avoid masking meaningful differences across AI capability clusters; and
3. Interpretive triangulation using the open-ended adoption-barrier responses to contextualize quantitative relationships and clarify small-market constraints.

To strengthen transparency and auditability, the study reports the full wording of all items (Appendix A) and provides a construct-to-operationalization mapping (Appendix B).

3.5 Data collection procedure

The questionnaire was distributed to eligible experts through channels relevant to Armenia's marketing ecosystem, including professional networks, industry contacts, and digital communities. Participation was voluntary, and responses were self-administered. After data collection, responses were exported for analysis and underwent standardized preparation procedures. These included: (i) assignment of anonymized respondent identifiers; (ii) standardization of role labels where needed to ensure consistent categorization; (iii) validation checks for completeness and admissible Likert response ranges; and (iv) preparation of open-ended responses for qualitative coding (including removal of potentially identifying details). Because the research design is cross-sectional, the dataset captures expert perceptions at a single time point and does not measure within-respondent change over time; findings are therefore interpreted as contemporaneous perceptions rather than longitudinal effects.

3.6 Ethical considerations

Given the small and highly networked nature of Armenia's marketing ecosystem, safeguards were implemented to minimize the risk of direct or indirect identification. An information statement at the start of the questionnaire described the study purpose, anonymity procedures, and the right to skip items; continuation to the survey constituted implied informed consent. No personal identifiers (e.g., names, email addresses, phone numbers) or company identifiers were collected.

To reduce indirect identifiability, results are reported only in aggregate form, and the manuscript avoids presenting rare combinations of professional attributes. Open-ended responses were screened to remove potentially identifying references and are reported as summarized themes or paraphrased content rather than distinctive verbatim excerpts. Data were stored on a password-protected drive with access restricted to the author and will be retained for three years before secure deletion. Pre-screening and eligibility checks were conducted without recording personal identifiers; only non-identifying professional descriptors (e.g., expertise domain) were used to confirm eligibility.

3.7 Data analysis plan

All analyses were conducted in Jamovi. Given the small expert sample ($N = 29$) and the ordinal nature of the 5-point Likert-type indicators, the analytic strategy prioritized descriptive and nonparametric procedures for primary hypothesis testing, supplemented by exploratory models to enhance robustness and interpretive support. Qualitative content analysis was applied to the open-ended adoption-barrier item to contextualize quantitative patterns.

3.7.1 Quantitative analysis

Test–hypothesis alignment and decision rules: The analytic approach was designed to align tests directly with the research questions and hypothesis structure. Friedman tests were used to compare perceived effectiveness across the four AI domains (C1) to assess whether the domains differ in perceived deplorability. Spearman rank-order correlations (ρ) were used to test monotonic associations among perception constructs (C1–C5), consistent with hypotheses H1–H8b and the conceptual model. Primary hypotheses were evaluated using two-tailed tests with $\alpha = .05$. A hypothesis was treated as supported when $p < .05$ and the observed association matched the hypothesized direction. Results with $.05 \leq p < .10$ were reported as directional trends but were not treated as hypothesis support. Interpretation prioritized effect sizes and pattern coherence rather than significance alone.

Descriptive reporting standards for ordinal indicators: For Likert-type indicators, descriptive reporting includes median and interquartile range (IQR) alongside mean and standard deviation to reflect ordinal measurement conventions.

Data screening and descriptive statistics: Valid ranges, completeness, and response distributions were checked. Descriptives were produced for respondent profile variables and all perception indicators (median, IQR, mean, SD, and min–max).
Scale diagnostics for the composite perceived tool-effectiveness index (ai_tools_mean): Internal consistency was evaluated using Cronbach's α and McDonald's ω, supported by item–rest correlations and α-if-deleted diagnostics. Because the four items represent conceptually distinct capability domains, ai_tools_mean was retained as an exploratory summary indicator while domain-level analyses were prioritized for H1–H4. Values below .70 were interpreted as indicating exploratory reliability rather than strong internal consistency.

Tool-domain effectiveness comparison (Friedman): The Friedman omnibus test was used to assess whether perceived effectiveness differed across the four AI domains. Where significant, Durbin–Conover post-hoc comparisons were used for pairwise contrasts. Effect sizes were reported as Kendall's W for the omnibus test and post-hoc r for pairwise comparisons, computed as $r = z / \sqrt{N}$. In addition to r, the corresponding z statistic was reported to increase transparency.

Hypothesis testing (Spearman associations): Spearman correlations were used to test H1–H8b. Tool-level correlations were prioritized for H1–H4. The composite ai_tools_mean was reported as supplementary, where it improved parsimony without obscuring domain-level patterns.

Confidence intervals and interpretive labels: To improve statistical transparency under small-sample conditions, key effect sizes are reported with 95% confidence intervals where feasible. For Spearman's ρ, 95% confidence intervals were approximated manually using Fisher-z transformation, where $z = 0.5 \ln((1 + \rho) / (1 - \rho))$ and $SE\_z = 1 / \sqrt{(n - 3)}$, followed by back-transformation to the correlation scale. Effect magnitudes are interpreted using conventional labels (small, moderate, large) as descriptive aids rather than rigid thresholds. Power and Type II error note: Given $N = 29$, the study has limited power to detect small-to-moderate effects. Accordingly, nonsignificant results, especially those with directional trends, are interpreted cautiously as potentially reflecting Type II error rather than the absence of a relationship.

Exploratory (secondary) models and robustness: To provide a descriptive robustness check and examine whether perceived tool effectiveness adds explanatory value beyond perceived ROI-oriented impact, exploratory OLS regression models were estimated (for example, adopt_growth modeled as a function of ai_roi alone and jointly with ai_tools_mean). Because the indicators are ordinal and the sample is modest, OLS coefficients are interpreted descriptively as indicative patterns rather than precise estimates and do not determine hypothesis support. No ordinal regression model was estimated in the present study; this remains a relevant avenue for future robustness testing.

Multiple comparisons and interpretive caution: The analysis includes six Durbin–Conover pairwise comparisons and multiple Spearman correlations. Because the study is exploratory and theory-driven, formal family-wise correction was not used as the primary decision rule. Instead, results were interpreted conservatively by prioritizing (i) effect-size magnitude (ρ, Kendall's W, post-hoc r), (ii) directional consistency with hypothesized signs, (iii) convergence across related tests, and (iv) confidence intervals rather than p-values alone. Trends were reported transparently but were not treated as hypothesis support.

