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Drivers of Intention to Adopt AI-Based Marketing: Evidence from Respondents in Vietnamese SMEs

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Abstract

Artificial intelligence (AI)-based marketing is increasingly recognized as a strategic tool for enhancing customer engagement and marketing performance; however, its adoption among small and medium-sized enterprises (SMEs) in emerging economies remains limited. This study examines the factors influencing the intention to adopt AI-based marketing among respondents working in Vietnamese SMEs by integrating perceived usefulness, perceived ease of use, trust, perceived cost, perceived risk, and social influence into an extended technology adoption framework. A quantitative survey was conducted with 473 valid respondents from Vietnamese SMEs, and the proposed research model was analyzed using confirmatory factor analysis and structural equation modeling. The results indicate that the structural model explains 59.0% of the variance in intention to adopt AI-based marketing. Trust emerged as the strongest predictor of adoption intention, followed by perceived risk, social influence, and perceived usefulness, whereas perceived ease of use and perceived cost were not statistically significant. The positive relationship between perceived risk and adoption intention suggests that respondents with greater awareness of AI-related risks may also possess higher levels of AI literacy and engagement, rather than indicating that risk itself promotes adoption. These findings highlight that AI-based marketing adoption is driven primarily by trust, social influence, and strategic perceptions rather than by traditional technology acceptance factors alone. The study contributes to the AI marketing and SME digital transformation literature by providing empirical evidence from Vietnam, an underexplored emerging-economy context, and offers practical implications for SME managers, AI solution providers, and policymakers seeking to promote responsible and effective AI adoption.

Keywords: *artificial intelligence; AI marketing; SMEs; adoption intention; technology acceptance; Vietnam.*

1. Introduction

Artificial intelligence (AI) is increasingly used to support marketing automation, customer analytics, personalization, predictive targeting, content generation, and data-driven decision-making (Islam et al., 2024; Vdovichena et al., 2024). These applications are particularly relevant to small and medium-sized enterprises (SMEs), which often need to improve marketing efficiency while operating with limited financial, human, and technological resources (Iakovets, Balog and Židek, 2023; Odukoya, 2024; Schönberger, 2023). In Vietnam, SMEs are commonly classified according to employee, revenue, capital, and sectoral criteria under the national SME support framework (Nguyen et al., 2024). Despite their economic importance, AI implementation in marketing remains uneven because adoption decisions are shaped by perceived benefits, usability, trust, cost, risk, external pressure, and organizational readiness (Alam, Ahmed and Kokash, 2024; Katebi et al., 2024).

Technology adoption literature has long emphasized perception-related factors such as perceived usefulness and perceived ease of use in explaining behavioral intention (Chai, Xu and Li, 2023; Keung, Lee and Luk, 2025). Later models also highlight social influence, facilitating conditions, and contextual pressures (Keung, Lee and Luk, 2025). However, AI-based marketing differs from many conventional information systems because it involves algorithmic recommendations, customer data processing, automation, and possible opacity in decision-making. Therefore, AI adoption also depends on trust, risk perception, cost concerns, and social legitimacy (Bedué and Fritzsche, 2022; Sarker and Nuruzzaman, 2024).

This study addresses three interconnected research gaps. First, much existing AI adoption research has focused on large firms, developed economies, or broad digital transformation contexts, whereas AI-based marketing possesses distinctive characteristics such as customer-data processing, algorithmic recommendation, content automation, personalization, and partially opaque decision logic (Abdullah and Hasan, 2023). Empirical evidence on AI-based marketing adoption among small and medium-sized enterprises (SMEs) in emerging economies, particularly Vietnam, remains markedly limited (Huynh, 2026; Nguyen, 2024). Unlike large corporations, SMEs often face tighter resource constraints, uneven digital

capabilities, strong dependence on external platforms, and greater uncertainty regarding data governance. Second, the study addresses a theoretical gap. Traditional technology acceptance models (TAM) predominantly emphasize operational perceptions, specifically perceived usefulness and perceived ease of use (Lin, 2025). However, because AI-based marketing fundamentally relies on autonomous algorithmic learning and intensive data usage, adoption decisions cannot be fully explained by usability factors alone. Instead, they require greater theoretical attention to trust, risk-related perceptions, cost concerns, and social legitimacy (Nguyen, 2024; Zhang et al., 2026). Third, this study addresses an empirical gap regarding the inconsistent findings in the literature concerning the role of perceived risk in AI (Wei et al., 2025). While conventional adoption paradigms treat perceived risk solely as a deterrent, empirical evidence suggests that risk perceptions may also reflect proactive risk awareness, active evaluation, and higher AI literacy among potential adopters (Wei et al., 2025). To bridge these gaps, the present study examines six determinants of intention to use AI-based marketing among respondents from Vietnamese SMEs: perceived usefulness, perceived ease of use, trust, perceived cost, perceived risk, and social influence. Therefore, this study contributes to theory by extending technology adoption research to a specific AI marketing context in an emerging economy and contributes to practice by identifying the conditions under which SME respondents' express readiness to adopt AI-based marketing responsibly and effectively.

2. Literature Review And Proposed Research Model

2.1. Intention to Use AI in Marketing

Artificial intelligence has increasingly transformed marketing activities by enabling firms to automate repetitive tasks, personalize customer interactions, predict consumer behavior, optimize advertising expenditure, and support data-driven decision-making (Lopez and Arjunan, 2023; Rosário and Cruz, 2025). Unlike conventional digital marketing tools, AI-based marketing systems are not limited to information storage or communication support; rather, they rely on algorithmic learning, large-scale data processing, and autonomous recommendation capabilities (Wilson and Anwar, 2024). This makes AI adoption more complex than the adoption of earlier information technologies because it involves not only perceived technological benefits but also concerns over trust, transparency, cost, risk, and organizational readiness (Sun and Fu, 2025).

For SMEs, AI-based marketing presents both opportunities and challenges. AI can help SMEs overcome resource limitations by improving marketing efficiency, reducing manual workload, and enhancing customer targeting. At the same time, SMEs often face constraints related to financial resources, technological infrastructure, managerial expertise, and employee capabilities. These constraints make AI adoption among SMEs highly dependent on managerial perceptions and perceived organizational feasibility (Kalleparambil and Akoum, 2025).

