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Not All Micro, Small, and Medium Enterprises Are Equal: A UTAUT-Based Multi-Group Analysis of AI Marketing Tool Adoption in the Philippines

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Abstract

This study investigates whether the determinants of AI marketing tool adoption, as theorized by the Unified Theory of Acceptance and Use of Technology (UTAUT), operate uniformly across the heterogeneous Philippine micro, small, and medium enterprise (MSME) sector or whether they are systematically conditioned by firm size and industry sector. Prior technology adoption research has largely treated MSMEs as a homogeneous analytical unit, producing aggregate parameter estimates that obscure structurally important differences within this sector. To address this theoretical and empirical gap, a quantitative cross-sectional survey was administered to 387 MSME owner-managers across Metro Manila, Philippines, from January to March 2025. Data were analyzed using partial least squares structural equation modeling (PLS-SEM) via SmartPLS 4.0, with measurement invariance established through the Measurement Invariance of Composite Models (MICOM) procedure prior to multi-group analysis (MGA). All five UTAUT structural paths were confirmed in the pooled model (R^2 = .587 for behavioral intention; R^2 = .483 for actual use). MGA revealed that firm size significantly moderates the adoption model: performance expectancy exerted substantially stronger influence among medium enterprises (β = .445) than micro enterprises (β = .198), while social influence showed the inverse pattern, significantly more salient among micro enterprises (β = .276) than medium enterprises (β = .098). Industry sector partially moderated the model, with service-based MSMEs demonstrating a significantly stronger effort expectancy effect than product-based counterparts ($\Delta\beta$ = .089, p = .041), reflecting the heightened ease-of-use sensitivity in service contexts where AI-powered customer interaction tools are most operationally demanding. These findings challenge the parameter invariance assumption embedded in prior UTAUT-based adoption research and establish that a segmented approach to MSME AI adoption support, differentiated by firm size and industry type, is both theoretically warranted and empirically necessary.

Keywords: AI marketing tools; MSME adoption; UTAUT; multi-group analysis; digital marketing

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1. Introduction

The rapid diffusion of artificial intelligence (AI) into marketing practice has fundamentally altered how organizations engage customers, allocate marketing budgets, and design promotional content (Davenport et al., 2020). AI marketing tools, spanning chatbot platforms, predictive analytics systems, automated content generation, and social media management applications, hold particular promise for small and medium enterprises (MSMEs) seeking to compete with larger, better-resourced rivals through digital channels (Soni et al., 2022). Yet the adoption of these tools across MSME populations remains uneven, shaped by resource constraints, digital literacy gaps, and organizational characteristics that vary considerably across firm types.

In the Philippine context, MSMEs account for 99.5% of all registered business enterprises and approximately 35.7% of gross domestic product, making their digital transformation trajectory a national economic priority (Philippine Statistics Authority, 2023). The post-pandemic transformation of Philippine retail marketing has placed new competitive pressures on MSME digital adoption, accelerating the imperative for AI-enabled marketing capabilities (Guillen, 2023). Despite growing policy interest in MSME digitalization under the Philippine Development Plan 2023–2028, empirical research on AI marketing tool adoption among Philippine MSMEs has largely relied on aggregate sample analyses that treat this inherently heterogeneous sector as a uniform population. A micro-enterprise operating a neighborhood food business and a medium enterprise managing a regional distribution network face categorically different adoption environment. These are distinctions that aggregate models systematically obscure where the volume and immediacy of customer interactions make manual response impractical (Huang & Rust, 2021; Mustak et al., 2021). The third is AI-enhanced social media advertising, exemplified by Meta Advantage+, TikTok Smart Performance Campaigns, and the recommendation engines embedded in platforms such as Shopee and Lazada, which automate audience targeting and campaign optimization and are most directly applicable to product-based MSMEs operating in e-commerce channels (BusinessWorld, 2025a). The fourth is predictive analytics and customer intelligence tools embedded in platforms such as Google Analytics 4 and CRM systems, which support data-driven marketing decisions across firm types. Despite this expanding toolkit, adoption among Philippine MSMEs remains structurally uneven and context-dependent. A Philippine Institute for Development Studies analysis reported that as of 2021, only 14.9% of Philippine firms had integrated AI into their operations (BusinessWorld, 2025b). More recent data indicates acceleration but persistent shallowness: the Philippine AI Report 2025 found that while 92% of Philippine organizations had deployed AI in some capacity, 65% remained at the proof-of-concept stage, suggesting that most MSMEs are AI consumers rather than AI integrators (Manila Bulletin, 2026). A 2025 Lazada-Kantar survey reinforced this picture, finding that while 76% of Filipino sellers were familiar with AI, 64% cited cost and complexity as adoption barriers and 37% described themselves as "AI agnostic" (BusinessWorld, 2025a). This landscape, where tool awareness outpaces operational deployment and where different tools serve fundamentally different MSME functions, provides the empirical backdrop against which the adoption heterogeneity examined in this study becomes both visible and consequential

The present study responds to this gap by applying the UTAUT (Venkatesh et al., 2003) combined with PLS-SEM and MGA to examine whether AI marketing tool adoption determinants differ significantly across Philippine MSME subgroups defined by firm size and industry sector. Seven hypotheses are tested: five main structural path hypotheses (H1–H5) and two MGA hypotheses (H6–H7). The central theoretical claim of this study is unambiguous: the UTAUT assumption of parameter invariance does not hold in MSME contexts. Rather than treating UTAUT structural paths as universal constants, this study demonstrates empirically that these relationships are moderated by fundamental organizational characteristics, rendering aggregate MSME adoption models theoretically inadequate and practically misleading. This study advances the literature in three ways: it challenges the parameter invariance assumption embedded in prior UTAUT-based MSME adoption research, which has largely neglected organizational-level subgroup testing in favor of aggregate models; it extends UTAUT to the AI marketing tool adoption context in an emerging Southeast Asian market with formal subgroup testing; and it generates subgroup-differentiated evidence that policymakers, platform developers, and MSME development practitioners can act on directly.