3.7.2 Qualitative analysis and integration logic

Open-ended responses were analyzed using qualitative content analysis to identify dominant perceived barriers to AI adoption in Armenian marketing practice. Coding followed an iterative single-coder procedure designed to support trustworthiness in a small dataset: responses were first grouped into preliminary categories, then re-coded in a second pass to refine category definitions and consolidate overlapping themes into higher-order concepts. A brief codebook (theme labels and inclusion criteria) was maintained during coding to improve consistency across passes.

Qualitative findings are reported as anonymized thematic patterns (summarized or paraphrased), avoiding distinctive verbatim excerpts and potentially identifying details. Importantly, the qualitative component is used for contextual interpretation and triangulation, not for hypothesis testing. Specifically, themes are used to explain why certain associations may be stronger or weaker under small-market constraints (e.g., data readiness, measurement discipline, skills gaps, integration limitations), thereby strengthening the mechanism interpretation of the deplorability–ROI evaluability distinction.

4. Results

4.1 Sample profile and AI exposure

The final sample comprised 29 marketing and digital professionals connected to the Armenian market. Respondents reported substantial professional experience, with the largest shares in the 4–7 years and >10 years bands. Roles spanned marketing, digital, and e-commerce functions; agency/service delivery; communications; and business leadership. Professional AI exposure was high. Twenty-eight of 29 respondents reported current use of AI in professional practice. This indicates that the findings reflect practice-informed judgments rather than hypothetical attitudes. The profile is therefore appropriate for an exploratory expert study focused on the perceived value of AI capabilities in small markets.

4.2 Perceived effectiveness of AI applications (tool-level comparison)

Respondents evaluated four AI-enabled marketing capability domains: AI-driven personalization, predictive analytics, sentiment analysis, and programmatic advertising. Descriptive results indicated generally positive perceived effectiveness across domains, with the highest mean ratings for personalization and programmatic advertising (Table 2). Median values were 4 for all indicators shown in Table 2. IQR = 1 for all indicators, suggesting relatively concentrated responses in the central 50% of the sample. Skewness and kurtosis diagnostics were also reviewed descriptively and did not indicate extreme distributional irregularities that would alter the choice of nonparametric analysis.

A Friedman test showed statistically significant differences in perceived effectiveness across the four domains, $\chi^2(3) = 18.60$, $p < .001$, with a small-to-moderate effect size (Kendall's $W = .21$). Durbin–Conover post-hoc comparisons indicated that personalization was rated higher than predictive analytics ($z = 2.895$, $p = .005$) and sentiment analysis ($z = 3.763$, $p < .001$). Programmatic advertising was also rated higher than predictive analytics ($z = 2.895$, $p = .005$) and sentiment analysis ($z = 3.763$, $p < .001$). No significant difference was observed between personalization and programmatic advertising ($z = 0.000$, $p = 1.000$), and predictive analytics did not differ significantly from sentiment analysis ($z = 0.868$, $p = .388$) (Table 3). These findings indicate that perceived tool effectiveness varies across AI capability domains, with stronger ratings for platform-visible execution tools than for analytics and diagnostics.

Table 2. Descriptive summaries of perceived AI application effectiveness and perceived ROI-oriented impact (N = 29)

Measure	Mean	SD	Median	IQR	Min–Max
AI personalization effectiveness	4.17	0.658	4	1	3–5
AI predictive analytics effectiveness	3.76	0.577	4	1	2–5
AI sentiment analysis effectiveness	3.62	0.820	4	1	2–5
AI programmatic advertising effectiveness	4.17	0.658	4	1	2–5
Perceived ROI-oriented impact (ai_roi)	4.14	0.639	4	1	3–5

Table 3. Friedman omnibus test and Durbin–Conover pairwise comparisons for perceived AI tool effectiveness (N = 29)

Section	Comparison / Test	Test statistic	df	p	Effect size
Omnibus test	Friedman test (4 AI tools)	$\chi^2 = 18.60$	3	< .001	Kendall's W = .21
Post-hoc pairwise (Durbin–Conover)	AI personalization > AI predictive analytics	z = 2.895	—	.005	r = .538
	AI personalization > AI sentiment analysis	z = 3.763	—	< .001	r = .699
	AI personalization = AI programmatic advertising	z = 0.000	—	1.000	r = .000
	AI predictive analytics ≈ AI sentiment analysis	z = 0.868	—	.388	r = .161
	AI programmatic advertising > AI predictive analytics	z = 2.895	—	.005	r = .538
	AI programmatic advertising > AI sentiment analysis	z = 3.763	—	< .001	r = .699

Note. N = 29. The omnibus effect is reported as Kendall's W. Pairwise effect sizes are reported as $r = z / \sqrt{N}$ and are interpreted descriptively. Hypothesis support is not determined from these pairwise contrasts; the table is used to describe differences in perceived tool effectiveness across AI domains.

4.3 Reliability of the tool-effectiveness index

To support parsimonious association tests, a composite index (ai_tools_mean) was computed as the mean of four domain ratings: AI-driven personalization, predictive analytics, sentiment analysis, and programmatic advertising. Higher scores indicate higher perceived overall tool effectiveness.

Reliability diagnostics indicated moderate internal consistency (Cronbach's α = .647; McDonald's ω = .666; N = 29). This level is acceptable for an exploratory composite, but it does not indicate strong internal consistency. Item–rest correlations ranged from .314 to .523, and α if item dropped ranged from .512 to .651. Dropping any single item did not materially improve reliability. The highest α-if-dropped value was observed for programmatic advertising (.651), but the gain relative to the full scale was negligible.

The inter-item correlation matrix further supports this interpretation. Correlations ranged from .114 to .490, indicating that the four items are related, but not highly redundant. The strongest inter-item association was observed between personalization and predictive analytics (r = .490), while the weakest was between predictive analytics and programmatic advertising (r = .114). This pattern is theoretically plausible. The four indicators represent distinct AI capability clusters rather than interchangeable indicators of a single narrow latent trait. The composite was therefore retained as a pragmatic summary indicator for selected association tests, while tool-level analyses remained primary to preserve domain specificity and avoid over-aggregation.

Table 4a. Scale reliability and item diagnostics (N = 29)

Component	**Item / Index**	**Item–rest correlation**	**Cronbach's α if item dropped**	**Cronbach's α (scale)**	**McDonald's ω (scale)**
Scale reliability	ai_tools_mean (4-item composite)	—	—	.647	.666
Item diagnostics	AI personalization effectiveness	.523	.512	—	—
	AI predictive analytics effectiveness	.464	.563	—	—
	AI sentiment analysis effectiveness	.441	.579	—	—
	AI programmatic advertising effectiveness	.314	.651	—	—

Table 4b. Pearson inter-item correlation matrix for the four AI tool-effectiveness indicators (N = 29)

Measure	**Personalization**	**Predictive analytics**	**Sentiment analysis**	**Programmatic advertising**
AI personalization effectiveness	—	.490	.324	.341
AI predictive analytics effectiveness	.490	—	.404	.114
AI sentiment analysis effectiveness	.324	.404	—	.258
AI programmatic advertising effectiveness	.341	.114	.258	—

Note. α and ω indicate moderate exploratory reliability rather than strong internal consistency. Inter-item correlations were based on Pearson's r, consistent with scale reliability diagnostics in Jamovi. Correlation magnitudes indicate that the four domains are related but not interchangeable, supporting the use of the composite as a pragmatic summary indicator while retaining tool-level analyses as primary.