2.2. Perceived Usefulness and Intention to Use AI in Marketing

Perceived usefulness refers to the extent to which individuals believe that using a particular technology can improve their performance, productivity, or organizational outcomes (Bolodeoku et al., 2022). According to the Technology Acceptance Model (TAM), perceived usefulness directly influences behavioral intention because individuals are more likely to adopt a technology when they expect that it will generate tangible benefits and improve task performance.

In the context of AI-based marketing, perceived usefulness reflects the extent to which decision-makers believe that AI technologies can enhance customer segmentation, automate repetitive marketing activities, improve campaign effectiveness, support predictive analytics, and strengthen customer relationship management (Ijomah et al., 2024; Odionu, Bristol-Alagbariya and Okon, 2024). For SMEs, where financial, human, and technological resources are often limited, technologies that improve efficiency and competitive advantage are particularly attractive. When managers perceive that AI-based marketing can reduce operational costs, improve marketing performance, and support better strategic decisions, they are more likely to develop positive intentions toward adoption.

Previous empirical studies have consistently reported a positive relationship between perceived usefulness and technology adoption intention in AI and digital marketing contexts(Khan and Emon, 2024). Therefore, it is reasonable to expect that respondents who perceive AI-based marketing as beneficial for business performance will demonstrate stronger adoption intentions.

H1: Perceived usefulness positively affects intention to use AI in marketing.

2.3. Perceived Ease of Use and Intention to Use AI in Marketing

Perceived ease of use refers to the extent to which individuals believe that a technology can be learned, operated, and applied with minimal effort (Aulia and Marsasi, 2024). According to the Technology Acceptance Model (TAM), technologies that are perceived as easy to use reduce cognitive and operational burdens, thereby increasing users' willingness to adopt them (FakhrHosseini et al., 2024).

In the context of AI-based marketing, perceived ease of use encompasses not only the operational simplicity of AI tools but also their accessibility, interpretability, and compatibility with existing business processes (Abbasi et al., 2025). For SMEs, which often have limited technical expertise and financial resources, technologies that require less training, lower implementation effort, and minimal technical support are generally more attractive. When AI-based marketing tools are perceived as easy to learn, integrate, and operate, managers and employees are more likely to develop favorable attitudes and stronger intentions to adopt them.

Moreover, complex technologies may increase uncertainty and implementation resistance, especially among SMEs with limited digital capabilities (Hansen, Christiansen and Lassen, 2025). Conversely, user-friendly AI systems can reduce perceived barriers, improve confidence in technology usage, and facilitate organizational acceptance. Previous studies have consistently reported that perceived ease of use positively influences technology adoption intention across various digital and AI-related contexts (Sharma, Goel and Taneja, 2025).

Therefore, it is expected that respondents who perceive AI-based marketing tools as easy to use will demonstrate stronger intentions to adopt such technologies.

H2: Perceived ease of use positively affects intention to use AI in marketing.

2.4. Trust and Intention to Use AI in Marketing

Trust has emerged as a critical factor in artificial intelligence adoption research because AI systems often operate through complex algorithms that users cannot fully understand, monitor, or explain (Shin, 2023). Trust refers to the extent to which individuals believe that a technology is reliable, secure, transparent, and capable of performing its intended functions appropriately (Chinnaraju, 2025).

Unlike conventional information systems, AI-based marketing technologies rely heavily on automated decision-making, predictive analytics, customer profiling, and algorithmic recommendations. These characteristics increase uncertainty and information asymmetry between users and the technology itself. According to uncertainty reduction theory, individuals are more likely to adopt a technology when they trust its reliability, accuracy, and safety. In contrast, a lack of trust may increase perceived uncertainty and reduce willingness to adopt innovative technologies.

In the context of AI-based marketing, trust encompasses confidence in the accuracy of AI-generated recommendations, the reliability of automated decision-making processes, the protection of customer data, and the ethical behavior of AI solution providers (Calota, 2025). This issue is particularly important for SMEs because they often have limited technological expertise and resources to independently evaluate AI systems. Consequently, SME decision-makers may rely heavily on trust when assessing whether AI-based marketing technologies are suitable for their organizations. Previous studies have consistently demonstrated that trust positively influences AI adoption intention across various technological and organizational contexts (Daly, Wiewiora and Hearn, 2025; Horani et al., 2025). When managers perceive AI systems as reliable, transparent, and secure, they are more likely to develop favorable attitudes and stronger intentions to adopt AI-based marketing solutions.

Therefore, it is expected that greater trust in AI-based marketing systems will increase respondents' intention to adopt such technologies.

H3: Trust positively affects intention to use AI in marketing.

2.5. Perceived Cost and Intention to Use AI in Marketing

Perceived cost refers to the extent to which individuals or organizations believe that adopting and implementing a technology requires substantial financial, operational, and organizational resources (Al-Kfairy, 2025). In technology adoption research, perceived cost is generally considered a barrier because organizations tend to evaluate whether the expected benefits of a technology justify the required investment.

In the context of AI-based marketing, perceived cost includes not only the direct financial expenses associated with acquiring AI software and infrastructure but also indirect costs related to employee training, system integration, maintenance, data management, and organizational change (Nantege, 2025). These cost considerations are particularly important for SMEs because they often operate with limited budgets, constrained human resources, and lower technological readiness compared with larger organizations.

According to resource constraint theory, organizations facing limited financial and technological resources are less likely to adopt innovations that require substantial investment or involve uncertain returns. When SME decision-makers perceive that AI-based marketing technologies are costly to implement and maintain, they may become reluctant to adopt such technologies due to concerns about financial risk, implementation complexity, and return on investment. Previous studies have reported that perceived cost negatively influences technology adoption intention, especially in contexts involving advanced digital technologies and organizational innovation (Amankona et al., 2025). High implementation costs may discourage organizations from investing in new technologies, even when they recognize their potential benefits.

Therefore, it is expected that higher perceived costs will reduce respondents' intention to adopt AI-based marketing technologies.

H4: Perceived cost negatively affects intention to use AI in marketing.

2.6. Perceived Risk and Intention to Use AI in Marketing

Perceived risk refers to the extent to which individuals believe that using a technology may expose them to potential losses, uncertainty, or undesirable outcomes(Houlroyd and Warren, 2026). In technology adoption research, perceived risk has traditionally been viewed as a barrier to adoption because uncertainty regarding performance, security, privacy, legal compliance, and ethical issues can discourage users from adopting innovative technologies.