The research problem addressed in this study is the persistent analytical treatment of MSMEs as a homogeneous unit in technology adoption research, despite the substantial organizational, resource, and operational differences that characterize micro, small, and medium enterprises. This homogeneity assumption, embedded in the majority of UTAUT-based MSME adoption studies, produces structurally misleading parameter estimates and, by extension, misdirected policy prescriptions. When technology adoption determinants vary systematically across MSME subgroups—as the present study demonstrates—an aggregate model does not merely simplify reality; it actively misrepresents it. To address this problem, the study is guided by three research questions: RQ1—Do the UTAUT core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) significantly predict AI marketing tool adoption intention and actual use among Philippine MSMEs? RQ2—Do UTAUT structural path relationships differ significantly across firm size subgroups (micro, small, and medium enterprises)? RQ3—Do UTAUT structural path relationships differ significantly across industry sector subgroups (product-based versus service-based MSMEs)?

The paper is organized as follows. Section 2 presents the theoretical foundations of the study, including the UTAUT, Innovation Diffusion Theory, and multi-group analysis as the analytical bridge between aggregate theory and subgroup empirical reality. Section 3 reviews the relevant literature, develops the seven study hypotheses, and identifies the theoretical, empirical, and methodological research gaps that motivate the study's design. Section 4 describes the quantitative research methodology, including sampling strategy, instrumentation, and analytical procedures. Section 5 presents the measurement model and structural model results. Section 6 discusses the findings in relation to existing theory and practical implications. Section 7 concludes with the study's contributions, limitations, and directions for future research.

2. Theoretical Foundation

2.1. The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT, developed by Venkatesh et al. (2003), is the primary theoretical framework guiding this study. The UTAUT synthesizes eight prior technology adoption models, including the Technology Acceptance Model (TAM; Davis, 1989), the Theory of Reasoned Action, the Theory of Planned Behavior, the Motivational Model, the PC Utilization Model, the Innovation Diffusion Theory (IDT; Rogers, 2003), the Social Cognitive Theory, and the Combined TAM and TPB, into a single, parsimonious model. As illustrated in Figure 1, the UTAUT identifies four core determinants of behavioral intention and technology use behavior: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These constructs capture the cognitive utility, ease-of-use, social normative, and infrastructural dimensions of technology adoption, respectively. In the original formulation, PE, EE, and SI predict behavioral intention, which in turn predicts use behavior, while FC predicts use behavior directly. The model further specifies four moderating variables (age, gender, experience, and voluntariness of use) as boundary conditions.

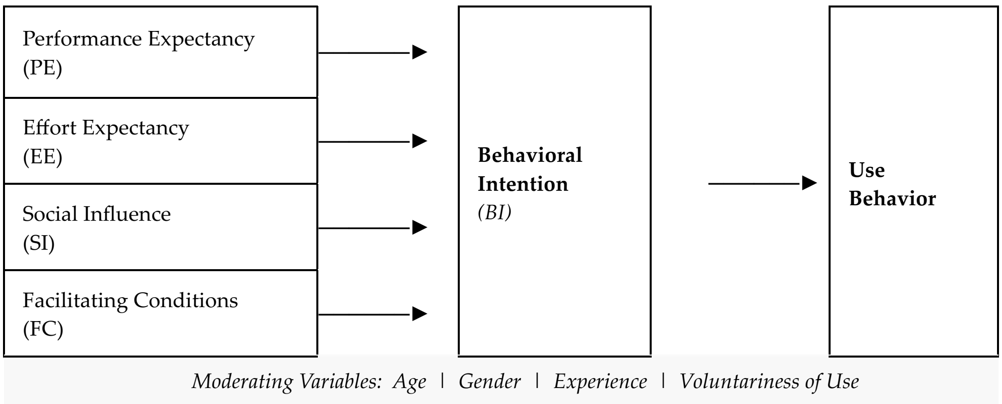

Figure 1. The Unified Theory of Acceptance and Use of Technology (UTAUT).

Note: Adapted from Venkatesh et al. (2003). In the original UTAUT, FC also directly predicts use behavior. The moderating variables (dashed box) condition the main effect relationships. This study adapts the model to the AI marketing tool adoption context among Philippine MSMEs.

The UTAUT was originally validated across six organizations in the United States, explaining approximately 70% of the variance in behavioral intention, substantially exceeding any single constituent model (Venkatesh et al., 2003). Subsequent studies confirmed its validity in mobile banking adoption (Alalwan et al., 2017), consumer information technology (Venkatesh et al., 2012), and e-commerce platforms in Southeast Asian contexts (Abdat, 2020). The original four-construct UTAUT formulation is retained for this study (rather than UTAUT2) because adoption decisions are made by MSME owner-managers in an organizational business context, for which the original constructs are better calibrated than the hedonic and price-value extensions designed for consumer settings (Venkatesh et al., 2012).

2.2. Innovation Diffusion Theory (IDT) as a Complementary Lens

Rogers' (2003) Innovation Diffusion Theory (IDT) provides a complementary theoretical perspective on how AI marketing tools spread through MSME networks. IDT posits that innovations diffuse through social systems via communication channels over time, with adoption driven by perceived relative advantage, compatibility, complexity, trialability, and observability. The social influence construct in the UTAUT directly resonates with IDT's emphasis on interpersonal and social network channels as primary diffusion mechanisms, particularly in collectivist societies such as the Philippines, where peer endorsement and community-based learning are powerful adoption drivers (Hofstede, 2001). This study draws on IDT to theoretically ground the social influence hypotheses (H3, H6) and to interpret the differential social dynamics observed across firm size subgroups.

2.3. Multi-Group Analysis as a Theoretical and Methodological Extension

While UTAUT and IDT provide the theoretical substrate, neither framework explicitly addresses structural heterogeneity across different organizational types. Multi-group analysis (MGA) serves as the bridge between the aggregate theoretical model and the subgroup empirical reality of the Philippine MSME landscape. By testing whether the five structural path coefficients of the UTAUT model (H1–H5) differ significantly across firm size and industry sector subgroups (H6, H7), MGA moves beyond the implicit parameter invariance assumption of aggregate analyses (Henseler et al., 2009). This approach reflects growing recognition that population heterogeneity is not merely a statistical nuisance but a substantively important theoretical phenomenon demanding dedicated empirical attention (Hair et al., 2022).

