Journal of Accounting, Finance, Economics, and Social Sciences
Vol 11, No 1, January - June 2026, pp. 25-38
Received: Aug 2025 | Revised: Dec 2025 | Accepted: Jun 2026
DOI: https://doi.org/10.62458/jafess11hus3

AI Maturity in Cambodia: Individual Usage and Organizational Deployment Across SME Firms and Large Corporations

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ABSTRACT

Purpose: *This study investigates individual AI use and organizational AI maturity among firms in Cambodia, focusing on differences between small and medium-sized enterprises (SMEs) and large corporations.*

Methodology*: The study adopts a quantitative, cross-sectional survey design. Data were collected from 168 respondents employed in SMEs, large firms, and multinational corporations across multiple industries in Cambodia.*

Findings*: The results indicate moderate levels of individual AI use but substantially lower organizational adoption. AI usage and investment intentions increase systematically with firm size. Overall, organizational AI maturity remains in an early stage, particularly in strategy, governance, and process integration.*

Implications*: The findings highlight the structural constraints SMEs face and underscore the importance of organizational capacity, leadership, and strategic alignment for fostering inclusive AI adoption.*

Originality*: This study offers empirical evidence on AI maturity in Cambodia, extending AI adoption research beyond high-income economies.*

Limitations and Future Research*: The cross-sectional design, self-reported data, and nonprobability sampling limit generalizability. Future research should employ mixed-methods approaches to examine organizational and institutional dynamics.*

Keywords*: Artificial intelligence; AI maturity; SME; Cambodia; Digital transformation*

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Publisher: CamEd Business School

Recommended Citation

Güngör, H. (2026). AI maturity in Cambodia: Individual usage and organizational deployment across SME firms and large corporations. *Journal of Accounting, Finance, Economics, and Social Sciences, 11*(1), 25 – 38. https://doi.org/10.62458/jafess11hus3

INTRODUCTION

Artificial intelligence (AI) has become one of the defining technological forces of the twenty-first century, transforming the ways organizations create value, optimize operations, and interact with customers. From the rule-based systems of the 1970s to the large language models of the 2020s, AI's trajectory reflects successive breakthroughs in computing, data processing, and algorithmic sophistication. Early symbolic approaches sought to emulate human reasoning through formal logic but were constrained by limited adaptability and the high cost of knowledge engineering (Finlay, 2021). The emergence of neural networks introduced a data-driven paradigm that enabled learning from examples, though hardware limitations initially slowed progress. Renewed advances in computing power, cloud infrastructure, and big data in the early 2000s sparked what many scholars refer to as the "deep learning revolution," characterized by multilayered neural architectures capable of recognizing patterns, generating insights, and improving through experience (LeCun et al., 2015). These developments repositioned AI from theoretical experimentation to an essential enabler of productivity and competitiveness across industries (Güngör, 2020; Borges et al., 2021).

The proliferation of large language models (LLMs), such as the GPT series, has recently extended AI's reach into generative and interpretive domains with immense economic potential (McKinsey, 2023; Fazi et al., 2024; Burgess, 2024). These systems can analyze and produce coherent text, synthesize knowledge, and support decision-making, enabling transformative applications in healthcare, education, marketing, and customer service (Kumar et al., 2025). In contrast to the speculative pursuit of Artificial General Intelligence (AGI), most practical innovation occurs within the domain of Artificial Narrow Intelligence (ANI), where AI serves to augment rather than replace human capabilities (Kelly et al., 2023; Mikalef & Gupta, 2021). Such augmentation has already become embedded in everyday routines through digital assistants, recommendation systems, and automated analytics. Yet, while global enthusiasm for AI adoption continues to accelerate, its diffusion remains highly uneven, particularly between small and medium-sized enterprises (SMEs) and large corporations (Ndlovu et al., 2025), and between advanced and emerging economies (Asian Development Bank, 2022).

Empirical evidence from both developed and emerging economies shows a similar pattern: technical capacity tends to outpace organizational and strategic maturity or readiness. In developed markets, firm size and resources remain the strongest predictors of adoption (Neumann et al., 2022), and technological maturity alone rarely ensures success without parallel progress in people, process, and data (Uren & Edwards, 2023). A 2025 survey of over 8,000 leaders across 30 countries found fewer than one in seven large organizations was fully AI-mature (Cisco, 2025). In emerging economies, Vietnamese medium-sized firms weigh perceived benefits against organizational trade-offs (Cao & Nguyen, 2025); Malaysian SMEs cite internal resistance and regulatory uncertainty as barriers (Rasdi & Baki, 2025); and AI diffusion across the Global South has more broadly been characterized as decentralized and bottom-up, driven by individual experimentation ahead of coordinated strategy (Bhatia et al., 2025), a dynamic this study returns to when interpreting its own findings.