In the context of AI-based marketing, perceived risk encompasses concerns related to data privacy breaches, cybersecurity threats, algorithmic bias, inaccurate recommendations, legal liability, reputational damage, and ethical issues associated with automated decision-making(Calota, 2025). These concerns are particularly relevant for SMEs because they often have limited technological expertise, fewer cybersecurity resources, and less experience managing AI-related risks.

According to perceived risk theory, individuals tend to avoid technologies that are associated with high levels of uncertainty or potential negative consequences. When managers perceive that AI-based marketing technologies involve substantial risks, they may become more cautious and less willing to adopt them. In particular, concerns regarding customer data protection, regulatory compliance, and the reliability of AI-generated outputs may reduce organizational confidence in AI adoption.

Previous studies have generally reported a negative relationship between perceived risk and technology adoption intention across various digital and AI-related contexts (Abdullah and Hasan, 2023). Higher levels of perceived risk have been associated with lower willingness to adopt emerging technologies because perceived uncertainty can undermine trust and increase resistance to change.

Therefore, it is expected that greater perceived risk will reduce respondents' intention to adopt AI-based marketing technologies.

H5: Perceived risk negatively affects intention to use AI in marketing.

2.7. Social Influence and Intention to Use AI in Marketing

Social influence refers to the extent to which individuals perceive that important others, such as customers, colleagues, competitors, business partners, and professional communities, believe that they should adopt a particular technology (Ahmed et al., 2025). In technology adoption research, social influence is considered an important determinant of behavioral intention because individuals and organizations often rely on external opinions, norms, and expectations when evaluating new technologies.

In the context of AI-based marketing, social influence reflects the impact of customers, competitors, suppliers, industry associations, professional networks, and government-supported digital transformation initiatives on organizational decision-making. According to social influence theory and institutional theory, organizations are more likely to adopt innovations when they perceive external pressure, observe successful adoption by peers, or believe that adoption enhances organizational legitimacy and competitiveness.

For SMEs, social influence may be particularly important because these firms often have limited internal resources and technological expertise. Consequently, SME managers may rely on recommendations from professional communities, business partners, industry leaders, and government programs when evaluating AI-based marketing technologies. Furthermore, increasing competitive pressure and the widespread diffusion of AI technologies may encourage SMEs to adopt AI-based marketing to maintain market relevance and competitiveness.

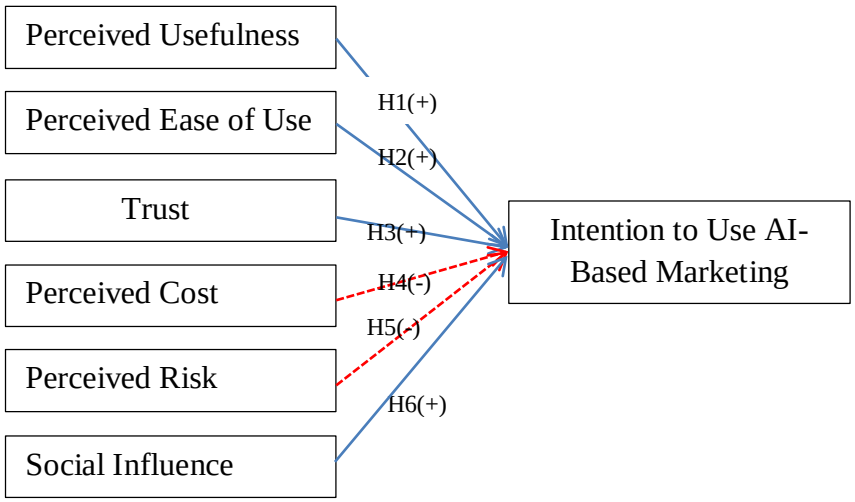
Previous studies have consistently found that social influence positively affects technology adoption intention across various organizational and digital technology contexts (Song, Qiu and Liu, 2025). Organizations are generally more willing to adopt innovative technologies when they perceive strong support, encouragement, or expectations from their external environment.

Therefore, it is expected that stronger social influence will increase respondents' intention to adopt AI-based marketing technologies.

H6: Social influence positively affects intention to use AI in marketing.

2.8. Proposed Research Model

Based on the above discussion, this study proposes an extended technology adoption model to explain intention to use AI-based marketing among respondents from Vietnamese SMEs. The model integrates benefit-related, usability-related, trust-related, cost-related, risk-related, and social-contextual determinants. Perceived usefulness, perceived ease of use, trust, and social influence are expected to positively influence intention, whereas perceived cost and perceived risk are expected to negatively influence intention. These hypothesized directions are shown in Figure 1.



Note: *Solid lines represent hypothesized positive relationships, whereas dashed lines represent hypothesized negative relationships.*

Figure 1. Proposed research model

3. Data And Methodology

3.1. Research Design and Sample

This study employed a quantitative cross-sectional survey design to investigate the determinants of intention to use AI-based marketing among respondents from Vietnamese SMEs. Data were collected using a structured questionnaire distributed through online and offline channels.

To ensure the relevance and validity of the responses, specific eligibility criteria were established for participant selection. First, respondents were required to be currently employed in a small or medium-sized enterprise (SME) operating in Vietnam, as defined under the Vietnamese SME classification framework. Second, respondents were required to have direct involvement in marketing activities, digital transformation initiatives, business management, or technology-related decision-making within their organizations. Third,

respondents were expected to possess at least a basic understanding or awareness of AI-based marketing technologies, such as marketing automation, customer analytics, AI-driven content generation, recommendation systems, or predictive marketing tools. Individuals who did not work in SMEs, had no involvement in business decision-making or marketing activities, or provided incomplete questionnaire responses were excluded from the final analysis.

Using these eligibility criteria, a total of 473 valid responses were retained for subsequent statistical analysis.

3.2. Sample Profile

This study employed a non-probability sampling approach, combining purposive and convenience sampling techniques. Purposive sampling was used to ensure that respondents were employed in Vietnamese SMEs and had relevant experience in marketing, management, digital transformation, or technology-related activities. Convenience sampling was adopted because a comprehensive sampling frame of Vietnamese SMEs was not available. Data were collected through online platforms, professional networks, and business communities. After data screening, 473 valid responses were retained for analysis.