3. Literature Review

Building on the UTAUT and IDT theoretical foundations established in Section 2, this section develops seven hypotheses organized in two categories: five main structural path hypotheses (H1–H5) corresponding directly to the five arrows in the conceptual framework (Figure 2), and two multi-group analysis hypotheses (H6–H7) testing whether those structural paths differ across subgroups.

3.1. AI Marketing Tools, Digital Transformation, and the MSME Context

The integration of AI into marketing practice represents one of the most consequential dimensions of contemporary digital transformation (Huang & Rust, 2021; Verhoef et al., 2021). AI marketing tools, including generative content platforms, conversational chatbots, algorithmic advertising systems, and predictive customer analytics, have fundamentally restructured how organizations identify, acquire, and retain customers (Kumar et al., 2021; Mustak et al., 2021). For MSMEs in particular, these tools offer the potential to overcome resource disadvantages by automating tasks that previously required specialist personnel, enabling smaller firms to execute marketing at a scale and sophistication previously available only to larger organizations (de Bruyn et al., 2020). Davenport et al. (2020) established that AI marketing systems deliver performance advantages across customer engagement, budget allocation, and promotional content creation—functions that are especially consequential for resource-constrained MSMEs.

Research on SME digital transformation, however, documents that adoption trajectories are not uniform. Verhoef et al. (2021) identified digital business model innovation as a multi-dimensional process conditioned by firm-level resource endowments, managerial digital literacy, and competitive environment—factors that vary systematically across firm size categories. Recent meta-analytic evidence confirms that performance expectancy, conceptualized as the perceived utility of AI tools for business outcomes, consistently emerges as the primary adoption driver, though its relative strength is moderated by organizational characteristics including firm size and operational context (Mustak et al., 2021; Dwivedi et al., 2023). In emerging market contexts, AI adoption among SMEs confronts additional structural barriers including digital infrastructure constraints, talent scarcity, and limited access to formal market information channels, conditions that amplify the role of social networks and interpersonal diffusion as adoption mechanisms (Abdat, 2020). These dynamics establish the need for subgroup-differentiated adoption models in contexts such as the Philippine MSME sector, where firm size and industry type produce categorically different adoption environments.

3.2. Performance Expectancy and Adoption Intention

Performance expectancy (PE) refers to the degree to which an individual believes that using a technology will yield gains in business or job performance (Venkatesh et al., 2003). In the AI marketing tool context, PE captures MSME owner-managers' assessments of whether AI tools will meaningfully improve customer reach, campaign efficiency, and marketing ROI. PE has consistently emerged as the strongest predictor of adoption intention across a wide range of organizational technology adoption studies (Alalwan et al., 2017; Venkatesh et al., 2012):

H1: Performance expectancy positively influences behavioral intention to adopt AI marketing tools among Philippine MSMEs.

3.3. Effort Expectancy and Adoption Intention

Effort expectancy (EE) reflects the perceived ease of using a technology (Venkatesh et al., 2003). Given documented gaps in digital literacy among micro and small enterprise operators in the Philippines (DOST-DICT, 2022), EE is expected to play a significant role in shaping adoption decisions. The salience of EE is particularly pronounced in the AI marketing tool context, where many MSME owner-managers lack prior experience with AI interfaces and may overestimate the complexity of deployment (Dwivedi et al., 2023). Studies in comparable emerging market settings consistently affirm the positive influence of EE on adoption intention (Tarhini et al., 2017):

H2: Effort expectancy positively influences behavioral intention to adopt AI marketing tools among Philippine MSMEs.

3.4. Social Influence and Adoption Intention

Social influence (SI) is defined as the degree to which an individual perceives that important others believe they should use the new technology (Venkatesh et al., 2003). The collectivist cultural orientation of Filipino society (Hofstede, 2001) combined with IDT's emphasis on interpersonal diffusion channels (Rogers, 2003), suggests that SI carries amplified explanatory weight in the Philippine MSME context relative to individualistic market settings. Recent evidence on technology diffusion in SME ecosystems further demonstrates that horizontal peer networks serve as primary information channels for adoption decisions in markets with limited formal advisory infrastructure (de Bruyn et al., 2020)—a dynamic expected to be most pronounced among micro-enterprises, where access to formal market intelligence is most restricted:

H3: Social influence positively influences behavioral intention to adopt AI marketing tools among Philippine MSMEs.

3.5. Facilitating Conditions and Adoption Intention

Facilitating conditions (FC) refer to the organizational and technical infrastructure perceived to support system use (Venkatesh et al., 2003). For Philippine MSMEs, FC encompasses internet connectivity, device availability, financial capacity to license AI platforms, and access to technical assistance. Although the original UTAUT routes FC directly to use behavior, this study adapts FC as a predictor of behavioral intention, consistent with MSME adoption studies in which owner-managers' perceptions of infrastructure availability shape adoption decisions prior to actual system deployment (Awa et al., 2015). These conditions vary markedly across firm size and industry sector, making FC an especially consequential construct in the subgroup context of this study.

H4: Facilitating conditions positively influence behavioral intention to adopt AI marketing tools among Philippine MSMEs.

3.6. Behavioral Intention and Actual AI Marketing Tool Use

Consistent with the UTAUT (Venkatesh et al., 2003) and the TAM (Davis, 1989), behavioral intention serves as the proximal predictor of actual technology use behavior. This relationship has been confirmed across diverse organizational and consumer technology adoption contexts, including digital marketing platform adoption in Southeast Asian settings:

H5: Behavioral intention positively influences actual AI marketing tool use among Philippine MSMEs.

3.7. Multi-Group Hypotheses: Firm Size and Industry Sector

Firm size, spanning micro (1–9 employees), small (10–99), and medium (100–199) enterprises, shapes organizational resource availability, managerial specialization, and digital infrastructure investment, all of which condition how UTAUT predictors operate (Premkumar, 2003). Industry sector (product-based versus service-based) shapes customer interaction patterns and the relative salience of specific AI tool functionalities. Prior UTAUT studies implicitly assume parameter invariance across these dimensions, an assumption that is empirically questionable in the Philippine MSME context:

H6: The structural relationships in the AI marketing tool adoption model (H1–H5 paths) differ significantly across firm size subgroups (micro, small, and medium enterprises).
H7: The structural relationships in the AI marketing tool adoption model (H1–H5 paths) differ significantly across industry sector subgroups (product-based versus service-based MSMEs).

