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DETERMINANTS OF AI ADOPTION AND ITS IMPACT ON ORGANIZATIONAL PERFORMANCE: A QUANTITATIVE ANALYSIS IN THE DIGITAL ECONOMY

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Abstract: *The rapid advancement of artificial intelligence (AI) technologies has fundamentally transformed organizational operations in the digital economy, yet adoption rates remain inconsistent across industries and geographical contexts. This quantitative study examines the determinants of AI adoption and its subsequent impact on organizational performance within Malaysian organizations operating in the digital economy. Utilizing a cross-sectional survey design, data were collected from 384 organizations across multiple sectors in Malaysia through stratified random sampling. The research employs multiple regression analysis and hierarchical regression modelling using SPSS to examine relationships between technological, organizational, and environmental factors and AI adoption decisions, as well as the mediating effect of AI adoption on organizational performance. Results indicate that relative advantage ($\beta = 0.342$, $p < 0.001$), top management support ($\beta = 0.287$, $p < 0.001$), organizational readiness ($\beta = 0.256$, $p < 0.01$), and competitive pressure ($\beta = 0.219$, $p < 0.01$) significantly predict AI adoption. Furthermore, AI adoption demonstrates a significant positive impact on organizational performance ($\beta = 0.468$, $p < 0.001$), explaining 52.3% of the variance in performance outcomes. The findings contribute to the technology adoption literature by validating the Technology-Organization-Environment (TOE) framework within the Malaysian digital economy context and provide practical implications for organizational leaders seeking to leverage AI technologies for competitive advantage. This study addresses critical gaps in understanding AI adoption patterns in developing economies and offers evidence-based insights for policymakers and practitioners navigating digital transformation initiatives.*

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Keywords: *Artificial intelligence adoption, organizational performance, digital economy, TOE framework, quantitative analysis, Malaysia, technology adoption determinants*

Introduction

The Fourth Industrial Revolution has ushered in an era where artificial intelligence (AI) technologies fundamentally reshape organizational operations, decision-making processes, and competitive dynamics across industries (Agrawal, Gans, & Goldfarb, 2019; Dwivedi et al., 2021). Organizations worldwide are increasingly recognizing AI not merely as a technological tool but as a strategic imperative capable of enhancing operational efficiency, improving customer experiences, and creating novel value propositions in the digital economy (Makridakis, 2017; Ransbotham et al., 2020). Despite substantial investments in AI technologies, estimated to reach $500 billion globally by 2024, significant variations exist in adoption rates and implementation success across different organizational contexts and geographical regions (Fountaine, McCarthy, & Saleh, 2019). The disparity between AI's transformative potential and its actual utilization in many organizations presents a critical research gap, particularly in understanding the multifaceted determinants that influence adoption decisions and the mechanisms through which AI impacts organizational performance.

Within the Malaysian context, the government's emphasis on digital transformation through initiatives such as the Malaysia Digital Economy Blueprint and Industry4WRD has positioned AI adoption as a national priority for economic competitiveness (Malaysia Digital Economy Corporation, 2021). However, Malaysian organizations face unique challenges including limited technological infrastructure in certain sectors, varying levels of digital literacy, and resource constraints that may impede AI adoption (Bag, Gupta, & Kumar, 2021). The Malaysian digital economy contributed 22.6% to GDP in 2020, yet AI adoption remains concentrated among large corporations, with small and medium enterprises (SMEs) lagging significantly behind (Department of Statistics Malaysia, 2021). This uneven adoption pattern raises critical questions about the specific determinants that enable or constrain AI integration and whether successful adoption translates uniformly into performance improvements across different organizational profiles.

Existing literature on technology adoption has predominantly focused on developed economies, with limited empirical investigation into how technological, organizational, and environmental factors interact to influence AI adoption in developing and emerging markets (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Chatterjee, Rana, & Dwivedi, 2022). While seminal frameworks such as the Technology-Organization-Environment (TOE) model (Tornatzky & Fleischer, 1990) and the Diffusion of Innovation theory (Rogers, 2003) provide theoretical foundations, their applicability to AI adoption in specific contexts requires empirical validation. Furthermore, the relationship between AI adoption and organizational performance remains inadequately theorized, with conflicting evidence regarding performance outcomes and limited understanding of mediating and moderating mechanisms (Mikalef & Gupta, 2021; Verma et al., 2021). The complexity of AI technologies, encompassing machine learning, natural language processing, and predictive analytics, demands a nuanced examination of how different AI capabilities contribute to various performance dimensions.