Across developing regions, AI promises both inclusion and inequality. Advanced economies are leveraging AI for strategic transformation, but many emerging markets still struggle with foundational digital infrastructure, skill shortages, and limited readiness or maturity (UNESCO, 2025; Tun et al., 2025; Putra, 2024). These challenges are acute in Southeast Asia, where SMEs constitute the majority of firms but often lack the technical, financial, and organizational capacity to implement advanced digital tools (Asian Development Bank, 2022; OECD, 2025; Cao & Nguyen, 2025; HV et al., 2026). Cambodia exemplifies this developmental tension. The Royal Government of Cambodia (RGC) has identified AI as a key driver of economic modernization, embedding it in national strategies, such as the Pentagonal Strategy: Digital Economy and Society Policy 2021–2035 (UNESCO, 2025). These frameworks signal a high-level commitment to fostering innovation and digital literacy through multi-ministerial coordination. Progress has been made in connectivity, pilot AI initiatives, and the creation of open-source Khmer language models. However, persistent barriers remain: limited R&D investment, weak infrastructure, and uneven awareness of AI's potential restrict the pace of diffusion (Savuth & Sothea, 2023).

This disconnect between policy ambition and organizational capability frames the central problem of AI maturity in Cambodia (Heng et al., 2022), a challenge that will be even more pronounced in rural areas (Hendrian, 2025). Despite international momentum toward AI adoption, systematic empirical research examining how Cambodian firms, especially SMEs, perceive, use, and prepare for AI technologies is almost non-existent. The absence of such evidence limits both theoretical understanding and policy design, risking a widening maturity gap between large corporations and smaller enterprises. To address this gap, the present study seeks to assess levels of AI awareness and usage among Cambodian professionals and organizations, measure their current and intended use of AI tools, and evaluate their organizational maturity for broader AI integration. These objectives are pursued through a quantitative survey of firms across industries, offering insight into how national strategies translate into organizational realities.

The significance of this investigation lies in its contextual specificity. By focusing on a developing digital ecosystem, the study contributes to the global discourse on AI adoption beyond the Western, high-infrastructure settings that dominate existing research. Its findings aim to inform policymakers, educators, and business leaders seeking to strengthen national competitiveness while promoting inclusive participation in the digital economy. The guiding research questions are: What is the level of awareness and use of AI among Cambodian professionals? To what extent are AI tools currently used across industries and firm sizes? And how ready are these organizations to invest and adopt AI in the future?

LITERATURE REVIEW

AI's evolution has produced a rich theoretical and empirical literature on how technology diffuses within organizations and societies. Classical frameworks such as the Technology Acceptance Model (TAM) (Davis et al., 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) remain foundational for explaining user intentions to adopt new technologies. Both models highlight perceived usefulness, ease of use, and social influence as central determinants of behavioral intention, and later extensions incorporate facilitating conditions and demographic moderators (Venkatesh & Bala, 2008). However, these models primarily operate at the individual level and are limited in their ability to capture organizational or environmental contingencies that affect complex innovations like AI.

To address these limitations, the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990) broadens the analysis to include technological infrastructure, organizational capacity, and external pressures. The TOE perspective has proven particularly relevant to digital transformation and AI research, showing that the success of adoption depends not only on perceived benefits but also on alignment between internal resources and external support systems (Chatterjee et al., 2021; Neumann et al., 2022). Contemporary studies increasingly integrate TAM, UTAUT, and TOE to build multi-level models that explain both user intention and organizational maturity or readiness (Pumplun et al., 2019).

Within organizations, AI maturity has emerged as a multidimensional construct encompassing strategy, leadership, culture, data maturity, and technological infrastructure (Jöhnk et al., 2021). Maturity is not a static condition but an iterative process that requires continuous alignment between human and technical systems. Firms with strong leadership vision and robust data ecosystems are more likely to integrate AI sustainably, whereas organizations lacking digital literacy or coherent governance frameworks struggle to move beyond pilot projects (Tehrani et al., 2024). Empirical evidence also shows that cultural adaptability and cross-functional collaboration significantly influence successful implementation (Uren & Edwards, 2023). These findings suggest that technical investment alone is insufficient; effective adoption requires organizational transformation at both structural and behavioral levels.

Before turning to adoption barriers, it is useful to clarify why firms engage with AI and which functions it typically supports. Firms most often deploy AI to automate repetitive tasks, extract insight from data, and personalize customer interactions, with reported applications clustering around customer service, marketing and sales, and internal process automation and supply chain optimization (Schwaeke et al., 2024). For SMEs, these functions carry particular strategic weight because they substitute for capabilities larger firms already hold internally: predictive analytics and AI-enabled CRM enable small firms to anticipate customer needs without dedicated data-science teams, while automation eases the burden of repetitive administrative work, freeing scarce staff for core activities (Chaudhuri et al., 2024). AI thus functions less as a discretionary add-on and more as an equalizing technology, which is precisely why assessing SMEs' maturity to adopt it matters: firms unable to build this capacity risk falling further behind competitors who can absorb AI more readily.

