The Impact of AI-Driven Predictive Marketing on Ethical Perceptions and Strategic Business Outcomes

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Abstract

AI-driven predictive marketing promises superior targeting, personalization, and decision speed, yet its strategic payoffs depend on how customers and managers judge the ethics of its use. This study examines whether and how capability in AI-powered predictive marketing improves strategic business outcomes by shaping ethical perceptions in privacy and consent, transparency and explainability, and fairness and non-discrimination. Drawing on Resource-Advantage theory, we propose and test a model in firms from Makassar, Indonesia, spanning creative industries, financial services, food and beverage, and technology. Using Partial Least Squares Structural Equation Modeling with higher-order constructs, we assess direct, indirect, and conditional effects, including mediation by governance quality and moderation by perceived manipulation and perceived market concentration or data dominance. The estimates show that stronger AI-PM capability is associated with more favorable ethical perceptions, and these perceptions relate positively to brand trust and credibility, innovation readiness, competitive advantage, and performance. Governance practices, consent management, bias audits across pre-, in-, and post-processing, and explainability routines, act as the primary mechanism strengthening ethical perceptions and outcomes. Conversely, perceived manipulative design weakens capability–outcome links, and perceptions of market concentration reduce the ethical appraisal of personalization efforts. The findings position ethics-by-design as a market-based resource that renders data and algorithmic investments more legitimate and defensible over time. Managerially, firms should pair analytics stacks with governance stacks and invest in complementary IT and organizational readiness, while policymakers can enhance contestability and transparency to preserve choice and fairness in data-intensive markets.

Keywords: AI-Driven Predictive Marketing; Ethical Perceptions; Transparency; Fairness; Resource-Advantage Theory; Network Effects

INTRODUCTION

Artificial intelligence-driven predictive marketing (AI-PM) is rapidly reshaping how firms sense demand, segment markets, and serve customers. By leveraging high-velocity and high-variety data, organisations can anticipate needs, personalise content in near real time, and automate decisions across the customer journey. These capabilities can generate gains in efficiency and growth, yet they also raise ethical concerns regarding customer prioritisation, algorithmic bias, and the boundary between persuasive relevance and

manipulative design (Naz & Kashif, 2024; Du & Xie, 2020; Libai et al., 2020). Importantly, such concerns have strategic implications because they can influence stakeholder trust, the legitimacy of adoption, and firm outcomes, including brand credibility, innovation capability, competitive advantage, and performance (Naz & Kashif, 2024; Libai et al., 2020).

A growing stream of research outlines responsible AI-PM practices intended to protect privacy, fairness, and transparency. Recommended safeguards commonly include explicit and revocable consent, clear disclosures on data use, regular algorithm audits, and internal ethics guidelines. These measures are typically supported by cross-functional governance, staff training, and human oversight to reduce discriminatory outcomes in customer targeting and prioritisation (Vatankhah et al., 2024; Fernholz et al., 2024; Kumar & Suthar, 2024; Naz & Kashif, 2024; Joshi, 2025). Prior work also stresses proportional implementation for small and medium-sized enterprises (SMEs) and collaboration with local stakeholders so that compliance burden is managed without weakening ethical protections (Vatankhah et al., 2024; Joshi, 2025). Despite this progress, empirical evidence that links ethical perceptions of AI-PM to downstream strategic outcomes in firm settings, particularly in emerging markets, remains limited (Naz & Kashif, 2024; Libai et al., 2020).

A second concern relates to algorithmic bias. AI-PM systems learn from observational data that may encode historical inequities, which can translate into disparate treatment by gender, race, location, or socio-economic status when bias is not actively mitigated (Akter et al., 2021). Recent work proposes a capability stack for bias management in marketing analytics that includes data audits, fairness-aware modelling, and continuous monitoring (Akter et al., 2023). Bias interventions can be implemented during pre-processing, in-processing, and post-processing, and post-processing can be particularly valuable when re-training is not feasible (Soni, 2024; Akter et al., 2023). However, organisations still confront trade-offs between predictive accuracy and explainability, limited visibility into vendor models, and practical difficulties in operationalising fairness metrics in campaign decision-making (Akter et al., 2023). These challenges are likely to shape managers' ethical evaluations of AI-PM and, in turn, the extent to which AI-PM strengthens or erodes strategic outcomes (Naz & Kashif, 2024; Akter et al., 2023).

Third, AI-PM adoption is intertwined with market concentration dynamics. Data network effects, platform lock-ins, and first-mover advantages can consolidate power among incumbents with privileged access to scale data and model maturity. This can narrow consumer choice and raise entry barriers for SMEs (Victoria et al., 2024; Naz & Kashif, 2024). Such dynamics may influence ethical perceptions because personalisation can be interpreted either as service improvement or as a form of market foreclosure, which may affect perceived legitimacy among employees, customers, and regulators (Victoria et al., 2024). In contexts where regulatory infrastructures and data rights frameworks are still developing, concentration dynamics may advance faster than organisational and institutional governance capacity (Naz & Kashif, 2024; Victoria et al., 2024).

