# IMPACT OF TECHNOLOGICAL, ORGANIZATIONAL, AND ENVIRONMENTAL FACTORS ON AI ADOPTION LEVEL: AN EMPIRICAL STUDY OF SMALL AND MEDIUM-SIZED ENTERPRISES IN HO CHI MINH CITY

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**ABSTRACT:**

This study examines how Technology - Organization - Environment (TOE) factors differentially shape AI adoption maturity in small and medium-sized enterprises (SMEs). Drawing on the TOE framework (Tornatzky & Fleischer, 1990), Diffusion of Innovation Theory (Rogers, 1995), and Dynamic Capabilities Theory (Teece, 2007), it develops a research model comprising ten TOE factors: three technological, four organizational, and three environmental. The study argues that these factors exert stage-specific effects across five levels of AI maturity, with the drivers of early-stage AI experimentation, such as competitive pressure and top management commitment, differing fundamentally from those that support strategic AI integration, including digital capability and organizational readiness. Using data from at least 200 SMEs in Ho Chi Minh City, Vietnam, the study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (PLS-MGA) to examine variations in adoption drivers across maturity stages.

**Keywords:** AI adoption maturity, TOE framework, SMEs, PLS-SEM, multi-group analysis.

## 1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies of the twenty-first century, reshaping competitive landscapes across industries and firm sizes. Large enterprises have been the main adopters of AI, but small and medium-sized enterprises (SMEs) are also beginning to see AI as important for maintaining competitiveness and long-term survival. In Vietnam, SMEs make up more than 97% of all businesses and contribute around 45% of the country's GDP (General Statistics Office, 2023).

Recent empirical data underscore this urgency. According to AWS (2025), the number of Vietnamese firms using AI reached nearly 170,000 in 2024, a 39% year-on-year increase. Yet 74% of those adopters remain at basic, task-automation levels, exploiting AI primarily for cost reduction rather than strategic value creation. This striking gap between initiation and maturity reflects a fundamental challenge: the factors that motivate a firm to experiment with AI may differ substantially from those that enable it to embed AI into its core business model.

The Technology - Organization - Environment (TOE) Framework of Tornatzky & Fleischer (1990) is the dominant theoretical lens for studying organizational technology adoption. Despite a rich body of TOE-based AI adoption research (Badghish & Soomro, 2024; Soomro et al., 2025; Pinto et al., 2024; Arroyabe et al., 2024), a critical gap persists: virtually all existing studies treat AI adoption as a binary or undifferentiated continuous variable, implicitly assuming that TOE factors exert homogeneous effects regardless of the firm's maturity stage. This homogeneity assumption is theoretically indefensible. Rogers (1995) Diffusion of Innovation theory distinguishes adoption, routinization, and infusion as mechanistically distinct processes; Teece's (2007) Dynamic Capabilities framework further posits that sensing, seizing, and reconfiguring resources demand fundamentally different organizational endowments.

Motivated by this gap, this study proposes a stage-contingent TOE model in which ten factors are hypothesized to exert statistically different effects at each of five AI maturity levels. The central proposition is that competitive pressure and top management commitment are the dominant drivers at Levels 1–2 (experimentation), whereas digital capability and organizational readiness become the decisive factors at Levels 4–5 (strategic integration). Empirical testing of this proposition through PLS-MGA on 200+ SMEs in Ho Chi Minh City, Vietnam, constitutes the core contribution of this research.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical foundations and related empirical literature. Section 3 develops the research model and propositions. Section 4 presents the conclusion, theoretical implications, limitations, and directions for future research.

## 2. Literature review

### *2.1. AI adoption in SMEs*

AI adoption in organizations has attracted substantial scholarly attention since the mid-2010s. In the SME context, Bag et al. (2021) identify financial constraints, data quality deficits, and talent shortages as primary barriers, while Ghobakhloo et al. (2021) emphasize the organizational inertia that impedes digital transformation in resource-constrained settings. Wamba-Taguimdje et al. (2020) demonstrate that AI's performance impact is conditional on the depth of integration and surface-level adoption yields negligible returns.