4.4 Associations and hypothesis testing

Given the ordinal measurement and modest sample size (N = 29), all primary hypothesis tests (H1–H8b) were conducted using Spearman's rank-order correlations (ρ) with two-tailed significance tests. Results are interpreted as associations rather than causal effects. A hypothesis was treated as supported when $p < .05$ and the association matched the hypothesized direction. Results with $.05 \leq p < .10$ were treated as directional trends, not as hypothesis support. Because multiple correlations were examined, interpretation is conservative, prioritizing effect size magnitude, directional consistency, and coherence across related tests rather than p-values alone (Table 5).

4.4.1 Tool effectiveness and perceived ROI-oriented impact (H1–H4)

Spearman correlations were used to test associations between perceived effectiveness of each AI capability domain and perceived ROI-oriented impact (ai_roi). Only predictive analytics effectiveness showed a statistically significant positive association with ai_roi (ρ = .527, p = .003), supporting H2. Personalization (ρ = .288, p = .130), sentiment analysis (ρ = .326, p = .084), and programmatic advertising (ρ = .234, p = .222) did not reach the .05 threshold, although sentiment analysis showed a directional trend.

At the composite level, overall perceived tool effectiveness (ai_tools_mean) was positively associated with perceived ROI-oriented impact (ρ = .491, p = .007). This supplementary result suggests a positive overall relationship, but the domain-level pattern is more theoretically informative. The strongest ROI linkage appeared in predictive analytics, whereas the two highest-rated tool domains in Section 4.2—personalization and programmatic advertising—did not show significant ROI associations. This pattern is consistent with the article's central distinction between deplorability and the evaluability of ROI. Predictive analytics is more directly tied to measurable decision outputs, whereas personalization and programmatic advertising may be highly visible in execution without producing equally clear attribution.

Given the small sample size, the non-supported results for H1, H3, and H4 should be interpreted cautiously. In particular, the coefficient for sentiment analysis (ρ = .326) is not negligible in magnitude. The non-significant result likely reflects limited statistical power and measurement constraints. This possibility should be acknowledged in the interpretation of non-supported hypotheses.

4.4.2 Perceived ROI-oriented impact and adoption outlook (H5)

Perceived ROI-oriented impact (ai_roi) was positively associated with adoption outlook (adopt_growth), ρ = .395, p = .034, supporting H5. This indicates that respondents who viewed AI as contributing to ROI-relevant outcomes were also more likely to expect broader future adoption. Overall perceived tool effectiveness (ai_tools_mean) was also positively associated with adoption outlook (ρ = .379, p = .043). This composite-level association is supplementary and should be interpreted cautiously.

4.4.3 Ethical risk perceptions and adoption outlook (H6–H7)

Privacy concern (eth_privacy) showed a significant negative association with adoption outlook, ρ = −.498, p = .006, supporting H6. This indicates that higher privacy concern was associated with lower optimism regarding AI adoption in marketing practice.

By contrast, bias/fairness concern (eth_bias) showed a non-significant positive association with adoption outlook (ρ = .230, p = .229), which does not support H7. This is substantively important. In this sample, fairness concern did not suppress adoption optimism. Instead, as shown below, it was linked to stronger governance expectations. This asymmetry suggests that privacy and bias concerns may operate through different governance pathways rather than through a single undifferentiated ethical-risk mechanism.

4.4.4 Ethical risk perceptions and governance expectations (H8) and exploratory transparency

Governance expectations were operationalized as oversight/accountability expectations (eth_oversight). Privacy concern was not associated with oversight/accountability expectations ($\rho = -.096$, $p = .622$). Therefore, H8a was not supported. In contrast, bias/fairness concern showed a significant positive association with oversight/accountability expectations ($\rho = .413$, $p = .026$), supporting H8b. This indicates that fairness-related concern was more likely than privacy concern to translate into explicit demand for safeguards, accountability, and oversight.

Transparency expectations (gov_transparency) were examined as an exploratory governance outcome. Neither ethical risk indicator was significantly associated with transparency expectations (eth_bias ↔ gov_transparency: $\rho = -.252$, $p = .187$; eth_privacy ↔ gov_transparency: $\rho = .093$, $p = .633$). These findings remain exploratory and are not used to support or refute hypotheses.

Reporting note. Multivariable models examining incremental explanatory power are presented in Section 4.5 as exploratory analyses. They do not determine hypothesis support decisions.

Table 5. Primary hypothesis tests and decisions (Spearman correlations; two-tailed; N = 29)

Hypothesis	**Predictor → Outcome**	**Test**	**Effect (ρ)**	**Approx. 95% CI for ρ***	**p**	**Decision**	**Interpretation**
H1	AI personalization effectiveness → ai_roi	Spearman	.288	[−.088, .592]	.130	Not supported	Small-to-moderate positive; inconclusive
H2	AI predictive analytics effectiveness → ai_roi	Spearman	.527	[.199, .749]	.003	Supported	Moderate-to-strong positive
H3	AI sentiment analysis effectiveness → ai_roi	Spearman	.326	[−.046, .619]	.084	Not supported (trend)	Moderate positive trend
H4	AI programmatic advertising effectiveness → ai_roi	Spearman	.234	[−.145, .553]	.222	Not supported	Small positive; inconclusive
— (composite)	ai_tools_mean → ai_roi	Spearman	.491	[.152, .727]	.007	Supplementary association	Moderate positive
H5	ai_roi → adopt_growth	Spearman	.395	[.033, .665]	.034	Supported	Moderate positive
H6	eth_privacy → adopt_growth	Spearman	−.498	[−.731, −.161]	.006	Supported	Moderate negative
H7	eth_bias →	Spearman	.230	[−.149,	.22	Not supported	Small

Hypothesis	Predictor → Outcome	Test	Effect (ρ)	Approx. 95% CI for ρ*	p	Decision	Interpretation
	adopt_growth	n		.550]	9		positive; opposite to hypothesis
— (composite)	ai_tools_mean → adopt_growth	Spearman	.379	[.015, .655]	.043	Supplementary association	Moderate positive
H8a	eth_privacy → eth_oversight	Spearman	−.096	[−.447, .280]	.622	Not supported	Negligible; opposite to the hypothesis.
H8b	eth_bias → eth_oversight	Spearman	.413	[.055, .677]	.026	Supported	Moderate positive
Exploratory	eth_bias → gov_transparency	Spearman	−.252	[−.566, .126]	.187	Exploratory only	Small negative
Exploratory	eth_privacy → gov_transparency	Spearman	.093	[−.283, .444]	.633	Exploratory only	Negligible

Note. 95% confidence intervals for Spearman's ρ are approximate intervals calculated manually using Fisher-z transformation, with subsequent back-transformation to the correlation scale. Given the modest sample size, results are interpreted with emphasis on effect size magnitude, directional consistency, and coherence across related tests. Support requires $p < .05$ and the hypothesized direction. Results with $.05 \le p < .10$ are treated as directional trends rather than hypothesis support.