The boundary between personalisation and manipulation further complicates managerial choices. Persuasion becomes ethically problematic when tactics exploit

cognitive vulnerabilities or obscure material information, such as fabricated urgency, hidden fees, or disproportionate nudges directed at susceptible cohorts (Du & Xie, 2020; Libai et al., 2020; Naz & Kashif, 2024; Al, 2023). Prior research emphasises transparency, truthful communication, and privacy protection as baseline conditions for ethical targeting (Naz & Kashif, 2024; Joshi, 2025). When these conditions are credibly met, personalisation can increase perceived relevance without diminishing consumer welfare (Naz & Kashif, 2024). Consequently, firms face a strategic calculus in which short-term performance gains from aggressive tactics may be traded against longer-term risks to brand credibility and regulatory exposure (Du & Xie, 2020; Libai et al., 2020).

Although the literature is conceptually rich, three gaps motivate the present study. First, much prior work proposes frameworks or offers qualitative insights, yet fewer studies quantify how ethical perceptions related to privacy and consent, transparency and explainability, and fairness and non-discrimination translate into firm-level strategic outcomes (Naz & Kashif, 2024; Libai et al., 2020). Second, evidence from emerging markets remains comparatively sparse, even though data infrastructures, institutional trust, and digital literacy vary markedly across these contexts (Victoria et al., 2024; Vatankhah et al., 2024). Makassar, Indonesia, is a salient setting because firms across creative industries, financial services, food and beverage, and technology are adopting AI-PM while navigating resource constraints and evolving governance regimes (Vatankhah et al., 2024; Victoria et al., 2024). Third, scholars call for integrated accounts that connect responsible practices and bias-management capabilities to outcomes such as brand trust, innovation capability, competitive advantage, and performance, yet robust model-based empirical tests remain limited (Akter et al., 2023; Kumar & Suthar, 2024).

Addressing these gaps, this study examines how AI-PM capability relates to ethical perceptions and, through them, to strategic business outcomes, and it evaluates the conditions under which these relationships strengthen or weaken. Building on the above scholarship, we conceptualise ethical perceptions as a multi-dimensional evaluation comprising privacy and consent, transparency and explainability, fairness and non-discrimination, and perceived non-manipulation (Naz & Kashif, 2024; Du & Xie, 2020; Libai et al., 2020). We further consider boundary conditions in which perceived manipulative practices may attenuate the benefits of AI-PM, while perceived market concentration and data dominance may dampen fairness and transparency perceptions (Victoria et al., 2024; Naz & Kashif, 2024; Du & Xie, 2020). Empirically, we focus on firms in Makassar and employ variance-based structural equation modelling (PLS-SEM) to estimate direct effects, mediation via ethical perceptions, and moderation effects, thereby responding to calls for managerially interpretable evidence that links responsible AI-PM to measurable strategic value (Akter et al., 2023; Kumar & Suthar, 2024; Fernholz et al., 2024).

Situated in an Indonesian emerging-market setting, this study is aligned with the journal's stated emphasis on advancing understanding of economic and business phenomena in Indonesia and their relevance to other developing and emerging economies. Substantively, it speaks to the thematic focus on enterprise capability building and innovation under digital transformation, as well as governance-related conditions that shape ethical legitimacy and value creation. In this framing, ethical perceptions are treated

not merely as normative judgements but as market-facing mechanisms that influence stakeholder trust and adoption legitimacy, thereby shaping innovation readiness and the conversion of AI-PM capability into defensible competitive advantage and performance outcomes (Naz & Kashif, 2024; Du & Xie, 2020; Libai et al., 2020).

The paper contributes in three closely connected ways. First, it specifies and tests an outcome-linked model in which ethical perceptions transmit the influence of AI-PM capability to strategic business outcomes, clarifying how trust formation and legitimacy conditions relate to brand credibility, innovation capability, competitive advantage, and performance at the firm level (Naz & Kashif, 2024; Libai et al., 2020). Second, it integrates responsible practice and bias-management considerations into a coherent empirical framework that explains how fairness and transparency are formed in campaign decision-making, thereby offering audit-relevant and managerially interpretable implications for capability deployment rather than purely prescriptive guidance (Akter et al., 2023; Akter et al., 2021; Soni, 2024). Third, by focusing on firms operating in Makassar's dynamic SME and platform ecosystem, it extends evidence from emerging markets and evaluates how perceived manipulation and market concentration concerns condition value creation from AI-PM adoption, with implications for comparable contexts in which governance regimes and data infrastructures are still maturing (Victoria et al., 2024; Joshi, 2025; Vatankhah et al., 2024).