The demographic profile of the respondents is presented in Table 1. Regarding age, the largest group was respondents aged 26-35 years, accounting for 40.2% of the sample, followed by those aged 36-45 years at 30.0%. Male respondents represented 54.5% of the sample, while female respondents accounted for 45.5%. In terms of education, most respondents held either a university degree or a college/diploma qualification. Regarding tenure, the majority of respondents had between one and ten years of working experience.

Characteristic	Category	Frequency	Percentage
Age	Below 25 years	78	16.5%
	26-35 years	190	40.2%
	36-45 years	142	30.0%
	46 years and above	63	13.3%
Gender	Male	258	54.5%
	Female	215	45.5%
Education level	High-school degree	77	16.3%
	College/diploma	172	36.4%
	University degree	190	40.2%
	Postgraduate degree	34	7.2%
Tenure	Below 1 year	82	17.3%
	1-5 years	178	37.6%
	5-10 years	157	33.2%
	10 years and above	56	11.8%

Table 1. Respondent characteristics

3.3. Measurement Instruments

The questionnaire was developed by adapting validated measurement scales from prior studies on technology acceptance, UTAUT, AI adoption, digital marketing, and organizational technology use. Perceived usefulness and perceived ease of use were adapted mainly from TAM-based measures (Yurder, 2025) and AI marketing adoption studies. Social influence was adapted from UTAUT-related measures (Mardiani and Utami, 2026) and SME technology adoption studies. Trust, perceived cost, and perceived risk were adapted from AI trust, SME digital adoption, and AI risk literature. All items were modified to fit the context of AI-based marketing adoption among Vietnamese SMEs. All constructs were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. In addition to latent construct items, the revised profile section specifies firm-level and respondent-role variables that can be used as descriptive information, control variables, or moderators in future analyses rather than as reflective indicators of the latent constructs.

Perceived usefulness measured the extent to which respondents believed that AI could improve marketing effectiveness and business outcomes. Perceived ease of use captured the degree to which AI-based marketing tools were considered easy to learn, operate, and integrate into existing marketing practices. Trust reflected respondents' confidence in the reliability, transparency, and security of AI systems. Perceived cost measured financial and operational concerns associated with AI adoption. Perceived risk captured concerns related to data privacy, inaccurate recommendations, cybersecurity, and reputational consequences. Social influence measured the extent to which external stakeholders encouraged AI adoption. Intention to use AI-based marketing was originally measured with five items. However, IU1 and IU5 were excluded from the final analysis because their standardized loadings were below 0.60 in the original SEM diagram. The final IU construct was therefore measured by IU2, IU3, and IU4.

A pilot test was conducted before the main survey to assess the clarity, relevance, and contextual suitability of the questionnaire. Based on feedback, minor wording adjustments were made to improve readability, reduce ambiguity, and ensure that the items reflected AI-based marketing rather than general digital marketing. The final measurement items, adapted sources, and standardized factor loadings are presented in Table 2.

Code	Item wording	Source	Loading
PU1	Using AI-based marketing improves our firm's overall marketing performance.	(Bataineh and Qasim, 2023; Chen, Zhou and Frankwick, 2025; Gołąb-Andrzejak, 2023; Mikalef et al., 2023; Vij et al., 2024); adapted to AI-based marketing usefulness	0.897
PU2	Using AI-based marketing enhances customer segmentation and targeting for our firm.	(Abdullah and Hasan, 2023; Al Rafi, 2022; Mallikraj et al., 2025); adapted to AI-based marketing usefulness	0.890
PU3	AI-based marketing increases the effectiveness of our marketing campaigns.	(Bataineh and Qasim, 2023; Saboune, 2024); adapted to AI-based marketing usefulness	0.901
PU4	AI-based marketing supports better strategic decision-making in our firm.	(Al-Surmi, Bashiri and Koliousis, 2022; Magableh et al., 2024); adapted to AI-based marketing usefulness	0.864
PU5	AI-based marketing improves our firm's customer relationship management.	(Li and Xu, 2022; Li et al., 2023); adapted to AI-based marketing usefulness	0.880
PEOU1	Learning to use AI-based marketing tools would be easy for our firm.	(Alqasa, 2023; Mikalef et al., 2023); adapted to AI-based marketing usability	0.674
PEOU2	AI-based marketing tools would be easy to operate.	(Alqasa, 2023; Jumaat, Sania and Mohamad, 2025); adapted to AI-based marketing usability	0.777
PEOU3	AI-based marketing tools would be easy to integrate into existing marketing activities.	(Jumaat, Sania and Mohamad, 2025; Vij et al., 2024); adapted to AI-based marketing usability	0.861
PEOU4	Using AI-based marketing tools would not require excessive effort.	(Buschmeyer, Hatfield and Zenner, 2023; Kolesnik, 2025); adapted to AI-based marketing usability	0.858
PEOU5	Our employees could become skillful at using AI-based marketing tools.	(Joshi and Masih, 2023; Mikalef et al., 2023); adapted to AI-based marketing usability	0.827
TR1	We trust AI-based marketing tools to provide reliable outputs.	(McGrath et al., 2025) adapted to AI trust	0.726
TR2	We believe AI-based marketing systems can produce accurate recommendations.	(Chang and Park, 2024; Habil, El-Deeb and El-Bassiouny, 2023) adapted to AI trust	0.919
TR3	We believe AI-based marketing systems can protect customer data.	(Tasnim et al., 2025); adapted to AI trust	0.717
TR4	We trust the transparency of AI-based marketing systems.	(Wang, Sauka and Situmeang, 2025; Wanner et al., 2022); adapted to AI trust	0.760
TR5	We trust AI solution providers to support responsible implementation.	(Bedué and Fritzsche, 2022; Kosasi et al., 2025); adapted to AI trust	0.918
PC1	The cost of AI-based marketing tools is high for our firm.	(Abrokwah-Larbi and Awuku-Larbi, 2024; Chen, Zhou and Frankwick, 2025); adapted to SME technology cost	0.794
PC2	AI-based marketing would require substantial financial investment.	(Gabelaia and Hendieh, 2025; Magableh et al., 2024); adapted to SME technology cost	0.774
PC3	AI-based marketing would require additional training costs.	(Mikalef et al., 2023; Vij et al., 2024); adapted to SME technology cost	0.789
PC4	AI-based marketing would require additional maintenance or integration costs.	(Vij et al., 2024); adapted to SME technology cost	0.751
PC5	Overall, adopting AI-based marketing would create a considerable cost burden.	(Sharma et al., 2024); adapted to SME technology cost	0.755
PR1	Using AI-based marketing may create customer data privacy risks.	(de Matos, Rohden and Lourenço Azevedo, 2026; Tasnim et al., 2025); adapted to AI risk	0.771
PR2	AI-based marketing may expose our firm to cybersecurity risks.	(Sardana, Mishra and Tayyab, 2024; Schreiber and Schreiber, 2025); adapted to AI risk	0.876
PR3	AI-generated recommendations may be inaccurate or biased.	(Beck et al., 2026; Salah et al., 2025; Saxena, 2024); adapted to AI risk	0.577
PR4	AI-based marketing may cause reputational risks if used improperly.	(Ağtaş, 2025); adapted to AI risk	0.885
PR5	AI-based marketing may create legal or ethical risks.	(Kumar and Suthar, 2024); adapted to AI risk	0.843
SI1	Important customers expect firms to use advanced digital marketing tools.	(Homburg and Wielgos, 2022; Jung and Shegai, 2023; Sharabati et al., 2024); adapted to social influence in AI marketing	0.691
SI2	Competitors are encouraging our firm to consider AI-based marketing.	(Homburg and Wielgos, 2022; Jung and Shegai, 2023; Sharabati et al., 2024); adapted to social influence in AI marketing	0.755