3.8. Conceptual Framework

Figure 2 presents the adapted conceptual framework. Each of the four UTAUT antecedent constructs occupies an individual box on the left, connected by individually labeled arrows (H1–H4) to the Behavioral Intention (BI) box at the center. The BI box is connected to the Actual AI Marketing Tool Use (AU) box by the H5 arrow. H6 and H7, positioned at the base of the framework, designate the multi-group analysis subgrouping variables that condition all five structural paths.

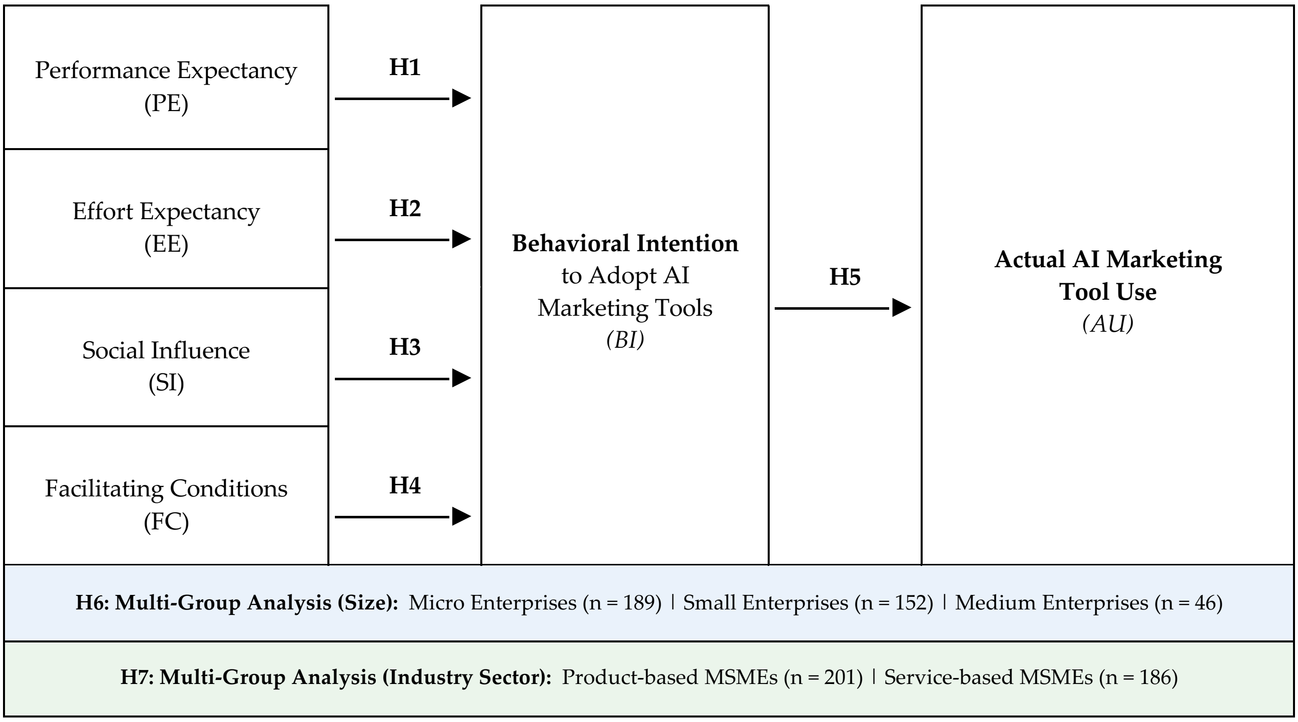

Figure 2. Conceptual Framework of AI Marketing tool adoption among Philippine MSMEs.
Note: Adapted from the UTAUT (Venkatesh et al., 2003). H1–H5 correspond to the five structural arrows. H6 and H7 designate firm size and industry sector as MGA subgrouping variables testing whether H1–H5 path relationships differ across subgroups.

3.9. Research Gaps and Study Positioning

A review of the existing literature identifies three interrelated gaps that motivate and justify the present study.

Theoretical gap: Extant UTAUT-based technology adoption research, while robust in its aggregate explanatory power, embeds an implicit assumption of parameter invariance: the premise that UTAUT structural relationships are universally stable across the population under study (Henseler et al., 2009). This assumption has rarely been empirically interrogated in MSME contexts. Prior UTAUT applications in Southeast Asian markets have demonstrated the framework's explanatory power within specific samples but have not systematically tested whether its structural paths differ across organizational subgroups defined by firm size or industry sector. The theoretical gap lies in the absence of organizational-level boundary condition testing within UTAUT-based MSME adoption research.

Empirical gap: Research on AI marketing tool adoption in the Philippine MSME sector remains scarce and predominantly aggregate in design. Existing studies conflate micro, small, and medium enterprises into a single analytical unit despite their substantial differences in resource availability, managerial formalization, digital infrastructure, and competitive environment. This empirical gap is particularly consequential given that Philippine MSMEs represent a highly internally differentiated sector. Moreover, AI marketing tool adoption as a distinct construct, differentiated from general information technology or e-commerce adoption, has received limited empirical attention in the Philippine context. The functional differentiation of AI tools across generative content, chatbot platforms, AI-powered advertising, and predictive analytics has not been systematically linked to subgroup-level adoption determinants.

Methodological gap: The predominance of aggregate PLS-SEM models in MSME adoption research constitutes a methodological gap: the absence of subgroup comparison procedures capable of detecting structural heterogeneity. Multi-group analysis using Henseler's nonparametric permutation approach (Henseler et al., 2009) paired with the MICOM procedure (Henseler et al., 2016) provides the methodological apparatus to address this gap directly, enabling empirical testing of whether observed path differences reflect genuine structural heterogeneity or measurement artifacts. Together, these three gaps—theoretical, empirical, and methodological—define the study's contribution and justify its research design.

4. Methodology

4.1. Research Design

This study employs a quantitative cross-sectional survey design, consistent with the positivist tradition of the UTAUT and the established methodological practice of MSME technology adoption research in Southeast Asia (Awa et al., 2015; Venkatesh et al., 2003). While the original UTAUT specifies four individual-level moderating variables—age, gender, experience, and voluntariness of use—this study focuses on organizational-level moderators, specifically firm size and industry sector, which are more theoretically relevant to the structural heterogeneity of the MSME population examined here. Individual-level UTAUT moderators were not the focus of this study; future research incorporating both levels of moderation simultaneously would provide a more complete picture of adoption dynamics in this context.