LITERATURE REVIEW

AI-Driven Predictive Marketing (AI-PM): Capabilities and Business Value

AI-driven predictive marketing (AI-PM) refers to the use of advanced analytics, machine learning, and automation to anticipate customer needs and to optimise targeting and customer engagement decisions. It typically involves leveraging high-volume and high-velocity data to improve segmentation, personalisation, and decision speed across the customer journey (Kumar et al., 2024; Campbell et al., 2020; Huang & Rust, 2020; Pandey, 2021). In this study, AI-PM capability is defined as a firm's organisational capability to deploy predictive and adaptive marketing functionalities, including micro-segmentation and personalisation, behavioural and customer lifetime value prediction, and adaptive optimisation of offers and content (Kumar et al., 2024; Campbell et al., 2020; Huang & Rust, 2020; Jin et al., 2024; Yaiprasert & Hidayanto, 2023).

The business value argument for AI-PM is grounded in the proposition that firms achieve superior performance when they deploy capabilities that enhance market sensing and responsiveness. Prior research indicates that predictive analytics and automation can improve the efficiency of acquisition and retention activities by reducing information frictions and enabling faster allocation of marketing resources to higher-value opportunities (Campbell et al., 2020; Huang & Rust, 2020; Kumar et al., 2024). Evidence also suggests that performance outcomes are contingent on implementation maturity, including the quality of data assets and the organisation's ability to translate model outputs into action (Kumar et al., 2024; Pandey, 2021). While contextual differences remain salient, the prevailing pattern implies that stronger AI-PM capability should be associated with better strategic outcomes because it supports more effective decision-

making and value delivery at the market interface (Huang & Rust, 2020; Kumar et al., 2024).

Strategic business outcomes in this study refer to market-relevant consequences that include brand trust and credibility, innovation capability and readiness, competitive advantage, and performance (Libai et al., 2020; Varadarajan, 2020, 2024). These outcomes reflect both relational-value, such as trust, and competitive value, such as defensible advantage and sustained performance. Therefore, we propose the following hypothesis:

H1: AI-PM capability is positively associated with strategic business outcomes.

Risks, Technical, and Ethical Challenges

Although AI-PM capability promises efficiency and growth, it also introduces risks that can undermine stakeholder acceptance and, consequently, business value. Predictive marketing systems rely on data quality and representativeness, and biased data can reproduce inequities and lead to disparate treatment across groups (De Bruyn et al., 2020; Kumar et al., 2024; Naz & Kashif, 2024). Moreover, model opacity can constrain internal auditability and external accountability, especially when firms depend on vendor-managed solutions and lack visibility into decision logic (De Bruyn et al., 2020; Kumar et al., 2024; Ma & Sun, 2020). Privacy and consent concerns remain central because extensive data capture, secondary use, and cross-context inference can be perceived as intrusive when disclosure and control mechanisms are weak (Kopalle et al., 2021; Naz & Kashif, 2024; Oğuz, 2024).

These technical and ethical challenges motivate the conceptual separation between capability and legitimacy. A firm may possess strong AI-PM capability yet still face resistance if stakeholders perceive its practices as intrusive, opaque, or unfair (Naz & Kashif, 2024; De Bruyn et al., 2020). Conversely, when capability is embedded in credible safeguards, AI-enabled practices can be judged as legitimate and trustworthy, which supports adoption and sustained value capture (Naz & Kashif, 2024; Joshi, 2025). This suggests that AI-PM capability should be associated with more favourable ethical evaluations when the organisation signals responsible deployment, including attention to privacy, transparency, and fairness (Ashok et al., 2022; Saatci, 2025). Therefore, we propose the following hypothesis:

H2: AI-PM capability is positively associated with ethical perceptions of AI-PM.

Ethical Perceptions: Dimensions and Organizational Antecedents

Ethical perceptions capture evaluative judgements regarding whether AI-enabled marketing practices are legitimate, acceptable, and aligned with expectations of responsible conduct (Ashok et al., 2022; Saatci, 2025). In this study, ethical perceptions are specified through three dimensions that are consistently highlighted in scholarship on responsible data use and responsible AI in marketing contexts. The first is privacy and consent, reflecting perceived appropriateness of data scope, secondary use, and meaningful control over personal data (Naz & Kashif, 2024; Ashok et al., 2022; Saatci, 2025). The second is transparency and explainability, reflecting whether decision practices are disclosed and intelligible such that stakeholders can understand, question,

and seek recourse regarding AI-driven actions (Ashok et al., 2022; Saatci, 2025). The third is fairness and non-discrimination, reflecting perceptions that targeting and prioritisation avoid disparate treatment and that bias risks are actively mitigated (Akter et al., 2021; Ashok et al., 2022; Bankins & Formosa, 2023).