The literature on AI adoption among SMEs highlights numerous challenges and barriers (Arachie et al., 2025; Ul Haq et al., 2025). SMEs play a crucial economic role yet often lack the scale and resources of large firms. Ingalagi et al. (2021) identify managerial commitment and organizational maturity as primary enablers of AI adoption. Similarly, Bak et al. (2024) categorize determinants into seven domains: strategy, culture, resources, support, entrepreneurship, competitiveness, and environmental conditions, emphasizing that awareness and resource availability jointly shape implementation success. Despite growing interest, many SMEs face significant internal barriers, including resistance to change, fear of job displacement, and skill shortages (Rasdi & Baki, 2025). External constraints include uncertain regulatory frameworks and rapidly evolving technologies that demand constant adaptation (Ingalagi et al., 2021; Lemos et al., 2025; Bak et al., 2024).

Studies from Southeast Asian countries, including Singapore, Malaysia, Thailand and Vietnam, reinforce these insights. Cao and Nguyen (2025) show that in medium-sized firms, perceived benefits and sacrifices jointly determine perceived value, which in turn drives adoption. According to a recent report (HV et al., 2026), Southeast Asian firms are scaling AI faster than the global average, but adoption has not yet consistently translated into financial value: 46% have progressed beyond piloting, while 60% report less than a 5% EBIT impact and 18% report no financial impact.

Beyond operational and financial performance, AI adoption carries strategic implications. Dora et al. (2021) suggest that leadership commitment and AI-related capabilities are decisive for successful implementation, and that higher maturity is positively correlated with adoption. Scholars such as Halim et al. (2024) argue that strategic foresight and data analytics capabilities, when coupled with AI, enhance the sustainable competitiveness of SMEs in developing economies. Agrawal (2023) introduces the notion of Technological Resource Proficiency (TRP) to describe the extent to which organizations possess the infrastructure, training, and leadership required to exploit AI effectively. Alet (2024) extends this perspective by identifying four axes of AI integration: focused strategy, customer knowledge, interaction quality, and implementation effectiveness, highlighting the need for continuous human-machine learning loops within business structures. These contributions converge on a central theme: AI's value-creation potential depends on the interplay among technology, strategy, and people.

At the same time, the expanding role of AI raises pressing ethical and governance questions, largely due to the risks inherent in its implementations. Morley et al. (2020), Zhu et al. (2021), and Ferrara (2023) emphasize the need for fairness, transparency, and accountability in AI design and deployment. Ryan et al. (2025) caution that existing ethical guidelines risk oversimplifying structural challenges and advocate for multi-level, interdisciplinary, and polycentric governance approaches. Complementing these views, Wirtz et al. (2022) introduce the concept of Corporate Digital Responsibility (CDR), urging firms to move beyond compliance toward proactive management of AI's social and environmental impacts. Together, these studies position ethical stewardship as integral to organizational maturity and public trust (Glikson & Woolley, 2020).

Across theoretical and empirical streams, the literature reveals converging evidence that successful AI adoption depends on a dynamic alignment of technological capability, organizational preparedness, and ethical responsibility. However, most existing studies rely on data from high-income economies, leaving critical gaps in understanding AI maturity in developing contexts. Research on Cambodia and similar emerging markets remains particularly limited, with little empirical insight into how national digital policies translate into firm-level practices. TAM, UTAUT, and TOE remain useful starting points for framing individual and organizational adoption, but the evidence behind them comes almost entirely from high-income settings, leaving open how AI maturity looks in a low-income, resource-constrained economy.

This study does not test or extend these frameworks. It uses them as a background lens and instead offers initial empirical evidence on AI usage and maturity in Cambodia, largely absent from the existing literature. By comparing SMEs with large and multinational firms, the study provides an early, exploratory picture of how AI adoption unfolds outside the high-income contexts the literature has focused on, offering a starting point for future research and practical insight for practitioners and policymakers in similar developing-economy settings.

METHODOLOGY

This study adopts a quantitative, cross-sectional survey design to examine individual usage and organizational maturity in AI adoption among firms operating in Cambodia. A survey-based approach was deemed appropriate given the study's objectives of capturing perceptions, current practices, and future intentions across a heterogeneous sample of organizations. The research design aligns with the study's research questions, which focus on levels of AI awareness, current organizational use of AI tools, perceived maturity, and investment intentions regarding AI.

Survey Questionnaire and Data Collection

Primary data were collected through a structured, self-administered online survey hosted on Qualtrics, enabling efficient distribution, anonymous participation, and secure data handling. The survey was conducted in December 2025 using a non-probability convenience sampling strategy that drew on the researchers' personal and professional networks as well as LinkedIn connections.

The questionnaire comprised four sections: (i) respondent and firm background characteristics, including gender, age, education level, industry sector, and firm size classification (small, medium, large, or multinational); (ii) individual-level AI usage and familiarity; (iii) organizational-level AI usage and investment intentions; and (iv) organizational AI maturity, assessed across six dimensions: AI strategy and vision, data infrastructure and quality, AI technology and tools, AI talent and skills, AI operations and processes and governance, and ethics and compliance. This six-dimensional structure was adapted from the multidimensional AI maturity construct identified by Jöhnk et al. (2021) as AI readiness, which spans strategy, leadership, culture, data maturity, and technological infrastructure. Item development for the maturity and adoption sections drew on the broader literature on AI adoption and organizational maturity or readiness (Dora et al., 2021; Bak et al., 2024; Alet, 2024; Zhu et al., 2021; Ferrara, 2023; Ryan et al., 2025).