4.2. Population and Sample

The target population comprised owner-managers or principal marketing decision-makers of formally registered MSMEs operating in Metro Manila, Philippines. Purposive sampling with quota controls on firm size and industry sector was employed to ensure theoretically meaningful subgroup representation. Data were collected from January to March 2025 through an online survey administered via Google Forms, distributed through the Federation of Filipino-Chinese Chambers of Commerce and Industry, the Philippine Chamber of Commerce and Industry Metro Manila Chapter, and targeted social media business communities. Following data cleaning, 387 complete responses were retained: 189 micro enterprises (48.8%), 152 small enterprises (39.3%), and 46 medium enterprises (11.9%); and 201 product-based MSMEs (51.9%) and 186 service-based MSMEs (48.1%). Minimum sample size for PLS-MGA was verified using G*Power 3.1 (Faul et al., 2009) at α = .05, power = .80, and f^2 = .15, requiring a minimum of 128 per subgroup. This threshold was met by all but the medium enterprise category (n = 46), which warrants interpretive caution.

4.3. Instrumentation

A structured self-administered questionnaire was developed from validated UTAUT scales (Venkatesh et al., 2003): performance expectancy (4 items), effort expectancy (4 items), social influence (3 items), and facilitating conditions (4 items). Behavioral intention (3 items) and actual AI marketing tool use (3 items) were adapted from Alalwan et al. (2017) and Dwivedi et al. (2021). All items were measured on a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). The instrument was pilot tested with 30 MSME respondents in December 2024 and refined for contextual relevance prior to full-scale data collection in January 2025. To ensure construct validity across industry sector subgroups, the survey items operationalizing actual AI marketing tool use explicitly encompassed all four functional tool categories identified in Section 1: generative AI for content creation, AI-powered chatbot platforms, AI-enhanced social media advertising, and predictive analytics tools. This typology ensured that both product-based and service-based MSME respondents could anchor their responses to tools directly relevant to their business context, rather than responding to an abstract or decontextualized construct.

4.4. Data Analysis

Data were analyzed using PLS-SEM via SmartPLS 4.0 (Ringle et al., 2022), appropriate for the study's predictive orientation, anticipated non-normality in MSME survey data, and multi-group comparison objectives (Hair et al., 2022). Analysis proceeded in three stages: (1) measurement model assessment, (2) structural model evaluation of path coefficients (H1–H5), variance explained, and effect sizes, and (3) measurement invariance assessment followed by MGA. Prior to MGA, the Measurement Invariance of Composite Models (MICOM) procedure (Henseler et al., 2016) was applied to both subgrouping variables to establish that observed path differences reflect genuine structural heterogeneity rather than measurement artifacts. MICOM assesses configural invariance, compositional invariance, and equality of composite means and variances. MGA using Henseler's nonparametric approach with 5,000 permutation subsamples was then applied to test H6 and H7. Common method variance (CMV) was assessed using two complementary procedures. First, Harman's single-factor test was conducted; the single factor accounted for only 24.3% of total variance, below the threshold of concern. Second, full collinearity assessment was performed by examining the variance inflation factor (VIF) for all constructs in the structural model; all VIF values fell below 3.3 (range: 1.87–2.61), the threshold recommended by Kock (2015) for PLS-SEM, indicating that common method bias does not substantially affect the structural estimates.

5. Results

5.1. Respondent Profile

Table 1 summarizes the demographic profile of the 387 respondents. The sample is slightly male-dominated (55.3%), with the majority of MSMEs having been in operation for more than six years (74.7%). A substantial proportion (62.8%) reported currently using at least one AI marketing tool, while 37.2% expressed intention to adopt within 12 months. All respondents therefore fell within one of these two categories, reflecting the AI-engaged composition of the business associations and communities through which the survey was distributed. Future studies should deliberately include non-adopters with no adoption intention to enable a fuller assessment of adoption barriers across the MSME population.

5.2. Measurement Model Assessment

Table 2 presents the measurement model results. All constructs demonstrated satisfactory internal consistency reliability, with Cronbach's alpha (α) values ranging from .807 to .891 and composite reliability (CR) values from .874 to .931. Convergent validity was confirmed through average variance extracted (AVE) values ranging from .598 to .818 (Fornell & Larcker, 1981). Discriminant validity was established via the heterotrait-monotrait (HTMT) ratio criterion, with all HTMT values below .85 (Henseler et al., 2015).

Table 1. Respondent profile.

Characteristic	Category	Frequency (n)	Percentage (%)
Firm Size	Micro (1–9 employees)	189	48.8
	Small (10–99 employees)	152	39.3
	Medium (100–199 employees)	46	11.9
Industry Sector	Product-based	201	51.9
	Service-based	186	48.1
Owner-Manager Gender	Male	214	55.3
	Female	173	44.7
Years in Operation	1–5 years	98	25.3
	6–10 years	134	34.6
	>10 years	155	40.1
Current AI Tool Status	Currently using	243	62.8
	Intend to adopt within 12 months	144	37.2
Total		**387**	**100.0**

Note: n = 387. Percentages may not sum to 100.0 due to rounding.

Table 2. Measurement model assessment results.

Construct	α	CR	AVE	Factor Loadings	HTMT Ratio
Performance Expectancy (PE)	.879	.912	.637	.768–.841	All < .85 ✓
Effort Expectancy (EE)	.842	.893	.621	.743–.821	All < .85 ✓
Social Influence (SI)	.807	.874	.598	.752–.809	All < .85 ✓
Facilitating Conditions (FC)	.856	.901	.645	.771–.847	All < .85 ✓
Behavioral Intention (BI)	.891	.931	.818	.893–.921	All < .85 ✓
Actual Use (AU)	.876	.920	.793	.871–.908	All < .85 ✓
Recommended Threshold	*> .70*	*> .70*	*> .50*	*> .60*	*< .85*

Note: α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted; HTMT = Heterotrait-Monotrait Ratio. All factor loadings exceeded the .70 threshold.