Recent studies have extended these findings. Soomro et al. (2025), combining PLS-SEM with Artificial Neural Network analysis across 305 multi-sector SMEs, identify top management support, employee capability, and relative advantage as the strongest predictors of AI adoption. Arroyabe et al. (2024), analyzing 12,108 European SMEs, demonstrate that internal digital capabilities exert a stronger effect on AI outcomes than external environmental support - with highly digitally capable firms showing up to 52% higher AI adoption success rates. In the Vietnamese context, Youssef et al. (2025) provide the first TOE-based empirical study of AI adoption in the banking sector, identifying organizational readiness as the dominant predictor.

Despite this growing body of evidence, a critical limitation pervades the literature: no study has yet examined whether TOE factors operate differently across distinct AI maturity stages. Badghish & Soomro (2024) applied multi-group analysis but segmented by firm size, not maturity level. Pinto et al.'s (2024) meta-analysis of 12 studies confirmed seven of eight TOE factors as significant but did not account for stage-contingency. This study addresses this gap directly.

### *2.2. Theoretical foundations*

This study integrates three complementary theoretical frameworks. The TOE Framework (Tornatzky & Fleischer, 1990) provides the structural backbone, conceptualizing adoption decisions as a function of the technological context (infrastructure readiness, compatibility, data capability), the organizational context (top management commitment, digital capability, organizational readiness, innovation culture), and the environmental context (competitive pressure, government support, partner ecosystem). The TOE Framework is extended to incorporate two variables absent from traditional IT adoption models: data capability (T3) - a prerequisite unique to AI - and innovation culture (O4), reflecting the cultural dimension of AI-driven organizational transformation.

Diffusion of Innovation Theory (Rogers, 1995) enriches the TOE Framework by articulating three post-decision stages: adoption (initial acceptance), routinization (normalization into standard practice), and infusion (deep integration for competitive advantage). These three stages map onto the five-level AI maturity model: Levels 1–2 correspond to adoption, Level 3 to routinization, and Levels 4–5 to infusion. Because each stage is mechanistically distinct - differing in the nature of organizational learning, resource requirements, and strategic commitment involved - the TOE factors that are most predictive at each stage should differ accordingly.

Dynamic Capabilities Theory (Teece, 2007) provides the micro-foundations for this stage-contingency argument. Teece distinguishes sensing capabilities (identifying AI opportunities), seizing capabilities (deploying AI resources), and reconfiguring capabilities (reshaping the business model around AI). Sensing operates primarily at Levels 1–2, seizing at Level 3, and reconfiguring at Levels 4–5. Each capability type is enabled by a different configuration of organizational and environmental resources - providing the theoretical rationale for why $\beta(\text{TOE factor} \mid \text{Level } 1\text{–}2) \neq \beta(\text{TOE factor} \mid \text{Level } 4\text{–}5)$.

### *2.3. AI maturity model*

This study adopts a five-level AI maturity model synthesized from Weill et al. (2024), Ransbotham et al. (2020, 2021), and Sawang & Sornlertlamvanich (2025), and adapted to the SME context. Level 1 (Ad-hoc/Exploration) represents isolated, unplanned AI experiments with no budget or policy. Level 2 (Departmental AI) denotes intentional deployment in one or two business units with dedicated ownership. Level 3 (Enterprise-wide AI) reflects cross-departmental integration with unified data governance and explicit AI strategy. Level 4 (AI-driven Optimization) characterizes AI-assisted or autonomous decision-making in core processes with measurable ROI. Level 5 (AI-Native Strategic) describes firms for which AI is a central component of the business model and a sustainable source of competitive advantage.

The five-level structure is motivated by three considerations. First, it provides sufficient granularity to distinguish the three mechanistically distinct DOI stages. Second, it aligns with the empirical distribution of Vietnamese SMEs: approximately 74% at Levels 1–2, 20% at Level 3, and below 6% at Levels 4–5 (AWS, 2025), necessitating a fine-grained scale to differentiate the dominant lower segment. Third, it follows the convention of widely validated maturity models (CMMI, ISO 15504), facilitating comparative research.

## 3. Research model

### *3.1. Model overview*

The research model integrates ten TOE factors as independent variables, five AI maturity levels as the dependent variable, and two firm-level moderators (industry sector and firm size). Figure 1 illustrates the proposed model.