4.5 Exploratory regression models

Table 6. Exploratory regression models (descriptive robustness checks; N = 29)

Model	Outcome	Predictors	R	R²	Predictor	b	SE	t	p
6.1	adopt_growth	ai_roi	.398	.158	Intercept	3.349	.571	5.87	< .001
					ai_roi	.307	.136	2.25	.033
6.2	adopt_growth	ai_roi + ai_tools_mean	.470	.221	Intercept	2.635	.747	3.53	.002
					ai_roi	.195	.154	1.26	.217
					ai_tools_mean	.300	.207	1.45	.160
6.3	adopt_growth	eth_privacy + eth_bias	.559	.313	Intercept	5.521	.4625	11.94	< .001
					eth_privacy	−.395	.1194	−3.31	.003
					eth_bias	.150	.0923	1.62	.117

Exploratory OLS regression models are presented as secondary descriptive robustness checks. They are used only to examine incremental explanatory value and joint predictor behavior and do not determine hypothesis support, which remains based on the nonparametric Spearman results reported in Table 5. Because the study relies on ordinal Likert-type indicators and a modest sample size, the regression findings are interpreted cautiously and only as supplementary evidence.

Model 6.1 examined whether perceived ROI-oriented impact predicted adoption outlook. The model explained 15.8% of the variance ($R^2 = .158$), and ai_roi was a significant positive predictor ($b = .307$, $SE = .136$, $t = 2.25$, $p = .033$). This pattern is consistent with the positive bivariate association reported in Section 4.4.

Model 6.2 added overall perceived tool effectiveness (ai_tools_mean) alongside ai_roi. Model fit increased to $R^2 = .221$, but neither predictor remained significant (ai_roi: $b = .195$, $p = .217$; ai_tools_mean: $b = .300$, $p = .160$), suggesting overlap between perceived ROI-oriented impact and overall tool effectiveness.

Model 6.3 examined privacy concern and bias/fairness concern as joint predictors of adoption outlook. This model showed the strongest fit ($R = .559$, $R^2 = .313$). Privacy concern was a significant negative predictor ($b = -.395$, $SE = .1194$, $t = -3.31$, $p = .003$), whereas bias/fairness concern was not ($b = .150$, $SE = .0923$, $t = 1.62$, $p = .117$). This result is consistent with the correlation analysis and suggests that privacy concern is the more salient negative predictor of adoption optimism in this sample.

Taken together, these models do not alter the primary hypothesis decisions. They are reported as descriptive robustness checks and broadly reinforce the nonparametric results in Table 5.

4.6 Qualitative findings: perceived barriers to AI adoption in Armenian marketing practice

Open-ended responses were consolidated into five recurring barrier themes. The qualitative component is used here for contextual interpretation, not for hypothesis testing, consistent with the study's mixed-method logic.

First, respondents repeatedly emphasized data readiness and measurement discipline. They referred to fragmented tracking, inconsistent CRM usage, and weak attribution routines. This theme is consistent with the paper's core argument that AI value depends on feedback loops, integration routines, and measurable decision quality rather than tool access alone (Abrardi et al., 2021; Mariani et al., 2021). It also helps explain why predictive analytics showed the clearest association with perceived ROI-oriented impact, while more deployable tool domains did not.

Second, respondents highlighted skills and capability gaps. They referred to limited analytics literacy and a weak ability to translate AI outputs into actions, experiments, and KPI-linked decisions. This pattern is consistent with prior work showing that organizational capability conditions shape whether AI use becomes performance-relevant in practice (Abrardi et al., 2021; Mariani et al., 2021).

Third, many responses pointed to weak strategic and process integration. AI was often described as an isolated tool rather than as part of planning cycles, customer-journey management, or performance-review routines. This theme reinforces the distinction developed earlier in the paper: some tools may be easy to deploy but harder to embed within measurable decision-making processes.

Fourth, respondents raised concerns about preserving the human element. They expressed concern that automation and AI-generated communication may reduce authenticity, weaken brand voice consistency, or erode trust when deployed without quality control. This theme adds interpretive depth to the broader concern that the use of AI without standards may create relational and reputational risks.

Fifth, responses reflected governance uncertainty. Participants referred to unclear practices around responsible data use, privacy, and accountability. This pattern is consistent with governance-focused literature and recent policy assessments that emphasize uneven readiness and standards in emerging digital environments (Akter et al., 2023; Schmauder et al., 2023; OECD, 2024; World Bank, 2024; United Nations, 2025). It also aligns with the quantitative finding that privacy concern is negatively associated with adoption outlook, while bias/fairness concern is more clearly linked to oversight/accountability expectations.

Overall, the qualitative evidence strengthens the interpretation of the quantitative results. The reported barriers converge around three practical conditions: measurement maturity, capability readiness, and governance clarity. This supports the article's broader conclusion that, in the Armenian marketing context, AI adoption is constrained less by awareness of tools than by the organizational conditions required to make those tools measurable, actionable, and governable.

5. Discussion

5.1 Overview of principal findings

This study examined how different AI capabilities contribute to perceived business value, adoption outlook, and governance expectations in a small-market digital marketing context. The results show a consistent pattern: respondents distinguish between AI tools that are easy to deploy in practice and those whose effects can be more credibly linked to ROI-relevant outcomes. This distinction is central to the study's contribution because it explains why perceived effectiveness does not automatically translate into perceived business impact.