5.3. Structural Model: Main Path Results

Table 3 presents the structural model results for the pooled sample (n = 387). The model explained 58.7% of the variance in behavioral intention ($R^2 = .587$) and 48.3% in actual AI marketing tool use ($R^2 = .483$). Performance expectancy was the strongest predictor (H1: $\beta = .312$, $t = 6.841$, $p < .001$, $f^2 = .098$). Effort expectancy (H2: $\beta = .241$, $p < .001$), social influence (H3: $\beta = .198$, $p < .001$), and facilitating conditions (H4: $\beta = .167$, $p = .001$) all significantly predicted behavioral intention. Behavioral intention strongly predicted actual use (H5: $\beta = .521$, $p < .001$, $f^2 = .272$). All five hypotheses are supported.

Table 3. Structural model results: Pooled Sample (n = 387).

Hypothesis / Path	β	SE	t-value	p-value	f^2	Decision
H1: PE → BI	.312	.046	6.841	< .001	.098	Supported ✓
H2: EE → BI	.241	.047	5.123	< .001	.058	Supported ✓
H3: SI → BI	.198	.050	3.987	< .001	.039	Supported ✓
H4: FC → BI	.167	.052	3.214	.001	.028	Supported ✓
H5: BI → AU	.521	.056	9.234	< .001	.272	Supported ✓

R^2 (BI) = .587; R^2 (AU) = .483; Q^2 (BI) = .341; Q^2 (AU) = .231. Bootstrap subsamples = 5,000.

Note: SE = Standard Error. t-values from 5,000 bootstrap subsamples (one-tailed); one-tailed tests are appropriate because all five hypotheses specify a positive directional relationship, consistent with Hair et al. (2022) recommendations for confirmatory PLS-SEM. f^2 = Cohen's effect size. All five hypotheses supported.

5.4. Measurement Invariance Assessment (MICOM)

Prior to MGA, the MICOM procedure (Henseler et al., 2016) was applied to both subgrouping variables. For both firm size and industry sector groupings, Step 1 confirmed configural invariance through identical model configurations and estimation algorithms across all subgroups. Step 2 assessed compositional invariance via 5,000 permutations; all construct correlations exceeded the 95% confidence interval lower bounds, confirming that composites are formed equivalently across subgroups and establishing full compositional invariance. Step 3 found no statistically significant differences in composite means or variances across groups ($p > .05$ for all constructs and both grouping variables), establishing full measurement invariance for both the firm size and industry sector groupings. These results confirm that the subsequent MGA path coefficient comparisons reflect genuine structural heterogeneity rather than measurement artifacts.

5.5. Multi-Group Analysis by Firm Size

Table 4 presents the MGA results for firm size subgroups. Three of five paths showed significant between-group differences. Performance expectancy was significantly stronger among medium enterprises (β = .445) than micro enterprises (β = .198), Δβ = .247, p = .023. Social influence showed the reverse pattern, significantly stronger among micro enterprises (β = .276) than medium enterprises (β = .098), Δβ = .178, p = .031. The BI→AU path also differed significantly (Δβ = .132, p = .048). H6 is supported.

Table 4. Multi-Group analysis results by Firm Size.

Path	Micro (n=189)	Small (n=152)	Medium (n=46)	Δβ (Micro–Med)	p-value (MGA)	Between-Group Difference
PE → BI (H1)	.198	.321	.445	.247	.023 *	Path differs ✓
EE → BI (H2)	.287	.231	.189	.098	.198	Path similar
SI → BI (H3)	.276	.187	.098	.178	.031 *	Path differs ✓
FC → BI (H4)	.145	.178	.231	.086	.187	Path similar
BI → AU (H5)	.489	.521	.621	.132	.048 *	Path differs ✓

Note: H6 Decision: Supported ✓, Firm size significantly moderates the adoption model. PE→BI, SI→BI, and BI→AU paths differ significantly across subgroups. MGA: Henseler's nonparametric approach, 5,000 permutations. * p < .05.

5.6. Multi-Group Analysis by Industry Sector

Table 5 presents the MGA results for industry sector subgroups. Only the effort expectancy to behavioral intention path differed significantly: service-based MSMEs demonstrated a stronger EE→BI relationship (β = .287) than product-based MSMEs (β = .198), Δβ = .089, p = .041. H7 is partially supported.

Table 5. Multi-Group analysis results by industry sector:

Path	Product-based (n=201)	Service-based (n=186)	Δβ	p-value (MGA)	Between-Group Difference
PE → BI (H1)	.289	.334	.045	.312	Path similar
EE → BI (H2)	.198	.287	.089	.041 *	Path differs ✓
SI → BI (H3)	.212	.178	.034	.298	Path similar
FC → BI (H4)	.187	.145	.042	.421	Path similar
BI → AU (H5)	.498	.543	.045	.267	Path similar

Note: H7 Decision: Partially Supported ~. Industry sector partially moderates the model; only EE→BI differs significantly (service-based vs. product-based). MGA: Henseler's nonparametric approach, 5,000 permutations. * p < .05.

6. Discussion

6.1. Main Path Effects

The confirmation of all five main path hypotheses is consistent with the UTAUT's theoretical predictions (Venkatesh et al., 2003) and resonates with prior technology adoption research in Southeast Asian emerging markets (Alalwan et al., 2017). Performance expectancy emerged as the dominant driver of adoption intention (β = .312), underscoring that Philippine MSME owner-managers are fundamentally motivated by tangible business performance benefits when evaluating AI marketing platforms, coherent with the resource-constrained decision calculus that characterizes MSME marketing practice (Premkumar, 2003). The strong BI→AU relationship (β = .521, f^2 = .272) confirms the structural integrity of the UTAUT intention–behavior chain in this context. These results are consistent with emerging evidence on the centrality of digital and AI-enabled competencies in post-pandemic retail marketing transformation within the Philippine MSME landscape, lending contextual validity to the adoption model tested here.