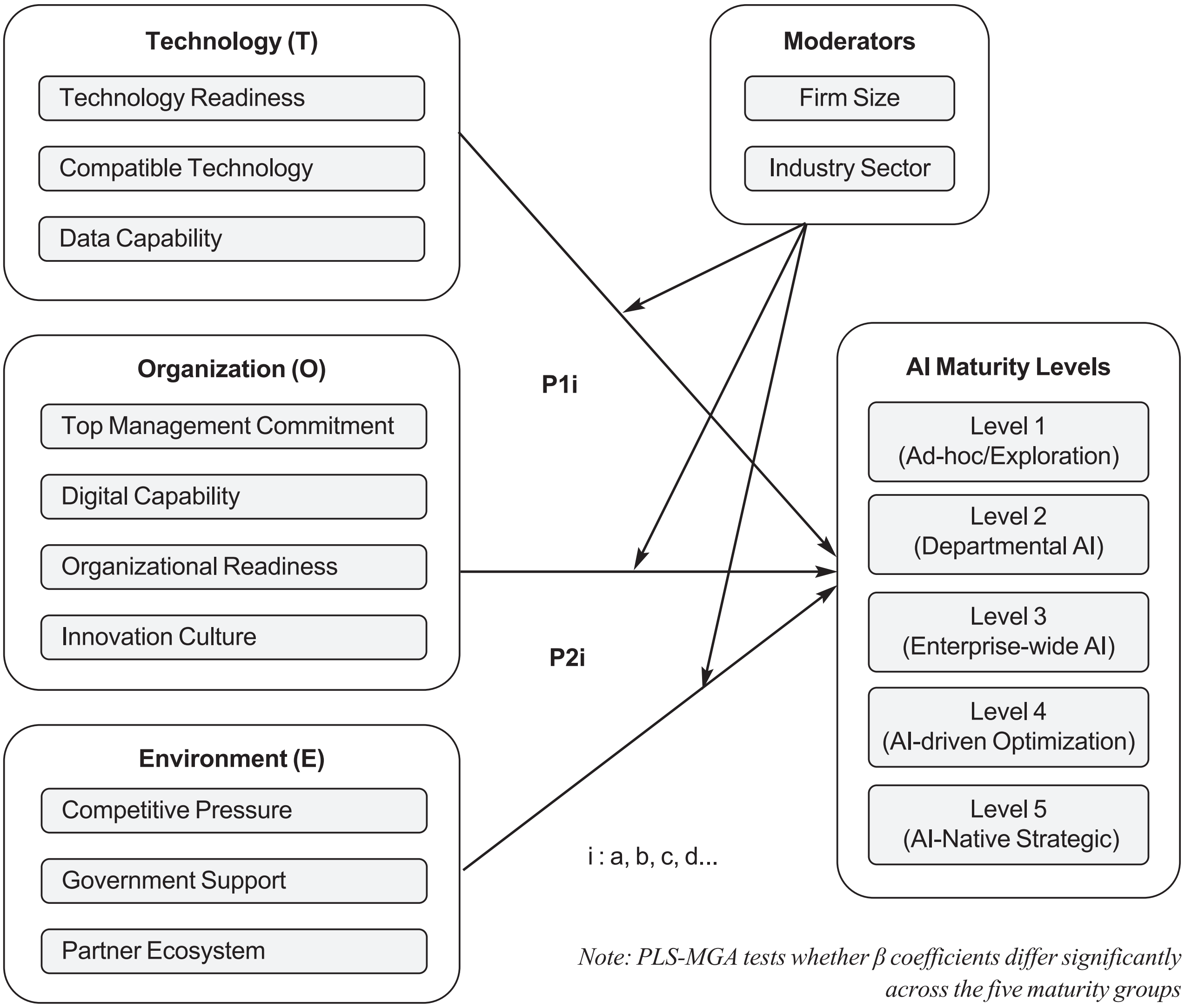
### *3.2. Constructs and propositions*

Technology Readiness (T1) is defined as the degree to which a firm's existing IT infrastructure can support AI implementation, including hardware capacity, software compatibility, and network connectivity (Tornatzky & Fleischer, 1990). Compatible technology (T2) reflects the degree of fit between AI solutions and the firm's current workflows, processes, and data standards (Qu & Kim, 2025). Data Capability (T3) - a construct absent from traditional TOE models but critical for AI - captures the quality, volume, and governance of organizational data assets (Russell & Norvig, 2020).