With the exception of background items, which used categorical response options, all other items were measured on five-point ordinal Likert-type scales, consistent with established practice for measuring technology acceptance and organizational maturity or readiness constructs (Davis et al., 1989; Venkatesh et al., 2003).

Ethical considerations were addressed throughout the research process. Participation was entirely voluntary, and respondents were informed at the outset that their responses would remain anonymous and confidential. No personally identifiable information was collected, and all data were reported only in aggregate form. Qualtrics ensured secure data storage and compliance with standard data protection practices. The research also adhered to principles of responsible and transparent research, particularly given the ethical concerns associated with AI adoption. By focusing on perceptions and perceived maturity rather than sensitive operational data, the study respects organizational confidentiality while providing empirical insight into AI maturity in a developing economy.

Sample (Respondent Characteristics)

All invited participants were based in Cambodia and were either employees or managers in SMEs, large corporations, or multinational firms. No additional eligibility criteria, such as a specific job function, a technical or IT-related role, or a minimum level of prior AI exposure, were applied. This broad inclusion criterion reflects a deliberate trade-off: given the scarcity of firm-level AI data in Cambodia and reliance on personal and professional networks for recruitment, further narrowing eligibility risked constraining an already limited respondent pool. Consistent with the exploratory, descriptive aim of this study, the priority was to capture a broad initial picture of AI usage and maturity across firm types, rather than to isolate a narrowly defined subpopulation. This is acknowledged as a limitation, as it may introduce variation in respondents' direct exposure to organizational AI decision-making that a more targeted sampling frame would have controlled for.

In total, 183 responses were received, of which 168 were fully completed and retained for analysis. The final sample comprised 40 small, 55 medium, 43 large, and 30 multinational firms across financial services, professional services, technology and telecommunications, consumer and travel services, manufacturing, and the public sector. Although this non-probability approach limits statistical generalizability, it is appropriate for an exploratory investigation in a context where firm-level AI data remain scarce.

Data Analysis Procedures

Data were analyzed in JASP Team (2025), version 0.95.4, using standard quantitative techniques appropriate for exploratory organizational research. Descriptive statistics summarized respondent demographics, organizational characteristics, and the distributions of AI usage and maturity scores. Correlation analysis examined relationships between firm size and both organizational AI usage and AI investment plans. One-way ANOVA tested for differences in organizational AI usage across industry sectors. All statistical tests used a significance threshold of $p < .05$.

This descriptive and bivariate analytical strategy was deliberately chosen over more advanced multivariate techniques, such as multiple regression or structural equation modeling. As an initial empirical study of AI maturity in a context largely absent from the existing literature, the aim was to establish a descriptive baseline of current usage and maturity patterns rather than to test causal or predictive models, especially given a non-probability convenience sample (N = 168). Future research, ideally drawing on a larger, probability-based sample, could build on these descriptive findings by using regression-based or structural equation modeling approaches to test explanatory and predictive relationships among firm size, industry, and the dimensions of AI maturity.

RESULTS

First, descriptive statistics (Table 1) were used to provide an overview of the current AI landscape among Cambodian firms and to enable comparisons across organizational sizes and industries.

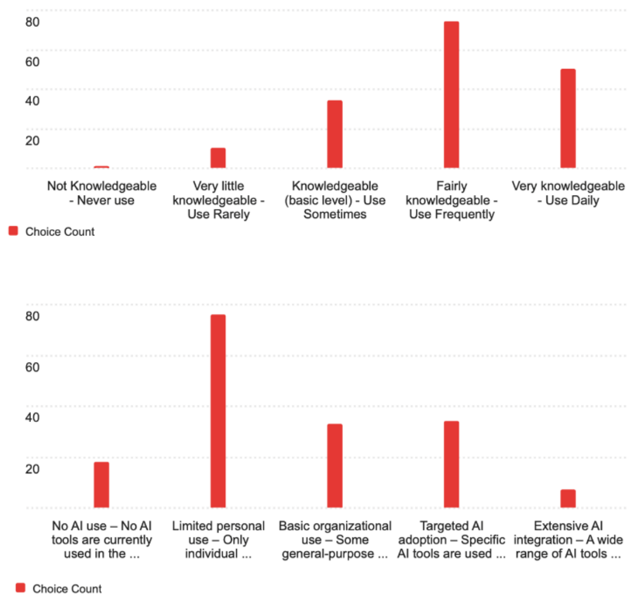
Table 1: Descriptive Statistics (*N* = 168)

Variable	Mean	Std. Deviation
Age	2.750	0.817
Education	2.827	0.379
OrgSize	3.375	1.036
Ai Usage	3.976	0.861
Org Ai	2.619	1.054
Invest Ai	3.631	1.187
AI Strategy & Vision	2.185	1.151
Data & Infrastructure	2.226	1.157
Talent & Skills	2.208	1.152
Technology & Tools	2.220	1.166
Operations & Process	2.113	1.118
Governance & Ethics	2.179	1.096
Avr Ai Maturity	2.188	1.082

Female respondents reported slightly higher levels of personal AI usage (M = 4.15) than male respondents (M = 3.82). Personal AI usage was highest among respondents in younger-to-middle age categories and lower among older respondents, suggesting a non-linear pattern in which AI usage peaks during mid-career stages. Respondents with a university degree reported substantially greater personal AI usage (M = 4.12) than those with lower education levels (M = 3.28). This result highlights education as a key individual-level factor shaping AI familiarity and usage.