The confirmation of performance expectancy as the dominant predictor (H1: β = .312, f^2 = .098) is consistent with recent evidence on AI marketing tool utility assessments in emerging market business contexts (Huang & Rust, 2021; Kumar et al., 2021). MSME owner-managers approach AI adoption with a fundamentally economic calculus: the tool must demonstrably improve business outcomes relative to its cost and learning curve. This finding also resonates with Mustak et al.'s (2021) observation that perceived business utility consistently outweighs other adoption considerations for business-context technology decisions, even when those decisions involve relatively novel tool categories. The moderate effect of social influence (H3: β = .198) across the pooled model is theoretically expected given the cultural collectivism of the Philippine business environment

(Hofstede, 2001) and is consistent with IDT's predictions about interpersonal diffusion channels in social systems where formal information infrastructure is less developed (Rogers, 2003). The significant facilitating conditions effect (H4: β = .167) further underscores that infrastructure enablers remain a genuine constraint in this context, not merely a control variable—a finding with direct policy implications for public investment in digital infrastructure for the MSME sector.

6.2. Firm Size Moderation

The substantially stronger performance expectancy effect among medium enterprises (β = .445 vs. β = .198 for micro enterprises) is theoretically coherent. Medium enterprises operate with more formalized marketing functions, greater stakeholder accountability for ROI, and higher absolute marketing expenditures; these are conditions that heighten sensitivity to demonstrable performance benefits. Micro-enterprise owner-managers, constrained by survival orientation and immediate cash-flow concerns, are comparatively less responsive to performance narratives that require medium-term time horizons to materialize (Premkumar, 2003). Small enterprises occupy a genuinely transitional position in this pattern. Their performance expectancy effect (β = .321) already trends toward the medium enterprise orientation, suggesting that as firms grow and marketing functions become more structured, the ROI calculus begins to dominate adoption decisions. Yet their social influence effect (β = .187) remains meaningfully elevated relative to medium enterprises, indicating that peer-based diffusion channels have not yet given way entirely to formal evaluation processes. This transitional dynamic has practical relevance: small enterprise owner-managers are responsive to both performance evidence and peer endorsement, making them the segment most receptive to adoption programs that combine demonstrated ROI with community-based social proof. The inverse pattern for social influence (β_{micro} = .276 vs. β_{medium} = .098) reflects the IDT-grounded argument that interpersonal diffusion channels are most potent in social systems with limited formal information infrastructure (Rogers, 2003), amplified by the collectivist orientation of Filipino business culture (Hofstede, 2001).

The transitional position occupied by small enterprises is particularly significant for digital transformation policy design. Their performance expectancy effect (β = .321) already approaches the medium enterprise orientation, while their social influence effect (β = .187) remains meaningfully elevated relative to medium enterprises, indicating that peer-based diffusion channels have not yet given way entirely to formal evaluation processes. This pattern is consistent with Verhoef et al. (2021) characterization of digital maturity as a developmental trajectory rather than a binary state: small enterprises are in transition, simultaneously responsive to performance evidence and community social proof. This transitional dynamic has direct practical relevance—small enterprise owner-managers represent the segment most amenable to adoption programs that combine demonstrated ROI evidence with community-based peer endorsement, making them a high-leverage target for sequenced AI adoption interventions.

6.3. Industry Sector Moderation

The partial support for H7, specifically the significantly stronger effort expectancy effect among service-based MSMEs, reflects the competitive logic of service enterprises whose differentiation rests on customer interaction quality. A poorly designed AI marketing interface represents a meaningful operational liability for a salon, restaurant, or professional services firm whose reputation depends on seamless, personalized customer engagement. Product-based MSMEs may tolerate greater implementation complexity when downstream efficiency gains are sufficiently compelling. The absence of significant sector-level differences in the remaining four paths highlights effort expectancy as the principal sector-differentiating lever, with clear implications for AI platform design and sector-specific onboarding strategies. This finding is particularly illuminating when read against the functional tool typology of the Philippine MSME context. The AI tools most directly useful to service-based MSMEs, specifically AI-powered chatbots for customer inquiry management and appointment scheduling, require owner-managers to configure conversational flows, train the system on their specific service offerings, and monitor ongoing interactions. These are operationally demanding tasks for businesses that typically lack dedicated IT personnel and where a poorly functioning chatbot can directly damage customer relationships. Product-based MSMEs, by contrast, tend to engage most with AI-enhanced advertising platforms such as Meta Advantage+ and Shopee recommendation tools, where the AI operates largely autonomously once campaign parameters are set and the performance payoff is more immediately measurable. The higher tolerance for implementation complexity among product-based MSMEs is therefore not surprising: the tools they use are designed to minimize ongoing user effort, shifting the adoption calculus back toward performance rather than ease of use.

The finding that effort expectancy is the principal sector-differentiating lever, rather than performance expectancy or social influence, has important theoretical implications for UTAUT boundary condition research. It suggests that the salience of specific UTAUT constructs is not only moderated by individual characteristics (as the original UTAUT moderators of age, gender, and experience capture) but also by the operational demands of the technology in its primary use context. AI-powered chatbots deployed by service MSMEs require ongoing configuration, content training, and interaction monitoring—tasks that impose sustained cognitive effort on owner-managers who typically lack dedicated IT support (Dwivedi et al., 2023). This operational reality makes effort expectancy a binding constraint for service-sector adoption in a way that it is not for product-based MSMEs, where AI tools such as Meta Advantage+ and Shopee recommendation engines operate more autonomously once initial campaign parameters are established. Platform developers and policymakers who fail to account for this sector-level effort asymmetry will design AI adoption support that is systematically misaligned with the operational realities of service-based MSMEs.

6.4. Managerial Implications

The findings of this study carry direct and actionable implications for four distinct groups of stakeholders: government policymakers, AI platform developers, MSME development organizations, and the owner-managers of MSMEs themselves. Rather than prescribing a single universal approach to AI marketing adoption, the evidence calls for differentiated strategies calibrated to firm size and industry type.

For micro-enterprise owner-manager: For micro-enterprises, the most powerful adoption driver is not a sales pitch about ROI; it is seeing a trusted peer or neighbor succeed with an AI tool first. This study found that social influence is the dominant adoption lever among micro-enterprises, a finding consistent with the deeply relational, community-embedded nature of small business culture in the Philippines. Practical steps follow directly from this: join or form a digital business group within your barangay, industry association, or online community. Seek out peers who have already adopted AI marketing tools and ask them to demonstrate what works. Sari-sari store operators, food vendors, and neighborhood service providers are more likely to try a new AI tool if someone they respect has tried it first than if they read a brochure about it. The social proof of adoption is a more persuasive argument than any feature list.