Code	Item wording	Source	Loading
SI3	Business partners or consultants encourage our firm to adopt AI-based marketing.	(Homburg and Wielgos, 2022; Jung and Shegai, 2023; Sharabati et al., 2024); adapted to social influence in AI marketing	0.880
SI4	Professional communities and industry networks encourage AI adoption in marketing.	(Homburg and Wielgos, 2022; Jung and Shegai, 2023; Sharabati et al., 2024); adapted to social influence in AI marketing	0.864
SI5	Government or business-support programs encourage AI-based marketing adoption.	(Homburg and Wielgos, 2022; Jung and Shegai, 2023; Sharabati et al., 2024); adapted to social influence in AI marketing	0.583
IU2	Our firm plans to adopt or expand AI-based marketing tools.	(Chen, Zhou and Frankwick, 2025; Jumaat, Sania and Mohamad, 2025); technology adoption intention literature; adapted to AI marketing intention	0.844
IU3	Our firm is willing to invest effort in AI-based marketing adoption.	(Chen, Zhou and Frankwick, 2025; Jumaat, Sania and Mohamad, 2025); technology adoption intention literature; adapted to AI marketing intention	0.797
IU4	Our firm would recommend using AI-based marketing for marketing activities.	(Chen, Zhou and Frankwick, 2025; Jumaat, Sania and Mohamad, 2025); technology adoption intention literature; adapted to AI marketing intention	0.751

Table 2. Measurement items, sources, and standardized factor loadings

3.4. Coding Check, Common Method Bias, and Non-Response Bias

Because the data were collected from the same respondents using a single questionnaire, common method bias was considered a potential concern. Procedural remedies were applied by assuring respondents of anonymity and confidentiality and by wording the questionnaire items clearly and neutrally. Statistically, Harman's single-factor test was conducted using the retained measurement items after IU1 and IU5 were excluded. The first unrotated factor explained 31.75% of the total variance, below the commonly used 50% threshold. As an additional diagnostic, full collinearity VIFs based on composite construct scores were examined; all values were below 3.00, suggesting no serious collinearity-related common method problem in the available data. These diagnostics reduce, but do not eliminate, the possibility of common method bias. Future studies should incorporate a marker variable or common latent factor design when the survey instrument is developed.

Because response-time indicators were not available in the cleaned dataset, non-response bias could not be statistically assessed in the present analysis. This issue is acknowledged as a limitation.

A coding audit was conducted for perceived cost and perceived risk using the cleaned dataset and the revised IU composite based on IU2-IU4. All PC and PR items used a 1-5 agreement scale, and all item-total correlations with their respective constructs were positive, indicating that the items were not accidentally reverse-coded. In addition, PC and PR were positively correlated with the revised IU composite (PC-IU = 0.285; PR-IU = 0.567). These results indicate that the positive SEM coefficient for perceived risk should be interpreted substantively rather than as a reverse-coding error.

Predictor	r with revised IU	VIF	Tolerance	Interpretation
PU	0.220	1.062	0.941	No multicollinearity
PEOU	0.326	1.379	0.725	No multicollinearity
TR	0.612	1.869	0.535	No multicollinearity
PC	0.285	1.333	0.750	No multicollinearity
PR	0.567	1.867	0.536	No multicollinearity
SI	0.561	1.932	0.518	No multicollinearity

Table 3. Coding and multicollinearity diagnostics based on composite scores

Item	Observed range	Mean	Correlation with revised IU	Corrected item-total corr.
PC1	1-5	3.552	0.211	0.737
PC2	2-5	3.605	0.268	0.706
PC3	2-5	3.569	0.245	0.727
PC4	1-5	3.535	0.206	0.701
PC5	1-5	3.476	0.239	0.702
PR1	2-5	3.624	0.430	0.723
PR2	2-5	3.700	0.568	0.793
PR3	1-5	3.594	0.329	0.558
PR4	2-5	3.636	0.547	0.809
PR5	2-5	3.658	0.510	0.789

Table 4. Item-level coding diagnostics for PC and PR

3.5. Data Analysis

The data were analyzed using a two-step approach. First, the measurement model was assessed to examine reliability, convergent validity, and discriminant validity. Cronbach's alpha and composite reliability were used to evaluate internal consistency. Convergent validity was assessed through standardized factor loadings and average variance extracted. Discriminant validity was examined using the Fornell-Larcker criterion; HTMT should also be reported in a final statistical appendix when item-level correlation output is available. Second, structural equation modeling was employed to test the hypothesized relationships among the constructs. Model fit was evaluated using CMIN/df, GFI, AGFI, IFI, CFI, NFI, TLI, RMSEA, and SRMR. The significance, direction, and standardized coefficients of the structural paths were then used to assess the proposed hypotheses.

4. Results And Analysis

4.1. Measurement Model Assessment

Confirmatory factor analysis (CFA) and structural equation modeling were re-estimated after removing two low-loading intention items, IU1 and IU5. The final measurement model consisted of seven latent constructs and 33 retained indicators. The re-estimated model achieved good fit to the data: Chi-square = 762.147, df = 474, $p < 0.001$, Chi-square/df = 1.608, IFI = 0.973, GFI = 0.933, AGFI = 0.925, NFI = 0.933, TLI = 0.970, CFI = 0.973, RMSEA = 0.036, and SRMR = 0.042. Although the Chi-square statistic was significant, this is common in studies with relatively large samples. The remaining indices indicate that the revised model fits the data well.