Three mechanisms organize the findings. First, perceived tool effectiveness reflects deplorability and visible operational utility, whereas perceived ROI-oriented impact reflects ROI evaluability under real measurement conditions. Second, measurement discipline appears to be the key pathway through which perceived effectiveness becomes ROI-relevant confidence. Third, governance concerns operate asymmetrically: privacy concern reduces adoption optimism, whereas bias/fairness concern is more clearly associated with stronger oversight/accountability expectations. The qualitative findings support these mechanisms by illustrating recurring barriers in data readiness, capability gaps, and governance uncertainty, rather than by introducing a parallel explanatory model.

5.2 Interpreting effectiveness in a small-market setting: deplorability versus ROI evaluability

In this study, respondents appear to interpret effectiveness primarily as deplorability and visible operational usefulness. By contrast, ROI-oriented impact is judged more strictly on the basis of measurability, attribution, and decision validity. This distinction helps explain why personalization and programmatic advertising received the highest effectiveness ratings, while their tool-level associations with perceived ROI-oriented impact were not supported. Predictive analytics, in contrast, showed the clearest positive association with perceived ROI impact.

This pattern can be interpreted through a resource–capability lens. AI tools can be understood as resources, while measurement discipline, analytics skills, and integration routines function as capabilities that convert those resources into performance-relevant outcomes. In this sense, deplorability alone is insufficient. Strategic value emerges when firms can connect AI-supported actions to measurable outcomes through tracking discipline, CRM linkage, and feedback loops. This framing strengthens the theoretical grounding of the discussion and is consistent with the study's earlier construct logic (Abrardi et al., 2021;

Mariani et al., 2021).

The contrast across AI domains is therefore meaningful. Personalization and programmatic advertising can deliver clear executional value by optimizing relevance and media allocation at scale (Gao & Liu, 2022; Haleem et al., 2022; Mariani et al., 2021). In SME-dominant, platform-mediated environments, these gains are often visible in operations. However, ROI confidence is harder to establish when attribution is opaque, outcomes are multi-touch, and CRM integration is uneven. Under these conditions, their value may be easy to observe in execution but harder to validate as ROI-accountable impact. Predictive analytics differs because it is more directly connected to measurable managerial decisions such as targeting, forecasting, prioritization, and resource allocation. These outputs are closer to outcome metrics and can be tested when even modest feedback loops are in place. This helps explain why predictive analytics showed the strongest association with perceived ROI-oriented impact in the current study. The predictive analytics appear more ROI-evaluable, whereas personalization and programmatic advertising appear more deployable.

Overall, the evidence suggests that AI creates strategic value in digital marketing not simply when tools are available, but when deployable tools are supported by measurable decision routines and organizational capability maturity. In the Armenian context, the findings indicate that uneven analytics readiness limits the conversion of operational AI use into credible ROI-oriented confidence. This interpretation is also consistent with the qualitative emphasis on fragmented tracking, weak CRM usage, and limited experimentation routines.

5.3 Why predictive analytics aligns with perceived ROI-oriented impact

The significant association between predictive analytics and perceived ROI-oriented impact is theoretically meaningful. Predictive analytics is closer to managerial decision-making than the more execution-oriented AI domains. It supports targeting, forecasting, prioritization, and resource allocation, which are directly linked to outcome metrics such as conversion, retention, and revenue proxies (Bag et al., 2021; Haleem et al., 2022; Mariani et al., 2021; Veenam, 2024). This makes its value easier to evaluate, even with modest feedback loops.

In constrained settings, this distinction matters. Predictive analytics can be judged against outcome-linked targets, so even limited tracking routines may be sufficient to support perceived ROI confidence. By contrast, personalization and programmatic advertising operate more visibly at the execution level, where outcomes are harder to attribute across multiple touchpoints. This helps explain why overall perceived AI tool effectiveness was positively associated with perceived ROI-oriented impact at the composite level, while predictive analytics remained the clearest tool-level predictor. Practitioners, therefore, appear to view AI as strategically valuable in general, but only some AI capabilities as readily ROI-evaluable under current measurement conditions.

In this context, measurement maturity appears to be the mechanism that narrows the gap between perceived tool usefulness and perceived business impact. In the Armenian setting, predictive analytics seems closer to that threshold because its outputs are more directly tied to measurable decisions.

5.4 Governance perceptions as adoption boundary conditions: privacy pessimism and bias-as-oversight

The governance results show that ethical concerns do not operate uniformly. Privacy concern was negatively associated with adoption outlook, whereas bias/fairness concern was not. At the same time, bias/fairness concern was positively associated with oversight/accountability expectations. This pattern indicates that governance concerns affect adoption through multiple pathways, not through a single general ethical-risk response.

The privacy finding is consistent with literature showing that AI-driven marketing relies on extensive data capture, profiling, and inference, which can intensify perceptions of surveillance, loss of control, and reputational exposure (Khrais, 2020; Mariani et al., 2021). In a small market, these concerns may carry greater practical weight because networks are concentrated and reputational effects can diffuse quickly. This helps explain why privacy concern is associated with lower optimism about future AI adoption.

The bias/fairness result points in a different direction. In this sample, fairness concern did not reduce adoption optimism, but it did increase demand for oversight and accountability. This suggests that practitioners treat bias less as a reason to reject AI and more as a reason to govern AI more carefully. This interpretation is consistent with work that frames bias management as a capability domain requiring monitoring, audit, and accountability structures (Akter et al., 2023; Schmauder et al., 2023).

Taken together, these findings have a broader strategic implication. In AI-enabled marketing, trust in data practices and algorithmic governance becomes a strategic asset. Firms that can demonstrate responsible data use, stronger privacy protection, and credible accountability structures may be better positioned to sustain adoption and stakeholder confidence.

The exploratory transparency results were weaker. This suggests that transparency may not function as a generalized pro-disclosure preference in this context. Instead, it may be evaluated more pragmatically through concrete control mechanisms such as oversight/accountability, rather than through disclosure alone.

5.5 Comparison to prior research: convergence and context-specific departures

The findings are broadly consistent with prior research that treats AI as an execution-enhancing capability in marketing, especially through personalization, automated optimization, and data-driven targeting (Gao & Liu, 2022; Haleem et al., 2022; Mariani et al., 2021). At the same time, the Armenian evidence reinforces that value realization is readiness-contingent. Perceived business value depends not only on access to tools but also on measurement discipline, data quality, organizational capability, and governance maturity (Abrardi et al., 2021; Mariani et al., 2021).

The study also aligns with responsible AI and marketing ethics research by showing that privacy and bias/fairness concerns are not peripheral. They shape adoption judgments and governance expectations, although not in the same way (Khrais, 2020; Akter et al., 2023; Schmauder et al., 2023). The main context-specific departure is that some AI capabilities are readily used and positively evaluated in practice, yet their value is not equally translated into ROI-oriented confidence. This suggests that, in a small-market setting, AI adoption may advance faster than the organizational conditions required for attribution, validation, and governance.