The differences between personal use of AI tools and organizational AI adoption were remarkable, with individuals ahead of their organizations in AI use and adoption (Figure 1).

Figure 1: Personal AI usage vs Organizational AI adoption (N = 168)



Results indicated that organizational AI usage and investment plans increase with firm size (Figures 2 and 3).

Figure 2: Firm size and organizational AI usage (N = 168)

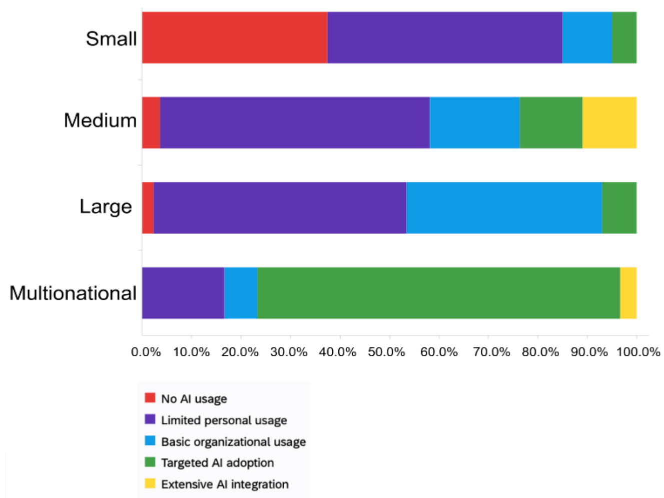
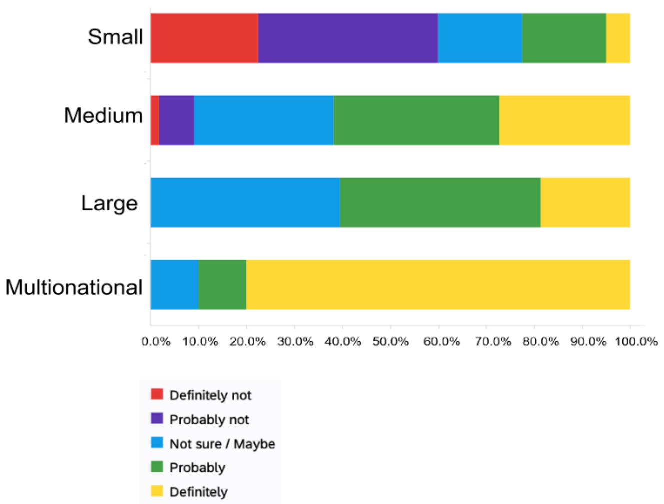


Figure 3: Firm size and AI investment plans (N = 168)



Spearman's rank-order correlation analyses examined the relationships among firm size, AI usage, organizational AI implementation, AI investment plans, and average AI maturity. Firm size was positively correlated with organizational AI implementation, r_s = .493, p < .001, and with AI investment plans, r_s = .552, p < .001, indicating that larger firms tended to report greater AI implementation and stronger intentions to invest further in AI. Firm size was also positively correlated with average AI maturity, r_s = .607, p < .001. Notably, organizational AI implementation showed a strong positive correlation with AI investment plans, r_s = .753, p < .001, and with average AI maturity, r_s = .679, p < .001. AI investment plans were also strongly correlated with average AI maturity, r_s = .724, p < .001. Overall, the findings suggest that firms with more extensive and mature AI implementation also tend to demonstrate stronger intentions to continue investing in AI.

Table 2: Correlation analyses (N = 168)

Spearman's Correlations

			Spearman's rho	p
OrgSize	–	Ai Usage	0.376	< .001
OrgSize	–	Org Ai	0.493	< .001
OrgSize	–	Invest Ai	0.552	< .001
OrgSize	–	Avr Ai Maturity	0.607	< .001
Ai Usage	–	Org Ai	0.523	< .001
Ai Usage	–	Invest Ai	0.590	< .001
Ai Usage	–	Avr Ai Maturity	0.497	< .001
Org Ai	–	Invest Ai	0.753	< .001
Org Ai	–	Avr Ai Maturity	0.679	< .001
Invest Ai	–	Avr Ai Maturity	0.724	< .001

Figure 4 presents the distribution of organizational AI usage across industries, revealing substantial sectoral variation in both the extent and depth of AI adoption. Overall, most industries cluster at the lower-to-mid levels of AI usage, with relatively few multinational firms reporting extensive AI integration. Technology, Media, and Telecommunications firms show comparatively higher engagement with AI, with a larger share of organizations reporting basic organizational use and targeted AI adoption. Similarly, professional and business services, as well as financial services, display moderate AI usage profiles, characterized by a mix of limited personal use and basic organizational deployment. In contrast, consumer, retail, and travel-related industries, as well as manufacturing and Industrial sectors, report noticeably lower levels of AI usage, with a substantial proportion of firms indicating no AI use or only limited personal-level engagement. The public sector and education category exhibit a more heterogeneous pattern, spanning from limited use to targeted adoption.