The re-estimated standardized factor loadings supported the retained measurement structure. After IU1 and IU5 were removed, the retained intention items showed satisfactory loadings: IU2 = 0.844, IU3 = 0.797, and IU4 = 0.751. Most retained indicators exceeded 0.60. PR3 (0.577) and SI5 (0.583) were marginally below 0.60 but were retained because they captured theoretically important aspects of AI risk and institutional support, and because the overall construct reliability and AVE values remained acceptable. This decision should nevertheless be treated cautiously and the two items should be refined in future scale development.

Descriptive statistics, reliability, and convergent validity are presented in Table 5. The mean values ranged from 3.51 to 3.81, suggesting that respondents generally held relatively positive perceptions toward AI-based marketing adoption. Cronbach's alpha values ranged from 0.838 to 0.948, composite reliability values ranged from 0.840 to 0.948, and AVE values ranged from 0.582 to 0.786. These results confirm satisfactory internal consistency and convergent validity for the retained constructs.

Construct	Mean	SD	Cronbach alpha	CR	AVE
Perceived usefulness (PU)	3.508	0.967	0.948	0.948	0.786
Perceived ease of use (PEOU)	3.666	0.641	0.898	0.900	0.643
Trust (TR)	3.811	0.648	0.902	0.906	0.661
Perceived cost (PC)	3.547	0.699	0.881	0.881	0.597
Perceived risk (PR)	3.642	0.733	0.886	0.896	0.638
Social influence (SI)	3.707	0.617	0.861	0.872	0.582
Intention to use AI-based marketing (IU2-IU4)	3.778	0.709	0.838	0.840	0.637

Table 5. Descriptive statistics, reliability, and convergent validity

Discriminant validity was examined using the Fornell-Larcker criterion. As shown in Table 6, the square root of AVE for each construct was greater than its correlations with other constructs. The corrected zero-order correlations based on the revised IU composite show positive associations between PC and IU (r = 0.285) and between PR and IU (r = 0.567), which is consistent with the positive coefficients observed in the structural model. Because correlations among trust, perceived risk, and social influence are relatively high, the discriminant-validity conclusion should be treated as provisional until HTMT values are reported from item-level correlations.

Construct	PU	PEOU	TR	PC	PR	SI	IU
PU	0.886						
PEOU	0.026	0.802					
TR	0.233	0.294	0.813				
PC	0.020	0.479	0.241	0.773			
PR	0.100	0.309	0.577	0.267	0.799		
SI	0.151	0.250	0.609	0.238	0.621	0.763	
IU	0.220	0.326	0.612	0.285	0.567	0.561	0.798

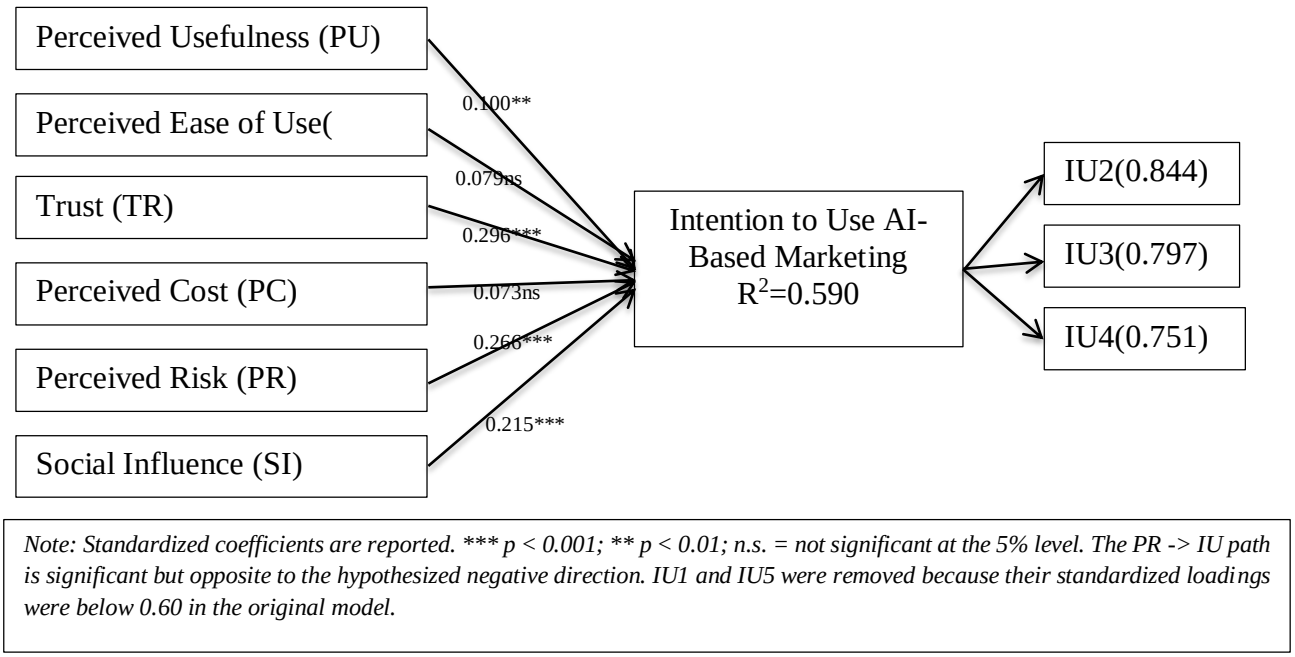
Table 6. Discriminant validity using the Fornell-Larcker criterion

4.2. Structural Model Assessment

After confirming the adequacy of the revised measurement model, SEM was conducted to test the proposed relationships among the constructs. The structural model examined the effects of perceived usefulness, perceived ease of use, trust, perceived cost, perceived risk, and social influence on intention to use AI-based marketing. Intention to use AI-based marketing was measured only by IU2, IU3, and IU4 in the final model.