5.6 Theoretical contribution

This study contributes to digital marketing management theory in two ways.

First, it shows that perceived AI value is not one-dimensional. Practitioners distinguish between AI capabilities that are readily deployable and operationally visible and capabilities that are more readily ROI-evaluable under constrained measurement conditions. In this study, personalization and programmatic advertising were rated highest in perceived effectiveness, whereas predictive analytics showed the clearest association with perceived ROI-oriented impact. This extends prior work that treats AI as a general performance-enhancing capability by showing that business judgments depend on whether a capability is mainly visible in execution or can be credibly linked to measurable outcomes (Abrardi et al., 2021; Mariani et al., 2021). Future research should therefore treat perceived effectiveness as multidimensional and test whether measurement maturity strengthens the link between effectiveness and ROI-oriented impact.

Second, the study identifies asymmetric governance pathways. Ethical risk perceptions did not operate uniformly. Privacy concern reduced optimism about adoption, whereas bias/fairness concern did not. At the same time, bias/fairness concerns increased expectations for oversight/accountability. These finding complements research that treats bias management as a governance capability requiring monitoring, audit, and control structures (Akter et al., 2023; Schmauder et al., 2023). It also indicates that governance in AI-enabled marketing should not be modeled as a single ethical-risk dimension. Different governance concerns influence adoption through different mechanisms.

In sum, the study suggests that AI creates strategic value in digital marketing only when deployable tools are supported by measurable decision routines and accountable governance. In small and emerging markets, this means that tool-led adoption may advance more quickly than the organizational conditions needed for sustained performance impact.

6. Implications

6.1 Managerial implications

AI in digital marketing no longer operates as a set of isolated tools. In practice, it increasingly operates within broader marketing systems that include marketing automation, omnichannel customer journey management, and data platform integration across advertising, web analytics, CRM, and lifecycle communication. The implications of this study, therefore, concern not only which AI applications appear useful but also how firms build the system conditions that make AI-supported decisions measurable, coordinated, and governable. The findings point to a pragmatic environment for AI adoption. Armenian marketing professionals report high AI use and rate personalization and programmatic advertising highest in day-to-day effectiveness. However, predictive analytics is the only domain that shows a clear positive association with perceived ROI-oriented impact. For managers, this means that visible usefulness and credible business impact should not be treated as equivalent outcomes.
The results also point to recurring barriers in measurement, capability, and integration.

Governance matters as well. Privacy concerns are negatively associated with adoption outlook, while bias/fairness concerns are positively associated with oversight/accountability expectations. In practical terms, competitive advantage is less likely to come from simply using more AI tools and more likely to come from building a minimum viable marketing analytics and governance infrastructure that makes AI measurable, accountable, and governable (Abrardi et al., 2021; Mariani et al., 2021; Gama & Magistretti, 2023).

6.1.1 Adopt a staged AI pathway: measurement, analytics, scale

A useful managerial response is a staged pathway built around measurement, analytics, and scale.

Stage 1: Build a minimum viable measurement discipline.

Before expanding AI use cases, firms should be able to consistently answer three basic questions: What counts as a conversion? Where did it come from? What did it cost? This does not require advanced infrastructure, but it does require standardization. Firms should:

- standardize conversion events and funnel definitions.

- apply consistent UTM and campaign naming rules;
- maintain basic attribution discipline;
- connect advertising data, web analytics, and CRM or lead records through structured fields and routine reporting.

This stage addresses the most frequently reported barriers in data readiness and weak integration and provides the minimum foundation for credible ROI evaluation (Mariani et al., 2021; OECD, 2024; World Bank, 2024).

Stage 2: Prioritize predictive analytics to validate ROI.

Because predictive analytics showed the clearest association with perceived ROI-oriented impact, early investment should focus on decision-support use cases that can be validated against outcomes. These include lead propensity scoring, churn-risk flags, demand forecasting, and next-best-action rules. Firms should keep models simple, define success metrics in advance, and validate outputs through controlled comparisons or pre/post tests (Bag et al., 2021; Khrais, 2020).

Stage 3: Scale deplorability tools with ROI guardrails.

Personalization and programmatic advertising were rated as the most effective in day-to-day use, but they did not show tool-level associations with perceived ROI-oriented impact in this sample. They should therefore be scaled with clear performance guardrails. Firms should:

- define objectives beyond surface metrics;
- evaluate segment-level outcomes such as qualified leads, repeat purchase, and retention;
- document targeting logic, exclusions, and escalation thresholds;
- conduct periodic automation audits to detect drift toward low-value outcomes (Gao & Liu, 2022; Haleem et al., 2022; Dumitriu & Popescu, 2020).

This staged pathway reflects the study's central managerial implication: AI creates stronger business value when tool deployment is supported by measurement discipline, decision routines, and governance safeguards, rather than by tool adoption alone.

6.1.2 Build an AI operating system inside the marketing function

To convert AI tool usage into repeatable performance, Armenian SMEs and agencies should formalize a limited set of routines that reduce ad hoc experimentation and make outcomes more measurable and governable.

First, firms should maintain a use-case portfolio rather than chasing tools opportunistically. A limited set of approved AI use cases should be mapped to funnel stages, responsible owners, and KPIs. Use cases that cannot be evaluated with the current measurement system should be deferred or retired.

Second, firms should establish a regular experiment cadence. A biweekly or monthly test cycle with a simple experiment log—hypothesis, variant, metric, decision—can create a minimum feedback loop for ROI learning and reduce intuition-led adoption.

Third, firms should define human-in-the-loop decision rights. AI may support recommendations such as audience selection, creative variation, or bid optimization, but human approval should remain mandatory for sensitive targeting, exclusion rules, and higher-risk customer segments.

Fourth, firms should require minimum documentation from vendors and platforms. External partners should specify what data are used, what the system optimizes, which exclusions or constraints apply, and what controls or audit trails are available.

These routines directly address the main barriers identified in the study—weak measurement, capability gaps, and poor strategic integration—and are consistent with the broader finding that AI value depends on complementary organizational capabilities rather than tool access alone (Abrardi et al., 2021; Mariani et al., 2021; Akter et al., 2023; Schmauder et al., 2023).

6.1.3 Manage trust and brand voice as performance assets

Respondents also raised concerns about preserving the human element. In managerial terms, this should be treated as both a performance issue and a risk issue, not simply as a creative preference.

Firms should therefore codify brand voice rules and prohibited claims for AI-assisted content. They should also define review thresholds for higher-risk customer communication, especially where pricing, promises, complaints, or sensitive categories are involved. In addition, firms should maintain authenticity checkpoints in lifecycle campaigns to ensure that automation does not weaken trust, consistency, or reputational control in a small-market environment.