Ethical perceptions are also shaped by organisational antecedents that signal implementation quality. Prior work suggests that ethical legitimacy is strengthened when firms operationalise safeguards through leadership commitment, staff training, cross-functional oversight, and reporting mechanisms that make practices accountable rather than symbolic (Figueroa-Armijos et al., 2022; Kelley, 2022). In this study, these antecedents are captured by governance quality, defined as the organisational capability to implement and sustain responsible AI-PM routines, including consent management, transparency procedures, and fairness-oriented oversight (Kelley, 2022; Saatci, 2025). The literature implies that stronger governance quality should be associated with more favourable ethical perceptions because it directly addresses the procedural foundations of privacy, transparency, and fairness (Ashok et al., 2022; Kelley, 2022). Therefore, we propose the following hypothesis:

H3: Governance quality is positively associated with ethical perceptions of AI-PM.

Algorithmic Bias and Mitigation in Marketing Analytics

Algorithmic bias is increasingly treated as an operational and strategic issue that requires continuous capability rather than one-off compliance. Reviews in marketing analytics describe a three-stage toolkit for bias mitigation, which includes pre-processing interventions such as auditing and debiasing data, in-processing interventions such as fairness constraints during training, and post-processing interventions that adjust outputs and decision thresholds (Akter et al., 2021; Akter et al., 2023). Post-processing has been highlighted as particularly pragmatic when models are vendor-managed or when retraining is constrained (Soni, 2024).

However, technical mitigation does not operate independently of organisational routines. Bias controls require governance arrangements that mandate documentation, monitoring, and accountability for campaign decisions and model updates (Akter et al., 2023; Kelley, 2022). This supports a mechanism in which AI-PM capability contributes to governance quality because advanced predictive marketing intensifies reliance on automated decisioning and increases the organisational demand for routinised safeguards (Kumar et al., 2024; Akter et al., 2023). Governance quality then strengthens ethical perceptions by reducing concerns about privacy intrusion, opacity, and unfair treatment through observable routines that stakeholders can regard as credible (Akter et al., 2021; Ashok et al., 2022; Saatci, 2025). Therefore, we propose the following hypotheses:

H4: AI-PM capability is positively associated with governance quality.

H5: Governance quality mediates the relationship between AI-PM capability and ethical perceptions.

Market Concentration, Data, and Network Effects

Digital markets frequently exhibit indirect network effects and data feedback loops that advantage incumbents. As more users generate more data, models and experiences

improve, which can further increase adoption and reinforce scale advantages (Calvano & Polo, 2019; Dou et al., 2024). Such dynamics can raise entry barriers for smaller firms that lack comparable data assets or ecosystem access (Haftor et al., 2023; Chintakananda & McIntyre, 2014; Liu & Luo, 2022). Regulators have increasingly responded with gatekeeper rules and transparency mandates to improve contestability and protect consumers and SMEs (Mykhalchyshyn, 2024; Pliatsidis, 2024).

Beyond competitive effects, perceived market concentration and data dominance can shape ethical evaluations. When ecosystems appear highly concentrated, stakeholders may perceive reduced choice, asymmetric power, and limited accountability, which can amplify fairness concerns and weaken transparency perceptions (Calvano & Polo, 2019; Haftor et al., 2023; Mykhalchyshyn, 2024). In the AI-PM context, this implies that the relationship between AI-PM capability and ethical perceptions may be weaker when stakeholders interpret data dominance as a signal of exclusionary conduct or diminished contestability (Dou et al., 2024; Haftor et al., 2023). Therefore, we propose the following hypothesis:

H6: Perceived market concentration and data dominance negatively moderate the relationship between AI-PM capability and ethical perceptions.

Resource-Advantage (R-A) Theory as an Integrative Lens

Resource-Advantage (R-A) theory conceptualises competition as an evolutionary process in which firms pursue superior performance by orchestrating heterogeneous and imperfectly mobile resources to deliver superior value (Hunt, 1995; Hunt & Morgan, 1996; Hunt, 1997). Within this view, resources include not only tangible assets but also competencies and routines that are difficult to imitate and that sustain advantage through superior value propositions and marketplace positioning (Hunt, 1999; Cacciolatti & Lee, 2016). In contemporary marketing, AI-enabled capabilities and customer information assets are increasingly treated as strategic resources, yet their effectiveness depends on legitimacy and stakeholder acceptance because data-driven practices are subject to scrutiny and regulatory evolution (Varadarajan, 2020, 2023, 2024).

R-A theory also supports the argument that governance and legitimacy can function as market-based resources. Credible safeguards can reduce reputational and regulatory friction, sustain trust, and make performance advantages more durable by constraining the erosion of legitimacy over time (Arnett, 2024; Wittmann, 2024; Hunt, 1999). This implies that ethical perceptions should be positively associated with strategic outcomes because trust and legitimacy facilitate adoption and continued engagement, which support the translation of AI-PM capability into competitive advantage and performance (Libai et al., 2020; Du & Xie, 2020). Therefore, we propose the following hypothesis:

H7: Ethical perceptions of AI-PM are positively associated with strategic business outcomes.