Top Management Commitment (O1) is the visible support and resource allocation provided by senior leadership for AI initiatives (Soomro et al., 2025). Digital Capability (O2) refers to the firm's existing digital skills, tools, and digital process maturity (Arroyabe et al., 2024). Organizational Readiness (O3) encompasses the structural, financial, and human resource preparedness to adopt and scale AI (Youssef et al., 2025). Innovation Culture (O4) reflects the organizational values, norms, and behavioral patterns that encourage experimentation and learning (Qu & Kim, 2025).

Competitive Pressure (E1) captures the degree to which industry rivalry motivates AI adoption as a defensive or offensive strategic response (Pinto et al.,

***Figure 1. TOE factors and AI maturity levels proposed research model***




*Note: PLS-MGA tests whether β coefficients differ significantly across the five maturity groups*

2024). Government Support (E2) reflects policy incentives, subsidies, and regulatory frameworks facilitating AI adoption - particularly salient in the Vietnamese context given the National AI Strategy 2030 (Decision 127/QD-TTg, 2021). Partner Ecosystem (E3) denotes the availability and quality of AI vendors, consultants, and technology partners (Badghish & Soomro, 2024).

Based on the theoretical frameworks outlined above, the following propositions are advanced. Regarding the direct effects of TOE factors on AI Maturity Level (P1):

*P1a: Technology readiness has a positive relationship with AI maturity level.*

*P1b: Compatibility has a positive relationship with AI maturity level.*

*P1c: Data capability has a positive relationship with AI maturity level.*

*P1d: Top management commitment has a positive relationship with AI maturity level.*

*P1e: Digital capability has a positive relationship with AI maturity level.*

*P1f: Organizational readiness has a positive relationship with AI maturity level.*

*P1g: Innovation culture has a positive relationship with AI maturity level.*

*P1h: Competitive pressure has a positive relationship with AI maturity level.*

*P1i: Government support has a positive relationship with AI maturity level.*

*P1j: Partner ecosystem has a positive relationship with AI maturity level.*

*Regarding stage-contingent effects (P2) - the central propositions of this study:*

*P2a: The effect of competitive pressure (E1) on AI maturity is significantly stronger at Levels 1–2 than at Levels 4–5.*

*P2b: The effect of top management commitment (O1) on AI maturity is significantly stronger at Levels 1–2 than at Levels 4–5.*

*P2c: The effect of digital capability (O2) on AI maturity is significantly stronger at Levels 4–5 than at Levels 1–2.*

*P2d: The effect of organizational readiness (O3) on AI maturity is significantly stronger at Levels 4–5 than at Levels 1–2.*

*P2e: The effect of data capability (T3) on AI maturity is significantly stronger at Levels 3–5 than at Levels 1–2.*

### *3.3. Model significance*

The proposed model contributes to the TOE-AI literature in four main ways. First, it questions the idea that AI adoption is the same across all firms by treating it as a five-level maturity process, where different factors may influence each stage differently. This idea is supported by DOI and Dynamic Capabilities theories but has not been tested empirically. Second, the study adds data capability (T3) as a new factor in the TOE framework for AI research, helping address a gap found in previous TOE-AI studies. Third, it uses PLS-MGA to examine how the effects of factors vary across different AI maturity stages, making it suitable for exploratory analysis and group comparison. Finally, the study provides new evidence for Vietnamese SMEs and is among the first in Southeast Asia to examine this issue with such a strong theoretical and methodological approach.

The model has direct practical implications. If the stage-contingency propositions are confirmed, policymakers and SME managers will have an empirically grounded roadmap specifying which interventions are most effective at each stage: government incentive programs and leadership development for Levels 1–2; digital skills investment and data infrastructure development for Levels 3–5. This specificity is absent from current policy frameworks, which tend to treat AI adoption support as a uniform intervention.