These descriptive differences are supported by the one-way ANOVA results (Table 3), which indicate a statistically significant effect of industry on organizational AI usage, F (6, 161) = 3.60, p = .002. As shown in the descriptive statistics, mean organizational AI usage ranges from 1.90 in consumer, retail, and travel to 2.92 in public sector, NGOs, and education. Industries such as manufacturing and industrial (M = 2.10) and the public sector and education (M = 2.76) exhibit greater dispersion in AI usage, as reflected in higher standard deviations and coefficients of variation, suggesting uneven adoption within these sectors.

Taken together, the results indicate that organizational AI usage varies systematically across industries, with knowledge- and technology-intensive sectors exhibiting higher average adoption levels, while more traditional or consumer-facing industries lag behind. At the same time, the relatively high within-industry variability observed in several sectors suggests that AI adoption among Cambodian firms remains uneven and emergent rather than fully institutionalized.

Figure 4: Organizational AI adoption in different industries (*N* = 168)

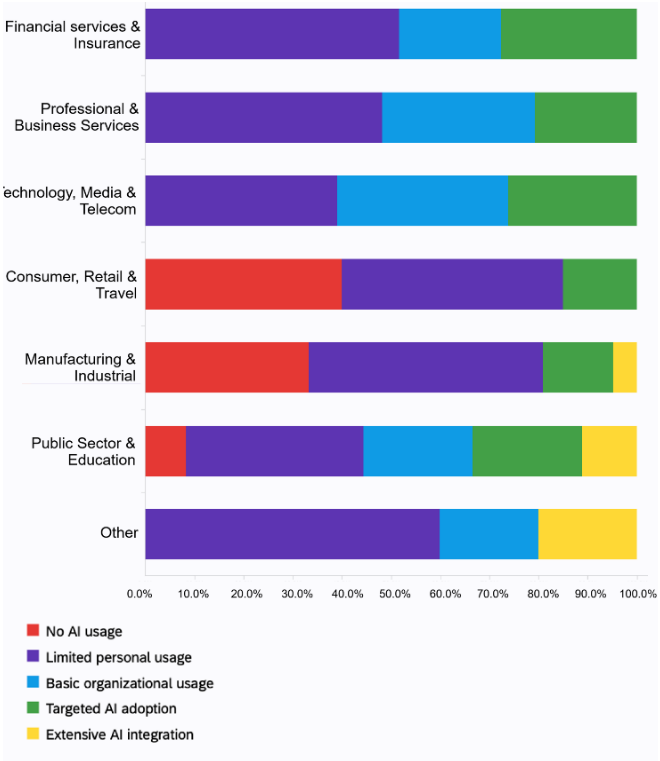


Table 3: ANOVA AI adoption in different industries (*N* = 168)

ANOVA - Org Ai

Cases	Sum of Squares	df	Mean Square	F	p
Industry	21.95	6	3.658	3.598	.002
Residuals	**163.67**	**161**	**1.017**		

Note. Type III Sum of Squares

Descriptives

Descriptives - Org Ai

Industry	N	Mean	SD	SE	Coefficient of variation
1 Finance	29	2.759	0.872	0.162	0.316
2 Professional	29	2.724	0.797	0.148	0.293
3 Technology	23	2.870	0.815	0.170	0.284
4 Consumer	20	1.900	1.021	0.228	0.537
5 Manufacturing	21	2.095	1.179	0.257	0.563
6 Public, NGO	36	2.917	1.180	0.197	0.405
7 Other	10	2.800	1.229	0.389	0.439

Table 4 presents descriptive statistics for the six dimensions of AI maturity. Across all dimensions, mean scores range from 2.11 to 2.23, indicating that, on average, firms in the sample are at an early stage of AI maturity. The highest mean scores are observed for data infrastructure and quality (M = 2.23, SD = 1.15), AI technology and tools (M = 2.22, SD = 1.16), and AI talent and skills (M = 2.21, SD = 1.15), suggesting that initial investments in technical capabilities and human capital are more advanced than other aspects of AI maturity. In contrast, AI operations and process exhibit the lowest mean (M = 2.11, SD = 1.11), indicating limited integration of AI into core organizational processes. AI strategy and vision (M = 2.18, SD = 1.15) and governance, ethics and compliance (M = 2.18, SD = 1.09) also score relatively low, suggesting that formal strategic alignment and governance for AI remain underdeveloped across firms.

Standard deviations are consistently high across all dimensions (SD ≈ 1.09–1.16), indicating substantial heterogeneity in firms' AI maturity levels. This variability shows that while some large and multinational organizations have begun to institutionalize AI capabilities, many small and medium-sized enterprises remain at very early or ad hoc stages of adoption.