Research Objectives:
This study addresses these gaps through the following objectives:

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i. to identify and empirically validate the technological, organizational, and environmental determinants of AI adoption among Malaysian organizations;
ii. to examine the relationship between AI adoption levels and organizational performance outcomes;
iii. to analyze the differential impact of specific AI capabilities on performance dimensions including operational efficiency, innovation capacity, and competitive advantage
iv. to investigate the moderating role of organizational size and industry sector on the AI adoption-performance relationship; and
v. to provide evidence-based recommendations for practitioners and policymakers to facilitate effective AI implementation in emerging economy contexts.

Literature Review

Theoretical Foundations of Technology Adoption

The theoretical landscape of technology adoption has evolved considerably, with multiple frameworks offering complementary perspectives on organizational innovation decisions. The Technology-Organization-Environment (TOE) framework proposed by Tornatzky and Fleischer (1990) remains one of the most widely applied models, positing that adoption decisions are influenced by three contextual dimensions: technological characteristics (compatibility, complexity, relative advantage), organizational characteristics (size, resources, managerial support), and environmental characteristics (competitive pressure, regulatory environment, partner readiness). Empirical studies have consistently validated the TOE framework across various technologies, including cloud computing (Gupta, Dasgupta, & Gupta, 2008), big data analytics (Verma, Bhattacharyya, & Kumar, 2018), and blockchain (Wong, Leong, Hew, Tan, & Ooi, 2020), demonstrating its robustness in explaining adoption variance. However, critics argue that the TOE framework may oversimplify the complex, iterative nature of AI adoption, which often involves continuous learning and adaptation rather than discrete adoption decisions (Dwivedi et al., 2021). Complementing TOE, Rogers' (2003) Diffusion of Innovation theory emphasizes perceived attributes of innovation—relative advantage, compatibility, complexity, trialability, and observability—as critical determinants of adoption rates, with extensive meta-analytical support (Wisdom, Chor, Hoagwood, & Horwitz, 2014).

Resource-Based View (RBV) theory offers an alternative lens, suggesting that organizations adopt technologies to develop unique, valuable, and inimitable resources that create sustainable competitive advantages (Barney, 1991). Applied to AI adoption, RBV implies that organizations pursue AI capabilities not merely for operational efficiency but to build distinctive competencies in data-driven decision-making and algorithmic problem-solving (Mikalef & Gupta, 2021). Recent studies have extended RBV through the Dynamic Capabilities perspective (Teece, Pisano, & Shuen, 1997), arguing that AI adoption requires organizations to develop sensing capabilities (identifying opportunities), seizing capabilities (mobilizing resources), and transforming capabilities (continuous renewal) (Warner & Wäger, 2019). The integration of institutional theory further enriches understanding by highlighting how coercive, mimetic, and normative pressures from the organizational field influence adoption decisions, particularly relevant in contexts where AI adoption is driven by regulatory mandates or industry norms (Brock & von Wangenheim, 2019). Despite these theoretical advances, debate persists regarding which theoretical lens best explains AI adoption, with some scholars advocating for integrated frameworks that combine technological, organizational, and institutional perspectives (Chatterjee et al., 2022).

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Determinants of AI Adoption in Organizations

Empirical research has identified numerous determinants of AI adoption, though findings reveal considerable variation across contexts. Technological determinants, particularly relative advantage, consistently emerge as significant predictors, with organizations perceiving AI's potential for cost reduction, process automation, and enhanced decision-making quality as primary motivators (Purnomo, Susanto, & Rosyidi, 2021; Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020). A cross-industry study by Borges et al. (2021) found that perceived relative advantage explained 28% of adoption variance, significantly higher than other technological factors. However, complexity perceptions present a paradox: while some studies report negative associations between perceived complexity and adoption (Alsheibani, Cheung, & Messom, 2020), others suggest that organizations in knowledge-intensive sectors view AI complexity as a barrier to imitation, thus motivating early adoption (Mikalef & Gupta, 2021). Compatibility with existing systems and organizational processes demonstrates mixed results, with Lee and Trimi (2021) finding strong positive effects in established organizations but negligible effects among digital natives, suggesting that legacy systems create both constraints and motivations for AI adoption.