## 4. Conclusion

### *4.1. Theoretical implications*

This study proposes a stage-contingent TOE model for AI adoption in SMEs, advancing a central theoretical claim: the factors that drive AI experimentation are fundamentally different from those that enable strategic AI integration. This proposition, grounded in DOI theory and Dynamic Capabilities, challenges the homogeneity assumption that pervades existing TOE-AI research. If confirmed through PLS-MGA analysis, this finding would make an important theoretical contribution by showing that AI adoption is not a one-time decision. Instead, it can be understood as a multi-stage process of building organizational capabilities, where each stage depends on different supporting factors.

The study also contributes methodologically. The application of PLS-MGA to compare structural coefficients across AI maturity groups provides a replicable template for future stage-contingency research in technology adoption contexts. The validated five-level AI Maturity Scale, adapted for SMEs in emerging economies, offers a standardized measurement instrument that can be deployed in future cross-national comparative studies in the ASEAN region.

### *4.2. Limitations and future work*

The current study presents a theoretical model awaiting empirical validation. Several limitations should be acknowledged. First, the cross-sectional design planned for Phase 3 will capture a snapshot of AI maturity at a single point in time; longitudinal data would better capture the causal dynamics of stage transitions. Second, the purposive sampling strategy in Ho Chi Minh City, while pragmatically justified by population density, limits generalizability to rural SMEs and those in secondary cities. Third, the five-level maturity scale, while theoretically grounded, will require confirmatory factor analysis and inter-rater reliability testing to establish measurement validity in the Vietnamese context.

Future studies can improve this research in several ways. First, researchers should collect longitudinal data to track the same SMEs across different AI maturity stages over time. Second, the sample should be expanded to include Hanoi and other secondary cities to allow regional comparisons. Third, future research could combine Necessary Condition Analysis (NCA) with PLS-MGA to identify which factors are necessary and which are sufficient for moving from one AI maturity stage to another. Finally, the model could be extended to examine the outcomes of AI adoption, such as firm performance, innovation, and employee well-being, at each stage of AI maturity ■

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# TÁC ĐỘNG CỦA CÁC YẾU TỐ CÔNG NGHỆ - TỔ CHỨC - MÔI TRƯỜNG (TOE) ĐẾN MỨC ĐỘ TRƯỞNG THÀNH TRONG VIỆC ỨNG DỤNG AI TẠI CÁC DOANH NGHIỆP NHỎ VÀ VỪA TẠI THÀNH PHỐ HỒ CHÍ MINH

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Trường Đại học Ngân hàng TP. Hồ Chí Minh

**TÓM TẮT:**

Nghiên cứu này nhằm đánh giác tác động của các yếu tố Công nghệ - Tổ chức - Môi trường (TOE) đến mức độ trưởng thành trong việc ứng dụng trí tuệ nhân tạo (AI) tại các doanh nghiệp nhỏ và vừa (SMEs). Dựa trên khung TOE (Tornatzky & Fleischer, 1990), Lý thuyết Khuếch tán Đổi mới (Rogers, 1995) và Lý thuyết Năng lực Động (Teece, 2007), nghiên cứu xây dựng một mô hình gồm 10 yếu tố TOE, bao gồm 03 yếu tố công nghệ, 04 yếu tố tổ chức và 03 yếu tố môi trường. Luận điểm trung tâm là các yếu tố này có tác động đặc thù theo từng giai đoạn trên 05 cấp độ trưởng thành AI. Trong đó, các yếu tố thúc đẩy giai đoạn thử nghiệm AI ban đầu (như áp lực cạnh tranh, cam kết của lãnh đạo cấp cao), khác biệt căn bản so với các yếu tố hỗ trợ tích hợp AI ở cấp độ chiến lược (như năng lực số, mức độ sẵn sàng của tổ chức). Sử dụng dữ liệu từ ít nhất 200 doanh nghiệp nhỏ và vừa tại TP.Hồ Chí Minh, nghiên cứu áp dụng Mô hình Phương trình Cấu trúc Bình phương Tối thiểu Từng phần (PLS-SEM) kết hợp với Phân tích Đa nhóm (PLS-MGA) nhằm xem xét sự khác biệt của các yếu tố thúc đẩy ứng dụng AI qua từng giai đoạn trưởng thành.

**Từ khóa:** mức độ trưởng thành AI, khung TOE, doanh nghiệp vừa và nhỏ, PLS-SEM, phân tích đa nhóm.