Table 4: Perceived AI maturity (*N* = 168; scale: 1-5)

Field	Mean	Standard Deviation
AI Strategy & Vision	2.18	1.15
Data Infrastructure & Quality	2.23	1.15
AI Talent & Skills	2.21	1.15
AI Technology & Tools	2.22	1.16
AI Operations & Process	2.11	1.11
Governance, Ethics & Compliance	2.18	1.09

DISCUSSION

Addressing the first research question on AI awareness and deployment among Cambodian firms, the results indicate moderate individual familiarity with AI tools but substantially lower organizational adoption. Respondents with higher educational attainment and those in younger-to-middle age groups reported significantly greater personal AI use, suggesting that human capital is critical to AI exposure. This pattern aligns with prior research emphasizing digital literacy and skills as foundational enablers of AI adoption (Jöhnk et al., 2021; Rasdi & Baki, 2025). Consistent with findings from other developing and emerging economies, individual-level engagement with AI appears to outpace organizational maturity, reflecting a bottom-up diffusion dynamic in which employees experiment with AI tools independently of formal firm strategies (Bhatia et al., 2025). A similar divergence between individual engagement and organizational structure has been documented more broadly across the Global South, including in ecosystem-level comparisons between Cambodia and other transitioning economies (Heng et al., 2022).

Regarding the second research question on the extent of current AI usage across firms, the findings reveal a clear, systematic relationship between firm size and AI adoption, consistent with global patterns (McKinsey, 2025). Larger and multinational organizations report significantly higher levels of organizational AI use and stronger investment intentions than SMEs. The positive correlations among firm size, AI usage, and planned investment provide empirical support for the TOE framework, which highlights organizational resources and scale as key drivers of adoption (Tornatzky & Fleischer, 1990; Neumann et al., 2022). These results align with earlier studies showing that SMEs face structural constraints such as limited financial resources and technical expertise that slow AI diffusion, particularly in developing economies (Ingalagi et al., 2021; Bak et al., 2024). This firm-size effect mirrors patterns documented well beyond Cambodia, from Neumann et al.'s (2022) German sample to recent evidence from Vietnamese (Cao & Nguyen, 2025) and Malaysian (Rasdi & Baki, 2025) SMEs, suggesting that resource-driven adoption gaps between SMEs and larger firms are a broadly recurring feature of AI diffusion rather than a Cambodia-specific phenomenon.

Industry-level analyses further demonstrate significant variation in AI adoption, with technology-intensive sectors such as technology, media, and telecommunications exhibiting higher average usage than consumer-facing or manufacturing-oriented industries. This sectoral pattern aligns with prior empirical evidence suggesting that knowledge-intensive industries benefit more immediately from AI applications due to data availability and process standardization (Chatterjee et al., 2021; Cao & Nguyen, 2025). However, the substantial within-industry variability across sectors indicates that AI adoption remains uneven and emergent rather than fully institutionalized, particularly among SMEs. This finding reinforces earlier observations that AI diffusion in developing contexts is fragmented and highly dependent on firm-specific maturity rather than industry membership alone (Rotter & Bailkoski, 2025).

Finally, addressing the third research question on organizational AI maturity, the results indicate that Cambodian firms, on average, are at an early stage of AI maturity across all dimensions. Although data infrastructure, AI tools, and talent score relatively higher, lower scores in strategy, governance, and process integration suggest that AI initiatives remain largely tactical rather than strategic. This imbalance closely mirrors patterns identified in prior research, in which organizations often invest in technical components before establishing coherent AI strategies and governance frameworks (Jöhnk et al., 2021; Tehrani et al., 2024). The high variability across maturity dimensions further indicates a widening gap between a small group of more advanced firms and a large number of organizations that are still experimenting with AI on an ad hoc basis, echoing concerns in the SME adoption literature about uneven maturity in low-resource environments.

This dimension-level imbalance is not unique to the present sample. Tehrani et al. (2024) similarly find that, among multinational corporations, technical and infrastructural maturity tends to outpace strategic and governance maturity, suggesting that the sequencing observed here - technology first, strategy and governance later - may reflect a general pattern of AI maturation rather than a constraint specific to low-resource settings. This pattern recurs at the national level in Cambodia: UNESCO's (2025) AI Readiness Assessment found strong regional engagement and growing research and education activity, alongside persistent gaps in legal frameworks, data governance, and cybersecurity maturity, the same imbalance this study observes at the firm level, echoed one level up. A comparable pattern is visible globally: a 2025 cross-country survey of over 8,000 senior leaders found that while a majority of large organizations report a defined AI strategy, only a minority have a formal change-management plan or a systematic process for measuring AI's impact, and fewer than one in seven qualify as fully AI-mature overall (Cisco, 2025). Taken together, these parallels suggest that the strategy-and-governance lag identified in Cambodian firms is part of a broader global pattern of uneven AI maturation, though the absolute maturity levels observed here remain lower than those reported in higher-resource contexts, consistent with the compounding effect of infrastructural and institutional constraints highlighted elsewhere in the developing-economy AI literature (Heng et al., 2022; Savuth & Sothea, 2023).