For small and medium enterprise owner-managers: As enterprises grow, the adoption calculus shifts decisively toward demonstrable business performance. For small and especially medium enterprises, the central question before adopting an AI marketing tool is: will this generate more customers, reduce my cost per lead, or improve my conversion rate? These are not abstract concerns; they are measurable. Medium enterprise owner-managers are advised to demand performance benchmarks and case studies from AI platform providers before committing to a subscription. Pilot campaigns with clear key performance indicators, tracked over 60 to 90 days, will generate the evidence base needed to justify broader organizational adoption. The data from this study suggest that medium enterprises that frame AI adoption as a performance investment rather than a technology experiment are far more likely to move from intention to actual, sustained use.

For AI platform developers and technology providers: Platforms targeting the Philippine MSME market need to recognize that a single interface design and onboarding process will not serve all firm types equally well. For service-based MSMEs such as restaurants, salons, clinics, freelance professionals, and the like, ease of use is not a nice-to-have feature; it is the primary adoption gate. These businesses operate in high-contact, reputation-sensitive environments where any marketing tool that is difficult to learn or prone to error directly threatens customer experience. Platform developers should invest in simplified, service-sector-specific onboarding pathways, offer live chat or dedicated support in Filipino, and consider freemium entry points that allow service businesses to experience the tool's ease before committing financially. For product-based MSME customers, the marketing emphasis should shift to performance outcomes: showcase conversion data, cost savings, and competitive advantages achieved by similar businesses in the same product category.

For government agencies and MSME development organizations: The Department of Trade and Industry, the Small Business Corporation, and DOST-DICT collectively anchor the Philippines' MSME digitalization agenda. This study's findings suggest that their AI adoption programs will be most effective when designed around the specific adoption barriers of each firm-size and sector segment, rather than through generalized digital literacy campaigns. For micro-enterprises, the most impactful interventions are community-based: digital adoption boot camps organized through barangay-level business associations, peer ambassador programs that recruit and incentivize early MSME adopters to demonstrate AI tools to their networks, and social media communities where owner-managers share real experiences. For small and medium enterprises, policy support should prioritize access to performance data, including subsidized AI platform pilots, industry-specific ROI calculators, and published case studies from comparable Philippine businesses provide the evidence base that performance-oriented managers need to act. Across all segments, the study underscores the importance of ensuring adequate facilitating conditions: affordable broadband, accessible devices, and Filipino-language technical support remain baseline requirements without which adoption programs will underperform regardless of how well they are designed.

Taken together, the MGA results deliver a clear theoretical verdict: the UTAUT assumption of parameter invariance does not hold in Philippine MSME contexts. The framework's structural paths are not stable universal constants; they are systematically moderated by firm size and industry sector. Aggregate MSME adoption models that ignore this heterogeneity produce structurally misleading parameter estimates and, by extension, misdirected policy prescriptions. Policymakers, platform developers, and MSME support organizations that apply a one-size-fits-all model to the heterogeneous Philippine MSME landscape do so at the cost of effectiveness.

7. Conclusions

This study contributes to three intersecting streams of scholarship: UTAUT boundary condition research, AI marketing adoption in emerging markets, and MSME digital transformation in Southeast Asia. By applying PLS-SEM and MGA to a sample of 387 Philippine MSME owner-managers, it produces the first formal empirical test of whether UTAUT structural paths are invariant across firm size and industry sector subgroups in the Philippine AI marketing tool adoption context. The answer is unambiguous: they are not. The aggregate UTAUT model, while statistically valid, masks structurally consequential differences that have both theoretical and practical significance. Firm size and industry sector are not demographic background variables in this context; they are organizational boundary conditions that determine which UTAUT predictors function as the primary adoption drivers for a given MSME subgroup. This study delivers a theoretically significant and empirically grounded challenge to mainstream UTAUT application: the assumption of parameter invariance does not hold in Philippine MSME contexts. Through a UTAUT-based PLS-SEM and MGA framework applied to 387 Metro Manila MSME owner-managers, the study established that UTAUT structural relationships are not universal; they are conditioned by firm size and industry sector in ways that prior aggregate analyses have systematically concealed. All five main path hypotheses (H1–H5) were confirmed in the pooled model, validating the UTAUT's overall explanatory power. Yet the MGA results reveal that firm size (H6) significantly moderates the model through the performance expectancy and social influence pathways, while industry sector (H7) exerts partial moderation through effort expectancy, demonstrating that a single aggregate UTAUT model is an inadequate representation of MSME adoption reality. For policymakers and practitioners, the implications are concrete. Micro-enterprise AI adoption programs should leverage peer community channels capitalizing on the primacy of social influence in this subgroup. Medium-enterprise engagement should foreground quantified ROI evidence aligned with the stronger performance expectancy orientation of this segment. AI platform developers targeting service-sector MSMEs should prioritize low-friction interface design given their elevated effort expectancy sensitivity. These recommendations collectively argue for a segmented approach to MSME digital transformation support in the Philippines and comparable Southeast Asian markets. The study is subject to several limitations. The cross-sectional design precludes causal inference, and the Metro Manila focus limits geographic generalizability to provincial and rural MSME populations. Most critically, the medium enterprise subsample ($n = 46$) falls substantially below the recommended minimum of 128 per subgroup established by G*Power analysis at conventional power and effect size parameters. This has a direct consequence for interpreting H6: the PE→BI and SI→BI path differences attributed to the medium enterprise subgroup should be treated as exploratory and directional rather than confirmatory findings. These differences require replication with an adequately powered medium enterprise sample before they can be treated as established empirical results. Future research should pursue longitudinal designs, extend sampling to provincial MSMEs with adequate medium enterprise representation, and incorporate additional subgrouping variables such as digital literacy, owner-manager age, and gender to enable both organizational- and individual-level UTAUT moderation testing. Comparative MGA studies across ASEAN economies would further enrich the regional literature. Future research should also examine adoption heterogeneity at the level of individual tool categories. The present study treats AI marketing tools as a unified construct; disaggregating by tool type—specifically comparing adoption drivers for generative AI, chatbot platforms, AI-powered advertising, and predictive analytics—would yield more precise and actionable findings for platform developers and policymakers operating in the Philippine and broader Southeast Asian MSME context.

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