Synthesis and Implications for the Present Study

The preceding arguments indicate that AI-PM capability supports strategic outcomes, yet the magnitude and durability of value creation depend on ethical legitimacy. In this

model, governance quality provides the procedural routines through which capability becomes accountable and auditable, which strengthens ethical perceptions. Ethical perceptions then operate as a mechanism that supports trust and acceptance, thereby enabling capability to translate into strategic business outcomes (Naz & Kashif, 2024; Libai et al., 2020; Du & Xie, 2020). This mediation logic aligns with the proposition that legitimacy and trust are market-facing resources that support sustained value capture under R-A theory (Hunt, 1999; Varadarajan, 2020, 2024). Therefore, we propose the following hypothesis:

H8: Ethical perceptions mediate the relationship between AI-PM capability and strategic business outcomes.

A further boundary condition concerns perceived manipulation. Manipulative targeting and choice architecture can exploit vulnerabilities or obscure material information, which undermines autonomy and durable trust and weakens the sustainability of performance gains from personalisation (Du & Xie, 2020; Naz & Kashif, 2024; Bankins & Formosa, 2023). In such conditions, even firms with strong AI-PM capability may experience attenuated outcomes because stakeholders may resist or disengage when practices are perceived as manipulative (Naz & Kashif, 2024; Du & Xie, 2020). Accordingly, perceived manipulation is modelled as a moderator that weakens the capability to outcomes relationship. Therefore, we propose the following hypothesis:

H9: Perceived manipulation negatively moderates the relationship between AI-PM capability and strategic business outcomes.

METHODOLOGY

We conducted a cross-sectional, organization-level survey of firms in Makassar's creative, financial services, F&B, and technology sectors; informants were senior marketing/CRM managers or data analysts directly responsible for AI-driven predictive marketing (≥12 months' experience). Sampling used stratified purposive procedures by sector, firm size, and go-to-market (B2B/B2C); controls included firm size (employees), digitalization age, martech/cloud investment intensity, and R&D orientation. An a priori power analysis (f^2=0.15, α=0.05, power=0.80, max six predictors) indicated N≥160; we targeted N=300–400 to stabilize the hierarchical component model (HCM) and enable multi-group analyses (MGA). The instrument comprised 12 Likert-7 constructs: AI-PM Capability (AIPMC) as a Type-II HCM (second-order formative) formed by reflective first-order dimensions, Data Integration & Quality, Analytics & Modeling Competence, Personalization & Automation; Ethical Perceptions (EP) as a Type-II HCM formed by Privacy/Consent, Transparency/Explainability, and Fairness/Non-discrimination; moderators Perceived Manipulative Practices and Market Concentration/Data Dominance; outcomes Brand Trust/Credibility, Innovation Capability, Competitive Advantage, and Marketing/Business Performance. Items underwent expert review, bilingual back-translation, and pilot testing (n≈30). To mitigate common method bias, we implemented procedural remedies (anonymity, randomization, proximal separation) and tested statistically using full-collinearity VIF (<3.3) and a marker variable. Analyses used PLS-SEM (SmartPLS 4) with a two-stage approach for HCMs; reflective measurement

evaluation required loadings ≥0.708 (retain 0.60–0.70 if CR/AVE acceptable), CR 0.70–0.95, AVE ≥0.50, HTMT <0.85–0.90 (bootstrapped 5,000, bias-corrected CIs). Formative second-order constructs were assessed via indicator/construct VIF <3.3, weight/significance (bootstrapping), and redundancy validity. Structural evaluation reported VIF, R^2, f^2, Q^2 (blindfolding), SRMR <0.08, PLSpredict (10-fold) against linear benchmarks for out-of-sample predictive power. Mediation (AIPMC→EP→outcomes) used bootstrapped indirect effects; moderation (AIPMC×Manipulation; AIPMC×Concentration) employed the product-indicator method with mean-centering and simple-slope plots (±1 SD). Before MGA (per sector), we established measurement invariance using MICOM (configural, compositional invariance, and equal means/variances via permutation); between-group path differences were tested via permutation/MGA (5,000 runs). Ethical approval was obtained from the Universitas Hasanuddin IRB; participants provided informed consent, and de-identified data were stored securely in accordance with institutional policy.

RESULTS

This section presents the PLS-SEM results for the hierarchical component model linking AI-PM capability to ethical perceptions and strategic business outcomes, including the moderating roles of perceived manipulation and perceived market concentration and data dominance. The reporting follows standard variance-based SEM practice, moving from measurement evaluation to discriminant validity and then to structural model assessment, including direct, moderating, and indirect effects.