The SEM results indicated that the structural model achieved

good fit to the data: Chi-square = 762.147, df = 474, p < 0.001, Chi-square/df = 1.608, IFI = 0.964, GFI = 0.903, AGFI = 0.915, NFI = 0.903, TLI = 0.960, CFI = 0.923, RMSEA = 0.045, and SRMR = 0.042. These indices indicate that the revised model was appropriate for hypothesis testing after the removal of IU1 and IU5.



*Note: Standardized coefficients are reported. *** p < 0.001; ** p < 0.01; n.s. = not significant at the 5% level. The PR -> IU path is significant but opposite to the hypothesized negative direction. IU1 and IU5 were removed because their standardized loadings were below 0.60 in the original model.*

Figure 2. Structural equation model with standardized coefficients

The squared multiple correlation value indicated that the structural model explained 59.0% of the variance in intention to use AI-based marketing, suggesting a substantial level of explanatory power for the revised IU construct.

The standardized path coefficients and regression weights are presented in Table 7. The results show that trust, perceived risk, social influence, and perceived usefulness significantly influenced intention to use AI-based marketing. Perceived ease of use and perceived cost did not reach statistical significance at the 5% level in the structural model.

Trust had the strongest positive effect on intention to use AI-based marketing (Estimate = 0.381, C.R. = 5.132, p < 0.001; beta = 0.296). This finding suggests that respondents from SMEs report stronger adoption intention when they have confidence in the reliability, accuracy, transparency, and security of AI-based systems.

Hyp.	Relationship	Estimate	S.E.	C.R.	p-value	Std. beta	Result
H1	PU -> IU	0.076	0.029	2.591	0.010	0.100	Supported
H2	PEOU -> IU	0.115	0.070	1.649	0.099	0.079	Not supported
H3	TR -> IU	0.381	0.074	5.132	<0.001	0.296	Supported
H4	PC -> IU	0.075	0.049	1.547	0.122	0.073	Not supported
H5	PR -> IU	0.304	0.072	4.209	<0.001	0.266	Significant but not supported (opposite direction)
H6	SI -> IU	0.290	0.085	3.424	<0.001	0.215	Supported

Table 7. Structural path estimates and hypothesis testing
Notes: Estimate = unstandardized regression coefficient; S.E. = standard error; C.R. = critical ratio; Std. beta = standardized path coefficient.

Perceived risk also had a significant positive coefficient in the structural model (Estimate = 0.304, C.R. = 4.209, p < 0.001; beta = 0.266). Because the original hypothesis expected a negative relationship, H5 was statistically significant but not supported in the hypothesized direction. This result should not be interpreted as evidence that risk itself encourages adoption. Rather, conditional on the other predictors, respondents who reported stronger awareness of AI-related risks also reported higher intention to use AI-based marketing. The result may reflect risk awareness, AI literacy, or active evaluation of AI tools among more engaged respondents.

Social influence had a significant positive effect on intention to use AI-based marketing (Estimate = 0.290, C.R. = 3.424, p < 0.001; beta = 0.215). This indicates that external pressures and encouragement from customers, competitors, business partners, professional communities, and digital transformation programs play an important role in shaping respondents' intention to adopt AI-based marketing.

Perceived usefulness had a positive and significant effect on

intention to use AI-based marketing (Estimate = 0.076, C.R. = 2.591, p = 0.010; beta = 0.100). This result confirms that respondents from SMEs are more willing to support AI-based marketing when they perceive that AI can improve marketing effectiveness, customer analysis, personalization, campaign performance, and decision-making. Perceived ease of use had a positive but non-significant effect in the structural model (Estimate = 0.115, C.R. = 1.649, p = 0.099; beta = 0.079). Therefore, H2 was not supported at the 5% level after IU1 and IU5 were removed.

Perceived cost did not significantly affect intention to use AI-based marketing at the 5% level (Estimate = 0.075, C.R. = 1.547, p = 0.122; beta = 0.073). Therefore, H4 was not supported. Because the coefficient was positive and non-significant, the result provides no evidence that perceived cost acted as a barrier in this sample when trust, risk-related perceptions, social influence, usefulness, and ease of use were considered simultaneously.

Overall, the empirical findings provide partial support for the proposed research model. The revised model explained 59.0% of the variance in intention to use AI-based marketing. Trust emerged as the strongest predictor, followed by perceived risk, social influence, and perceived usefulness. Perceived ease of use and perceived cost did not significantly affect adoption intention at the 5% level. The unexpected positive risk coefficient indicates that the perceived risk construct may capture risk awareness or engagement with AI rather than only risk deterrence.

5. Discussion And Conclusions

5.1. Discussion

The findings provide partial support for the proposed research model and demonstrate that trust, perceived risk, social influence, and perceived usefulness significantly influence respondents' intention to use AI-based marketing among Vietnamese SMEs.

First, H1 was supported, indicating that perceived usefulness positively influences intention to use AI-based marketing. This finding suggests that respondents are more willing to adopt AI-based marketing technologies when they perceive that such technologies can improve marketing effectiveness, customer targeting, personalization, and decision-making processes. This result is consistent with the Technology Acceptance Model and previous studies reporting that expected performance benefits positively influence technology adoption intentions (Mastour, Yousefi and Niroumand, 2025; Wang et al., 2025).

Second, H2 was not supported because perceived ease of use did not significantly affect adoption intention. This finding suggests that ease of operation alone may not be sufficient to encourage AI adoption when respondents are more concerned with strategic benefits, trust, and risk-related issues. Similar findings have been reported in studies indicating that ease of use becomes less important when technologies are perceived as complex or strategically significant (Hussain et al., 2025).

Third, H3 was supported and trust emerged as the strongest predictor of AI-based marketing adoption intention. This finding confirms that confidence in the reliability, transparency, security, and accuracy of AI systems plays a crucial role in reducing uncertainty and facilitating adoption decisions. This result is consistent with previous studies emphasizing the central role of trust in AI adoption and acceptance (Dang and Li, 2026; Kauttonen, Rousi and Alamäki, 2025).

Fourth, H4 was not supported because perceived cost did not significantly influence adoption intention. This result suggests that respondents may evaluate AI adoption primarily based on expected strategic value rather than direct financial costs. The finding is partially consistent with studies suggesting that perceived benefits and organizational readiness may outweigh cost concerns in digital technology adoption contexts (Nguyen, 2025).