This implication extends the study's governance argument. In AI-enabled marketing, trust is not only an ethical concern but also a performance asset that shapes customer responses and adoption confidence (Frank et al., 2023).

6.1.4 Governance as a competitive advantage: practical privacy and accountability controls

The governance results are asymmetric. Privacy concern is negatively associated with adoption outlook, whereas bias/fairness concern is positively associated with oversight/accountability expectations. This implies a practical managerial stance: treat privacy as a prerequisite for scaling AI use, and treat accountability as an operating discipline. Even where regulation is still evolving, firms can implement minimum viable governance.

Priority actions include:

- applying consent and data-minimization rules for profiling and personalization;
- assigning internal accountability for AI-assisted targeting decisions;
- auditing targeting exclusions and segment-level outcomes periodically;
- defining a response procedure for data misuse or mis-targeting.

These controls are consistent with the study's broader finding that responsible AI use depends on governance routines that protect trust and reduce uncertainty, not only on tool deployment (Akter et al., 2023; Schmauder et al., 2023; Mariani et al., 2021).

Taken together, these implications suggest that Armenian firms are moving from opportunistic AI use and tool experimentation toward a more mature stage in which AI must be performance-validated, operationally integrated, and supported by accountable governance routines.

6.2 Policy implications

The findings suggest that Armenia's progress in AI-enabled marketing is constrained less by awareness than by capability, infrastructure, and operational standards. Policy actors, donor programs, and business associations can support responsible adoption by helping SMEs build a minimum viable marketing analytics and governance infrastructure, with emphasis on measurement readiness, workforce capability, and governance clarity.

6.2.1 Shift support from AI promotion to measurement and readiness infrastructure

Because perceived ROI relevance is most clearly linked to analytics capability, and because data readiness emerged as a primary barrier, support programs should prioritize the foundations of measurable AI use. This includes:

- SME toolkits for conversion definitions, tracking standards, and CRM discipline;
- subsidized implementation support through short, applied projects rather than lecture-based training.
- sector-specific playbooks that map KPIs to feasible AI use cases across e-commerce, services, and tourism/HoReCa.

This recommendation is consistent with the study's central finding that AI value realization depends on feedback loops and measurable decision quality rather than tool access alone (Abrardi et al., 2021; Mariani et al., 2021).

6.2.2 Create practical governance templates for marketing data use

As privacy concerns reduce optimism about adoption, policy actors can lower uncertainty by issuing practical governance templates that SMEs can apply without strong legal or technical capacity. Useful instruments include:

- standard privacy notice and consent language for targeting and personalization.
- minimum data retention guidance for marketing datasets.
- recommended disclosure practices for AI-mediated interactions where appropriate.

These templates should remain operational and easy to adopt. Their value lies in reducing ambiguity and helping firms translate abstract governance requirements into routine practice.

6.2.3 Standardize procurement and vendor transparency requirements

Many SMEs depend on agencies and platforms to implement AI-enabled marketing. Policy actors and business associations can therefore reduce governance risks and improve accountability by establishing standardized procurement requirements. Vendors should be expected to specify:

- what data are collected and processed;
- which outcomes are optimized;
- whether data are retained, reused, or shared onward;
- what controls, audit trails, and escalation paths are available.

This would strengthen both performance accountability and governance transparency in outsourced or platform-mediated AI use.

6.2.4 Invest in applied upskilling tied to implementation outcomes

The study highlights persistent gaps in skills, analytics literacy, and strategic integration. Effective support programs should therefore be tied to implementation outcomes rather than attendance alone. Useful deliverables include:

- basic tracking implementation;
- operational dashboards;
- simple experiment logs linked to decisions and KPIs.

Training priorities should include:

- applied analytics literacy for marketers;
- governance literacy for non-technical teams;
- managerial capability in embedding AI use cases into processes, roles, and accountability structures.

6.2.5 Establish communities of practice and benchmarking in a small-market ecosystem

Given Armenia's concentrated professional ecosystem, coordination can generate strong spillover effects. Industry associations, accelerators, and donor-supported networks can help by creating:

- benchmarking frameworks for a minimum viable analytics stack and a minimum viable governance stack;
- shared case repositories documenting what worked, what failed, and why;
- cross-firm learning groups that support peer exchange and practical standard setting.

In a small-market setting, these collective mechanisms can reduce duplication, accelerate learning, and improve the quality of AI adoption across firms.

7. Limitations And Future Research

7.1 Limitations

This study provides an expert-based snapshot of how professionals engaged with the Armenian market perceive the use of AI in consumer behavior analysis and digital marketing. Several limitations constrain interpretation and generalizability.
Sample size and non-probability sampling: The study used purposive expert sampling and a modest sample (N = 29). This limits statistical power, increases uncertainty around effect estimates, and restricts generalization beyond the expert pool. It also prevented subgroup analyses by role, sector, or firm size.

Early-adopter composition of the sample: Nearly all respondents (28/29) reported using AI professionally. This strengthens the practical relevance of the findings, but it likely overrepresents digitally mature and adoption-positive professionals relative to the broader SME landscape in Armenia (OECD, 2024; World Bank, 2024; United Nations, 2025). The findings should therefore be interpreted as perceptions among AI-exposed practitioners, not as evidence of population-level readiness.

Perception-based measures: The study relies on self-reported perceptions of tool effectiveness, ROI-oriented impact, adoption outlook, and governance concerns. These perceptions are analytically useful for understanding adoption dynamics, but they are not equivalent to objective performance indicators or causal ROI. Observed associations may therefore reflect shared beliefs, shared constraints, or common experience rather than verified performance differences (Gama & Magistretti, 2023). Because key variables were collected from the same respondents in a single instrument, some associations may also reflect common-method variance rather than only substantive relationships.

Construct precision and measurement constraints: Several variables were measured using single-item indicators, and the composite tool-effectiveness index combined distinct AI capability domains. Internal consistency was moderate, which is acceptable for exploratory analysis but limits construct precision and latent inference. Future research should use short multi-item measures to assess ROI-oriented impact, adoption outlook, privacy, bias/fairness, oversight, and transparency, thereby strengthening reliability and validity testing (O'Dea et al., 2025).

Cross-sectional design: The study captures perceptions at one point in time. It therefore cannot assess change in capability maturity, governance routines, or adoption logic over time. Directionality cannot be inferred. For example, stronger ROI perceptions may increase adoption optimism, but stronger adoption optimism may also shape ROI judgments. Context specificity: Armenia is a small, platform-dependent market with concentrated professional networks and uneven measurement infrastructure. These conditions may shape perceptions differently than in larger, more mature, or more regulated environments. Transferability should therefore be argued through contextual similarity, such as other small and emerging markets, rather than assumed directly.