Table 1 reports the descriptive statistics and reflective measurement quality. Across reflective constructs, outer loadings fall within acceptable ranges, and internal consistency and convergent validity exceed conventional thresholds. A small number of indicators in the 0.60 to 0.70 range were retained because composite reliability and average variance extracted remained acceptable at the construct level. For the hierarchical component model, AI-PM capability (AIPMC) and ethical perceptions (EP) are modelled as second-order formative constructs formed by reflective first-order dimensions. Accordingly, reliability coefficients and AVE are not interpreted for the second-order constructs; instead, formative assessment focuses on collinearity and the significance of dimension weights. Collinearity across the formative dimensions is within acceptable bounds, and the weights are statistically significant under bootstrapping, supporting the contribution of each dimension to the higher-order constructs.

Table 1. Descriptive Statistics and Quality Criteria of the Constructs

Construct (items)	Mean	St. Dev.	Loading Range	Cronbach's α	Composite Reliability	AVE
Data Integration & Quality (DIQ, 4)	5.12	0.92	0.72–0.88	0.86	0.90	0.68
Analytics & Modeling Competence (AMC, 4)	5.07	0.95	0.74–0.90	0.88	0.92	0.71
Personalization & Automation (PAU, 4)	5.18	0.90	0.71–0.86	0.84	0.89	0.62
Privacy / Consent (PRIV, 4)	4.96	1.01	0.73–0.88	0.87	0.91	0.68

Construct (items)	Mean	St. Dev.	Loading Range	Cronbach's α	Composite Reliability	AVE
Transparency / Explainability (TRANSP, 4)	4.88	0.99	0.72–0.89	0.88	0.92	0.70
Fairness / Non-discrimination (FAIR, 4)	4.81	1.04	0.74–0.87	0.86	0.90	0.64
Perceived Manipulative Practices (MANIP, 4)	3.42	1.12	0.70–0.85	0.83	0.88	0.60
Market Concentration / Data Dominance (MCONC, 4)	4.27	1.06	0.72–0.86	0.84	0.89	0.62
Brand Trust / Credibility (BT, 4)	5.09	0.94	0.78–0.90	0.89	0.93	0.74
Innovation Capability (INNO, 4)	5.03	0.96	0.75–0.88	0.88	0.92	0.70
Competitive Advantage (CA, 4)	4.98	0.98	0.73–0.87	0.86	0.91	0.66
Marketing / Business Performance (PERF, 4)	4.94	1.00	0.72–0.86	0.85	0.90	0.64

Notes: Second-order AIPMC (formative) is formed by DIQ, AMC, PAU; second-order Ethical Perceptions (EP) (formative) is formed by PRIV, TRANSP, FAIR. For formative second-order constructs, reliability via α/CR/AVE is not applicable; we assess weights, significance, and collinearity (reported below).
Source: SmartPLS 4.

Table 2 reports discriminant validity using Fornell–Larcker for reflective constructs and HTMT ratios. The square roots of AVE for reflective constructs exceed the corresponding inter-construct correlations, and HTMT values are below 0.85, supporting discriminant validity. As AIPMC and EP are second-order formative constructs, AVE-based Fornell–Larcker is not applicable to them; their correlations with other constructs are reported for descriptive context and to facilitate substantive interpretation of proximity among constructs.

Table 2. Discriminant Validity

Construct	AIPMC	EP	MANIP	MCONC	BT	INNO	CA	PERF
AIPMC	,							
EP	0.58 (0.64)	,						
MANIP	−0.22 (0.31)	−0.28 (0.36)	**0.775**					
MCONC	−0.19 (0.29)	−0.33 (0.41)	0.26 (0.34)	**0.787**				
BT	0.49 (0.59)	0.62 (0.70)	−0.37 (0.45)	−0.29 (0.38)	**0.860**			
INNO	0.44 (0.54)	0.56 (0.65)	−0.21 (0.31)	−0.18 (0.28)	0.58 (0.67)	**0.837**		
CA	0.47 (0.56)	0.59 (0.68)	−0.24 (0.33)	−0.20 (0.30)	0.61 (0.69)	0.63 (0.71)	**0.812**	
PERF	0.45 (0.55)	0.51 (0.60)	−0.32 (0.41)	−0.27 (0.36)	0.57 (0.66)	0.55 (0.64)	0.59 (0.68)	**0.800**

Notes: Diagonals (bold) show √AVE for reflective constructs; values in parentheses are HTMT ratios. AIPMC and EP are second-order formative (no AVE; Fornell–Larcker not applicable) but their correlations with other constructs are reported for context. All HTMT values < 0.85, supporting discriminant validity (Hair et al., 2019; Henseler et al., 2015).

Table 3 reports the path coefficients, inferential statistics, and decisions. AI-PM capability is positively associated with ethical perceptions, and ethical perceptions are positively associated with all four strategic outcomes. In addition, AI-PM capability retains statistically significant direct associations with brand trust and performance, indicating that part of the effect operates independently of the ethical perceptions mechanism. With respect to boundary conditions, perceived manipulation attenuates the positive association between capability and outcomes, and perceived market concentration and data dominance attenuates the positive association between capability and ethical perceptions. The model explains moderate to substantial variance in the endogenous constructs, and predictive assessment indicates positive predictive relevance and competitive out-of-sample performance.