Fifth, H5 was statistically significant but not supported in the hypothesized direction because perceived risk exhibited a positive relationship with adoption intention. Rather than indicating that risk encourages adoption, this finding may suggest that respondents with greater awareness of privacy, security, ethical, and regulatory risks are also more knowledgeable, engaged, and prepared to evaluate AI technologies. Similar arguments have been proposed in recent AI adoption studies emphasizing the distinction between risk deterrence and risk awareness (Kilian, 2026; Ludwig, 2025).

Finally, H6 was supported, indicating that social influence positively affects intention to use AI-based marketing. This finding suggests that customers, competitors, business partners, professional communities, and institutional support mechanisms significantly influence AI adoption decisions among SMEs. This result supports previous studies emphasizing the importance of external legitimacy, peer learning, and institutional pressure in technology adoption processes (Duan et al., 2025).

Overall, the findings indicate that AI-based marketing adoption among Vietnamese SMEs is influenced primarily by trust, risk awareness, social influence, and perceived usefulness rather than by ease of use or perceived cost.

5.2. Theoretical Implications

This study extends technology adoption research by applying an integrated model to AI-based marketing adoption intention among respondents from SMEs in an emerging economy. While traditional technology acceptance models emphasize usefulness and ease of use, the findings show that AI-based marketing adoption also depends strongly on trust, risk-related perceptions, and social influence.

The dominant role of trust suggests that AI adoption should not be understood simply as a performance-improvement decision. Because AI systems often involve algorithmic recommendations and customer-data processing, respondents appear to require confidence in system reliability, transparency, security, and provider credibility before expressing intention to adopt.

The unexpected positive coefficient of perceived risk indicates the need to refine risk-related constructs in AI adoption research. Future studies should distinguish risk deterrence from risk awareness, risk tolerance, AI literacy, and risk-management capability. Such distinctions may help explain why some respondents recognize AI-related risks yet still express willingness to adopt AI-based marketing.

The significant effect of social influence confirms the importance of ecosystem-level influences in SME technology adoption. AI adoption among SMEs is not only an internal managerial decision; it is also shaped by peer learning,

customer expectations, business networks, industry trends, and institutional support.

5.3. Practical Implications

For SME managers, the results suggest that AI-based marketing adoption should begin with building internal trust and AI literacy. Managers should evaluate not only whether AI tools are useful but also whether employees understand system limitations, data privacy requirements, cybersecurity concerns, and ethical risks. Training programs should therefore combine practical marketing applications with responsible AI use.

For AI solution providers, trust-building should be central to market development strategies. Providers should communicate how their tools process data, how recommendations are generated, how customer data are protected, and what limitations users should consider. Transparent documentation, trial versions, customer support, sector-specific demonstrations, and case studies can help SME managers evaluate AI-based marketing solutions more confidently.

For policymakers, digital transformation programs should go beyond financial support. Since trust, risk-related perceptions, and social influence significantly shape adoption intention, policy initiatives should focus on AI literacy, responsible AI guidelines, data protection awareness, and institutional mechanisms that increase SME confidence in AI-based marketing.

For business associations and professional communities, the results emphasize the importance of peer learning and knowledge sharing. Forums, seminars, mentorship programs, and case-sharing platforms can reduce uncertainty, legitimize AI adoption, and encourage informed decision-making among SMEs.

For researchers and SME-support agencies, future surveys should retain firm-level and respondent-role profile variables such as firm size, industry, firm age, decision involvement, prior AI use, digital marketing use, and marketing budget or digital capability. These variables would allow more precise segmentation of SMEs and help identify whether AI adoption intention differs across micro, small, and medium enterprises, across industries, or across different levels of digital readiness.

5.4. Limitations and Future Research

First, the study used a cross-sectional survey design and non-probability sampling, which limit causal inference and statistical generalization. Future research should employ longitudinal designs and more systematic sampling to examine how SMEs move from initial awareness to actual AI adoption and post-adoption usage.

Second, the study focused on intention to use AI-based marketing rather than actual adoption behavior. Future research should examine actual AI usage, usage intensity, implementation success, and marketing performance outcomes.

Third, the study was conducted in the Vietnamese SME context. Comparative studies across developing and developed economies would help validate and extend the findings and identify whether trust, risk awareness, and social influence operate similarly across institutional environments.

Fourth, perceived risk was measured as a general construct. Given the unexpected positive SEM coefficient, future studies should examine different dimensions of risk, such as privacy risk, security risk, financial risk, performance risk, ethical risk, legal risk, and reputational risk. Future research should also distinguish risk perception from risk awareness, risk tolerance, AI literacy, and risk-management capability.

Fifth, this study could not examine firm-level profile or organizational variables in the SEM because the cleaned dataset did not contain usable distributions for firm size, industry type, firm age, respondent role, decision involvement, current digital marketing use, prior AI marketing experience, marketing budget, or digital capability. Future research should collect, report, and analyze these variables to provide a more complete SME-level explanation of AI-based marketing adoption and to test whether respondent role, prior AI use, or digital readiness moderates the proposed relationships.

Sixth, common method bias was assessed using Harman's single-factor test and supplementary VIF diagnostics, but future studies should still add stronger ex ante and ex post controls, such as a marker variable, common latent factor, temporal separation, or source separation (Rubenstein et al., 2025). Discriminant validity was assessed with the Fornell-Larcker criterion; future studies should additionally report the heterotrait-monotrait ratio when item-level correlation output is available (Calota, 2025). The marginal loadings of PR3 and SI5 also suggest that future research should refine the risk and social influence measures.

5.5. Conclusion

This study investigated determinants of intention to use AI-based marketing among respondents from Vietnamese SMEs. Based on survey data from 473 valid respondents and a revised IU construct measured by IU2-IU4, the findings show that trust, perceived risk, social influence, and perceived usefulness significantly influence intention to use AI-based marketing. Trust emerged as the strongest predictor, followed by perceived risk and social influence. Perceived ease of use and perceived cost did not significantly affect adoption intention at the 5% level. Because the analysis is based on respondent-level perceptions, the findings should be interpreted as reported adoption intention rather than verified firm-level adoption behavior.

The findings suggest that adoption intention in this context is shaped mainly by trust in AI systems, risk-related perceptions, external social influence, and perceived marketing benefits. The positive coefficient of perceived risk should be interpreted as a signal that risk awareness may coexist with adoption readiness, not as evidence that risk itself promotes adoption. Overall, the study contributes empirical evidence from the Vietnamese SME context and offers practical recommendations for promoting responsible and effective AI-based marketing adoption.

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