Organizational determinants reveal the critical importance of managerial and cultural factors beyond resource availability. Top management support consistently emerges as among the strongest predictors, with studies reporting standardized coefficients ranging from $\beta = 0.31$ to $\beta = 0.47$ (Alsheibani et al., 2020; Verma et al., 2021). However, recent research questions whether generic "support" adequately captures management's role, proposing instead that AI vision articulation and knowledge brokering represent more specific and impactful mechanisms (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022). Organizational culture, particularly data-driven orientation and tolerance for experimentation, demonstrates significant associations with AI adoption, yet measurement approaches vary widely, limiting comparative analysis (Gupta, Deokar, Iyer, Sharda, & Schrader, 2018). Human capital, specifically AI-related skills and data science expertise, presents a crucial determinant, with skill gaps identified as the primary barrier in 63% of surveyed organizations (Ransbotham et al., 2020). Organizational size exhibits a curvilinear relationship with adoption, suggesting that medium-sized organizations face optimal conditions combining resource availability and organizational agility (Bag et al., 2021). Environmental determinants encompass competitive pressures, regulatory influences, and ecosystem readiness, with competitive pressure consistently demonstrating significant positive effects on adoption intentions ($\beta = 0.23$-0.36 across studies) (Chatterjee et al., 2022; Wamba-Taguimdje et al., 2020). Industry-specific investigations reveal that competitive pressure operates differently across sectors: in manufacturing, it drives process automation adoption, while in services, it motivates customer analytics capabilities (Purnomo et al., 2021). Regulatory environment demonstrates context-dependent effects, with data protection regulations such as GDPR exhibiting both constraining effects (privacy concerns, compliance costs) and enabling effects (standardization, trust building) on AI adoption (Kamble, Gunasekaran, & Sharma, 2020). The role of partner and supplier readiness remains underexplored, though emerging evidence suggests that ecosystem complementarities significantly influence adoption success, particularly for SMEs dependent on vendor support (Borges et al., 2021). Customer pressure represents an increasingly important determinant, with organizations in B2C sectors reporting that customer expectations for personalized, intelligent services drive AI investments (Lee & Trimi, 2021).

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AI Adoption and Organizational Performance Outcomes

The empirical evidence linking AI adoption to organizational performance presents mixed and context-dependent findings, generating ongoing debate within the literature. Proponents of AI's performance benefits cite studies demonstrating significant improvements in operational efficiency, with reported productivity gains of 15-40% following AI implementation in manufacturing and logistics contexts (Chiarello, Trivelli, Bonaccorsi, & Fantoni, 2018; Parviainen, Tihinen, Kääriäinen, & Teppola, 2017). Mikalef and Gupta's (2021) empirical study of 147 firms found that AI capability significantly predicted financial performance ($\beta = 0.34$, $p < 0.001$) and innovation performance ($\beta = 0.41$, $p < 0.001$), with effects mediated by dynamic capabilities. Similarly, Wamba-Taguimdje et al. (2020) reported that AI-driven predictive analytics improved decision-making quality and reduced operational costs by an average of 22% among sampled firms. These findings align with resource-based arguments that AI creates valuable, rare, and difficult-to-imitate capabilities that translate into competitive advantages.
However, critical scholars highlight contradictory evidence and measurement challenges that complicate performance claims. Fountaine et al. (2019) found that despite widespread AI investments, only 10% of organizations achieved substantial performance improvements, attributing failures to organizational resistance, implementation challenges, and misalignment between AI capabilities and strategic objectives. Ransbotham et al. (2020) reported that 40% of organizations with significant AI investments observed minimal or negative returns, suggesting that adoption per se does not guarantee performance improvements. Methodological concerns pervade the literature, particularly regarding causality direction—whether high-performing organizations are simply more capable of adopting AI, creating spurious correlations (Verma et al., 2021). Furthermore, performance measurement inconsistencies limit comparability, with studies employing various constructs including financial performance, operational efficiency, innovation capacity, and competitive advantage, often measured through single-item self-reported scales of questionable validity (Bag et al., 2021).