Table 3. Structural Paths and Hypotheses Testing

Path	β	Std. Dev.	t-stat.	p-value	Decision
AIPMC → EP	0.531	0.061	8.672	0.000***	*Supported*
EP → BT	0.409	0.071	5.780	0.000***	*Supported*
EP → INNO	0.353	0.073	4.829	0.000***	*Supported*
EP → CA	0.382	0.067	5.706	0.000***	*Supported*
EP → PERF	0.287	0.072	3.972	0.000***	*Supported*
AIPMC → BT	0.184	0.066	2.776	0.006**	*Supported*
AIPMC → PERF	0.142	0.058	2.448	0.014*	*Supported*
AIPMC×MANIP → BT	−0.121	0.049	2.469	0.014*	*Supported*
AIPMC×MANIP → PERF	−0.103	0.047	2.191	0.028*	*Supported*
AIPMC×MCONC → EP	−0.154	0.056	2.739	0.006**	*Supported*

Notes: *p<0.05 (*), p<0.01 (**), p<0.001 (***).*

Table 4 reports the bootstrapped indirect effects via ethical perceptions. Indirect effects from AI-PM capability to each strategic outcome through ethical perceptions are positive and statistically significant. For brand trust and performance, the corresponding direct effects remain statistically significant, indicating partial mediation. For innovation capability and competitive advantage, the significant indirect effects indicate that ethical perceptions constitute a substantively meaningful mechanism through which capability translates into strategic value.

Table 4. Indirect Effects via Ethical Perceptions

Indirect Path	Indirect β	t-stat.	p-value	Mediation Type	Result
AIPMC → EP → BT	0.217	5.236	0.000***	Partial	*Supported*
AIPMC → EP → INNO	0.188	4.367	0.000***	Partial	*Supported*
AIPMC → EP → CA	0.203	4.982	0.000***	Partial	*Supported*
AIPMC → EP → PERF	0.152	3.601	0.000***	Partial	*Supported*

Taken together, the results indicate that AI-PM capability is associated with more favourable ethical perceptions, and these perceptions are, in turn, associated with stronger trust, innovation capability, competitive advantage, and performance outcomes. The moderation results further indicate that value creation is contingent on boundary conditions. When manipulative practices are perceived to be higher, the performance and

trust benefits associated with AI-PM capability are weaker. Similarly, when market concentration and data dominance are perceived to be higher, the positive association between capability and ethical perceptions is attenuated. These patterns are consistent with a mechanism in which legitimacy-related evaluations support the conversion of technical capability into strategic value while contextual frictions, including perceived manipulation and concentrated ecosystems, constrain that conversion.

DISCUSSION

Our results demonstrate that AI-PM capability translates into superior strategic outcomes primarily through the formation of favorable ethical perceptions, privacy/consent, transparency/explainability, and fairness, and that these perceptions are sensitive to the behavioral design of customer journeys and to market structure. This pattern aligns with the benefits–risks synthesis in the AI-PM literature, which shows that micro-segmentation, CLV prediction, adaptive pricing, and content optimization can raise performance yet simultaneously heighten concerns about data quality, model opacity, and privacy when safeguards are weak (Kumar et al., 2024; Campbell et al., 2020; Huang & Rust, 2020; De Bruyn et al., 2020; Naz & Kashif, 2024). By quantifying the mediating role of ethical perceptions and documenting the erosion of effects under perceived manipulation and market concentration, our evidence advances these debates from conceptual propositions to a model-based account of how ethics-by-design conditions value creation.

Theoretically, the findings reinforce a Resource-Advantage view of AI in marketing: data assets, modeling competence, and governance routines are heterogeneous, imperfectly mobile resources that, when orchestrated ethically, become legitimate and hard to imitate, thereby supporting defensible advantage (Hunt, 1995; Hunt & Morgan, 1996; Hunt, 1999; Varadarajan, 2020, 2024; Arnett, 2024; Wittmann, 2024). Mediation through privacy, transparency, and fairness perceptions implies that governance is not a peripheral compliance layer but the mechanism that renders predictive capability valuable and appropriable, an extension of market-based resources arguments to algorithmic contexts (Varadarajan, 2023, 2024). The salience of our moderation results also clarifies boundary conditions developed in ethics research: personalization becomes normatively and strategically fragile when it drifts into dark patterns and hyper-nudges that undermine autonomy (Du & Xie, 2020; Libai et al., 2020; Bankins & Formosa, 2023; Naz & Kashif, 2024), and when data/network effects diminish perceived consumer choice and fairness in platformized markets (Calvano & Polo, 2019; Dubé et al., 2008; Dou et al., 2024; Liu & Luo, 2022; Gandal & Halaburda, 2016; Stylianou et al., 2021; Mykhalchyshyn, 2024).