Theoretical Contributions

This study makes three contributions to the frameworks introduced earlier. First, individual usage substantially outpacing organizational adoption extends TAM and UTAUT (Davis et al., 1989; Venkatesh et al., 2003) beyond their focus on individual perceptions: in low-resource settings, individual acceptance can become decoupled from organizational enablement, not merely ahead of it, a condition these frameworks do not explicitly anticipate. Second, the strong firm-size effect on AI usage and investment supports the TOE framework's emphasis on organizational resources and scale (Tornatzky & Fleischer, 1990), extending it to a developing-economy, multi-firm-size design that has rarely been tested empirically. Third, the imbalance across maturity dimensions - technical and data maturity ahead of strategic and governance maturity - adds granularity to organizational maturity frameworks (Jöhnk et al., 2021), showing that this asynchrony recurs at the firm, national (UNESCO, 2025), and global (Cisco, 2025) levels alike. Together, these findings suggest that TAM/UTAUT and TOE remain useful starting points, but fully explaining AI diffusion in Cambodia requires attention to how individual, organizational, and infrastructural maturity interact.

Managerial Contributions

For managers, particularly in SMEs, the gap between individual AI use and organizational maturity signals an opportunity: employees are already experimenting with AI, and firms that channel this into a formal strategy, governance structure, and change-management process, rather than tools and talent alone, can convert bottom-up experimentation into institutional capability faster than competitors who do not. That strategy and governance lag behind technical maturity, even among large global firms (Cisco, 2025), suggests this is a matter of managerial attention, not only resources. For policymakers, the firm-size gap indicates that Cambodia's digital transformation goals depend disproportionately on SMEs receiving targeted support for strategic planning and governance, rather than on access to technology alone. This priority was reinforced by UNESCO's (2025) national assessment, which finds the same gaps. For educators, the fact that individual AI engagement is already outpacing organizational structures suggests a role in formalizing this self-directed learning into structured organizational capability.

CONCLUSION

This study examined AI awareness, usage, and organizational maturity among firms in Cambodia, with particular emphasis on differences between SMEs and larger organizations. The findings provide a coherent picture across the three research questions. First, while individual-level familiarity with AI tools is relatively widespread, especially among respondents with higher educational attainment and those in mid-career stages, organizational-level adoption remains limited, indicating that AI engagement in Cambodia is currently driven more by individual experimentation than by formal organizational strategies. Second, AI usage and investment intentions increase systematically with firm size, with large and multinational firms reporting significantly higher adoption levels than SMEs. Third, the analysis of AI maturity dimensions shows that most organizations are at an early stage, characterized by modest development in technical components such as data infrastructure and tools, but weak strategic alignment, governance mechanisms, and process integration. Collectively, these findings suggest that AI adoption among Cambodian firms remains emergent and uneven rather than institutionalized.

As discussed earlier, these patterns extend technology-acceptance and TOE-based frameworks by revealing how individual, organizational, and infrastructural levels of AI maturity interact in a developing-economy context. They also have direct practical significance for managers and policymakers seeking to close the gap between Cambodia's national AI ambitions and firm-level capacity, particularly for SMEs, where targeted support in strategic planning and governance, rather than access to technology alone, appears most needed.

Several limitations should be acknowledged. The study relies on a cross-sectional survey design and non-probability sampling, which constrain causal inference and limit generalizability beyond the sampled firms. The absence of role- or experience-based eligibility criteria beyond firm location and employment status may also have introduced variability in respondents' direct exposure to organizational AI initiatives. In addition, AI usage and maturity were measured through self-reported perceptions, which may be influenced by respondents' interpretation or bias. The analysis itself was intentionally limited to descriptive statistics, correlation, and ANOVA, reflecting the exploratory aim of this initial study rather than an attempt at causal or predictive modeling. Future research could build on these initial findings in several concrete directions. Regarding sector differences, in-depth or longitudinal studies within the lowest-adopting industries identified here (e.g., manufacturing, consumer, retail, and travel) could clarify which sector-specific barriers beyond firm size drive the substantial within-industry variability observed, and cross-country replication could test whether the sectoral pattern found here is specific to Cambodia or holds more broadly across Southeast Asia. Regarding AI maturity, longitudinal or qualitative case-study designs following individual firms over time could examine whether strategic and governance maturity naturally catches up to technical maturity or requires targeted intervention and could probe the small subset of firms performing well across all six dimensions to identify what distinguishes them from the majority still at an early or ad hoc stage. Regarding firm size, future studies could disaggregate the broad SME category used here into finer size bands to test whether the relationship between size and AI usage is linear or reflects a threshold effect, and could examine which specific mechanisms- financial resources, IT capacity, managerial decision-making structures, or access to external expertise most explain the gap between SMEs and larger firms in this context.

In conclusion, this study offers novel empirical evidence to the limited body of research on AI maturity in developing economies. By highlighting the persistent gap between individual engagement and organizational maturity, as well as the structural disadvantages SMEs face, the research underscores that AI-driven transformation is as much an organizational and institutional challenge as a technological one. Addressing this challenge is essential if AI is to support inclusive and sustainable economic development in Cambodia and similar emerging markets.

Funding

The author declared that no funding was received for the research, authorship, and publication of this article.

Conflicts of Interest

The author declared no conflict of interest pertaining to the publication of this article.

AI Usage Disclosure

The author declared no AI was used in the creation of this research article.

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