These limitations also indicate where the theory should develop next. The current findings are useful because they identify a plausible distinction between deplorability and ROI evaluability, but stronger theory testing will require designs that more directly link AI capability maturity, governance routines, and observable performance outcomes. Future research should test these relationships with larger samples, multi-item measures, longitudinal or comparative designs, and, where possible, observable performance indicators.

7.2 Future research directions

Future research should extend this study in three priorities: direct theory testing, stronger measurement and design, and context extension.

7.2.1 Direct theory-testing priorities

The first priority is to test the study's central mechanism more directly. The present findings suggest that the gap between deplorability and ROI evaluability narrows as firms' measurement maturity increases. Future studies should therefore operationalize measurement maturity more explicitly, including tracking discipline, attribution routines, CRM integration, and experimentation cadence, and test whether it strengthens the relationship between perceived tool effectiveness and perceived ROI-oriented impact.

A second priority is to test governance maturity as a moderator rather than only as an outcome. Future work should examine whether routines such as human-in-the-loop controls, audit practices, and vendor transparency reduce the negative effect of privacy concerns on adoption confidence and shape how bias/fairness concerns translate into oversight expectations (Akter et al., 2023; Schmauder et al., 2023).

A third priority is to connect perceptual evidence to observable performance outcomes. Future studies should pair survey measures with indicators such as conversion rate, ROAS, CAC, retention, repeat purchase, or LTV proxies. This would allow more direct testing of whether ROI-oriented perceptions correspond to measurable business outcomes (Mulugeta et al., 2025).

7.2.2 Measurement and design improvements

Future studies should use larger, more structured samples across sectors, firm-size bands, AI maturity levels, and role types. This would allow subgroup comparisons and more reliable tests of boundary conditions.

Future work should also strengthen construct measurement. Key variables such as ROI-oriented impact, adoption outlook, privacy concerns, bias/fairness concerns, oversight, and transparency should be captured using short multi-item scales and evaluated for reliability and validity. This would reduce dependence on single-item indicators and support stronger latent inference.

Longitudinal and mixed-method designs are also needed. Repeated measures or staged designs would enable observation of how firms move from tool adoption to capability maturity and how measurement and integration routines evolve over time in SME settings. Combining surveys, interviews, and operational audits would be especially valuable.

7.2.3 Context extension

A complementary research stream should examine the consumer side of AI-enabled marketing in Armenia. Experimental studies could test how disclosure format, consent framing, perceived control, intrusiveness, and fairness shape trust and purchase intention in AI-mediated interactions (Janson, 2023; de Jong et al., 2025; Koning & Voorveld, 2025; Frank et al., 2023).

Future work could also broaden the expert pool by including Armenian practitioners working in international markets or supporting Armenian brands abroad. This would allow comparison between small-market and more mature-market implementation conditions and help test whether the current findings reflect Armenia-specific constraints or broader small-market dynamics.

In sum, future research should move from perception-based exploratory evidence toward designs that test mechanisms, moderators, and observable performance effects more directly. The most immediate next step is to examine how measurement maturity and governance maturity shape the conversion of AI tool use into credible business value.

8. Conclusion

AI-enabled capabilities are now embedded across digital marketing and e-commerce, but their strategic value depends on whether firms can convert AI outputs into measurable decisions supported by data integration, attribution routines, and accountable governance. In this sense, AI creates value not through access to tools alone, but through the organizational conditions that make its use measurable, interpretable, and governable (Gama & Magistretti, 2023; Islam et al., 2024).

This study examined how marketing professionals connected to the Armenian market evaluate four AI application domains—personalization, predictive analytics, sentiment analysis, and programmatic advertising—and how these evaluations relate to perceived ROI-oriented impact, adoption outlook, and governance concerns. In the expert sample (N = 29), AI exposure was high, and the outlook for adoption was generally positive. Personalization and programmatic advertising were rated highest in day-to-day effectiveness, but only predictive analytics showed a clear positive association with perceived ROI-oriented impact. This pattern supports the article's central conclusion: practitioners distinguish between deplorability and the evaluability of ROI. Some AI capabilities are easy to use and visibly useful in execution, yet harder to validate as ROI-accountable impact under constrained measurement conditions. In the Armenian context, confidence in AI value appears to depend less on operational usefulness alone and more on the maturity of measurement, integration, and decision routines (Pop, 2020; Avram et al., 2020).

The governance findings are equally important. Privacy concern reduced optimism about AI adoption, whereas bias/fairness concern did not. At the same time, bias/fairness concern increased expectations for oversight/accountability. This suggests that governance concern do not operate through one uniform mechanism. Privacy functions more directly as an adoption constraint, while fairness functions more clearly as a demand for control. AI scaling is therefore most defensible when firms treat privacy concern as a condition of adoption and accountability as a condition of responsible operation.

For digital marketing management theory, the study offers two connected implications. First, perceived AI effectiveness should not be treated as a single construct. It should be differentiated into deplorability and ROI evaluability. Second, governance should not be modeled as a single dimension of ethical risk. Different governance concerns shape adoption and control in different ways. In small and emerging markets, these distinctions are especially important because tool diffusion may advance more quickly than the organizational conditions needed for measurable, trusted value creation.

From a dynamic capability perspective, AI tools are resources, but strategic value emerges only when firms possess the organizational capabilities to measure, integrate, and govern AI-supported decisions. In performance measurement terms, deplorability can improve execution without generating credible ROI confidence unless attribution routines and decision infrastructures are in place. In this sense, the study refines prior optimistic AI-in-marketing evidence by showing that operational effectiveness and ROI-oriented confidence should not be treated as equivalent outcomes, particularly in small and emerging markets.

These conclusions remain bounded by the study design. The evidence is cross-sectional, perception-based, and drawn from a modest purposive expert sample with high AI exposure. Several constructs were measured with single-item indicators, and the findings do not establish causal direction or objective business impact. Future research should therefore use larger and more structured samples, stronger multi-item measures, and designs that connect AI capability use to observable performance indicators. The most important next step is to test whether measurement maturity and governance maturity shape the conversion of AI use into credible business value. Consumer-side research is also needed to examine trust, perceived intrusiveness, fairness, and disclosure effects in AI-enabled marketing contexts (O'Dea et al., 2025).

In sum, AI appears most strategically valuable when firms do not treat it as a standalone tool but as part of a measurable, governed marketing system. In small-market settings, sustainable value creation depends on whether firms can move from tool use to capability maturity, and from automation to accountable decision support.

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