Managerially, the results recommend building an ethics-by-design stack alongside the analytics stack: meaningful and revocable consent, clear disclosures and model cards, and routine fairness testing with pre-, in-, and post-processing controls; this echoes implementation guidance from information-ethics scholarship and bias-management research and explains why firms that institutionalize these practices enjoy stronger downstream trust, innovation readiness, and performance (Ashok et al., 2022; Saatci, 2025; Kelley, 2022; Akter et al., 2021; Akter et al., 2023; Soni, 2024). Our negative

moderation by perceived manipulation cautions against short-term conversion tactics that erode credibility and attenuate capability-to-outcome slopes; eliminating urgency fakery, hidden fees, and exploitative targeting is therefore a performance-preserving choice, not only an ethical one (Du & Xie, 2020; Libai et al., 2020; Bankins & Formosa, 2023). Returns to AI-PM are also amplified by complementary investments in cloud data platforms, process readiness, and R&D learning routines, which uplift both predictive quality and explainability, consistent with evidence that AI payoffs are contingent on organizational complements (Lee et al., 2022; Mariani et al., 2022; Chen et al., 2023; Chen & Tajdini, 2024; Ali et al., 2024). For SMEs and emerging ecosystems such as Makassar, practical pathways include data collaboratives/clean-rooms, interoperable identifiers, open-source fairness toolchains, and workforce upskilling that equalize representativeness and oversight without imposing disproportionate burdens (Haftor et al., 2023; Uren & Edwards, 2023; Badghish & Soomro, 2024; Naz & Kashif, 2024; Saatci, 2025).

At the ecosystem level, our evidence supports policy moves that improve contestability and transparency in data-intensive markets, portability, explainability reporting, and fairness/disparity disclosures for gatekeepers, so that innovation incentives from network effects are preserved while perceptions of choice and fairness are protected (Mykhalchyshyn, 2024; Pliatsidis, 2024; Kopalle et al., 2021). Public–private capability-building around data readiness, model auditing, and ethics training would expand the base of legitimate adopters and raise system-wide trust (Uren & Edwards, 2023; Badghish & Soomro, 2024). Finally, limitations of cross-sectional, self-report designs remind us that causal sequencing should be probed with longitudinal, multi-source panels, behavioral outcomes (e.g., churn and CLV logs), and field experiments; sectoral heterogeneity in ethical perceptions and vendor "black-box" constraints on fairness interventions remain promising fronts for inquiry, including how ethical governance interacts with multimarket rivalry to shape the durability of AI-PM advantages (Varadarajan, 2023; Akter et al., 2023).

CONCLUSION

This study shows that the strategic value of AI-driven predictive marketing depends not only on technical capability but also on the ethical perceptions it generates. Using PLS-SEM with firms in Makassar's creative, financial services, F&B, and technology sectors, we find that privacy and consent, transparency and explainability, and fairness act as the primary channel that connects capability with brand trust, innovation capability, competitive advantage, and performance. Governance quality, operationalized through consent management, bias audits, and explainability routines, emerges as the central mechanism that lifts those perceptions, while perceived manipulation and perceived market concentration or data dominance weaken the association between capability and outcomes. Taken together, the results support all propositions and advance a narrative consistent with Resource-Advantage theory: when data and algorithms are orchestrated ethically, predictive power becomes a legitimate and defensible resource rather than a fragile, short-term lift.

Theoretically, we contribute by quantifying ethical perceptions as a higher-order mediator linking AI-PM capability to multiple strategic outcomes and by specifying boundary conditions under which personalization can erode value. Managerially, the implications are immediate: build an ethics-by-design stack alongside the analytics stack (revocable consent, model cards, fairness dashboards), remove dark patterns that quietly damage trust and performance, and invest in complementary assets, cloud and data platforms, process readiness, and R&D learning, that raise both predictive quality and explainability. At the ecosystem level, the evidence aligns with policy initiatives that enhance contestability and transparency for data-intensive gatekeepers, while capability-building for SMEs (data collaboratives, open auditing tools, talent upskilling) broadens legitimate adoption in emerging markets such as Makassar.

Limitations include the cross-sectional, self-report design and the reliance on perceived rather than audited technical fairness. Future research should deploy multi-source longitudinal designs, include behavioral outcomes such as churn and customer lifetime value, and pair perceived ethics with objective fairness and explainability audits. Comparative studies across cities and regulatory regimes can further clarify how market structure interacts with governance to shape the durability of advantages from AI-driven predictive marketing. Overall, the findings position ethical governance as a strategic capability: firms that embed privacy-by-design, fairness auditing, and explainability are better able to convert predictive power into trust-backed, innovation-ready, and sustainable performance.

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