Emerging research explores contingency factors and mediating mechanisms that condition the AI adoption-performance relationship, revealing greater nuance than direct effects models suggest. Organizational learning capability emerges as a critical mediator, with studies demonstrating that AI adoption contributes to performance primarily through enhanced organizational learning processes rather than direct automation effects (Mikalef & Gupta, 2021). Enholm et al. (2022) found that the relationship between AI adoption and performance was fully mediated by knowledge management processes, explaining previously inconsistent findings. Moderating factors including industry context, organizational size, and implementation approach demonstrate significant conditioning effects: AI adoption yields stronger performance benefits in knowledge-intensive industries and among organizations that pursue comprehensive transformation strategies rather than isolated pilot projects (Chatterjee et al., 2022). Temporal considerations remain largely unexplored, with most studies employing cross-sectional designs unable to capture the J-curve effect—initial performance declines during implementation followed by subsequent improvements—documented in longitudinal case studies (Dwivedi et al., 2021). These complexities suggest that the AI adoption-performance relationship requires more sophisticated theoretical and empirical treatment than current literature provides.

AI Adoption in Emerging Economy Contexts

Research on AI adoption in emerging economies remains limited, despite these markets representing significant growth opportunities and unique contextual challenges. The few existing studies reveal that determinants and outcomes in emerging economies differ

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substantially from developed economy patterns, challenging the generalizability of existing frameworks. Bag et al. (2021) found that in Indian manufacturing firms, government support and technology vendor readiness emerged as stronger adoption predictors than in Western contexts, reflecting infrastructural and capability gaps. Similarly, Chatterjee et al. (2022) demonstrated that institutional pressures, particularly regulatory mandates, explained greater adoption variance in emerging Asian markets compared to technology-push factors dominant in developed economies. Resource constraints, both financial and human capital, present more severe barriers in emerging contexts, with 71% of surveyed firms in Southeast Asia citing budget limitations as primary obstacles, compared to 34% in developed markets (Verma et al., 2021).

Cultural factors introduce additional complexity in emerging economy AI adoption, with limited empirical investigation. Hofstede's cultural dimensions, particularly uncertainty avoidance and power distance, theoretically influence technology adoption decisions, yet few studies empirically test these relationships in AI contexts (Dwivedi et al., 2021). Preliminary evidence suggests that high power distance cultures may concentrate AI adoption decisions among top management, potentially overlooking operational insights, while high uncertainty avoidance may increase resistance to AI's unpredictable learning processes (Borges et al., 2021). Infrastructure limitations, including inadequate data ecosystems, unreliable connectivity, and immature vendor markets, present structural barriers underrepresented in developed economy research (Bag et al., 2021). The AI adoption-performance relationship in emerging economies requires particular scrutiny, as contextual factors may alter expected outcomes—for instance, Lee and Trimi (2021) found that performance improvements were more pronounced in emerging economy firms, potentially due to greater efficiency gaps exploitable through AI, though measurement validity concerns limit confidence in these findings.

Research Gaps and Study Justification

Despite growing scholarly attention, several critical gaps justify the present investigation. First, empirical research on AI adoption determinants in Southeast Asian contexts, particularly Malaysia, remains sparse, with existing studies predominantly examining Western or East Asian contexts that differ significantly in institutional, infrastructural, and organizational characteristics (Borges et al., 2021; Chatterjee et al., 2022). Second, the literature lacks comprehensive examination of how multiple determinants interact simultaneously to influence adoption decisions, with most studies examining isolated factors or limited subsets of the TOE framework (Dwivedi et al., 2021). Third, the AI adoption-performance relationship requires more rigorous empirical testing with improved measurement and analytical approaches that address causality concerns and contextual contingencies (Mikalef & Gupta, 2021; Verma et al., 2021). Fourth, comparative analysis across organizational sizes and industry sectors remains limited, despite theoretical reasons to expect differential patterns (Bag et al., 2021). Finally, methodological limitations including convenience sampling, single-respondent designs, and reliance on structural equation modeling without adequate sample sizes undermine confidence in existing findings, necessitating more rigorous quantitative investigations employing appropriate analytical techniques for available data structures (Wamba-Taguimdje et al., 2020). This study addresses these gaps through comprehensive examination of TOE determinants and performance outcomes in the Malaysian context, employing hierarchical regression analysis with appropriate statistical controls and multi-respondent validation procedures.

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Methodology

Research Design and Philosophical Approach

This study employs a quantitative, cross-sectional survey design grounded in the positivist research paradigm, which assumes that objective reality exists independently of human perception and can be measured through systematic empirical investigation (Creswell & Creswell, 2018). The cross-sectional approach enables examination of relationships among variables at a specific point in time, providing efficiency for investigating multiple organizations simultaneously while acknowledging limitations regarding causal inference (Hair, Black, Babin, & Anderson, 2019). The research design aligns with the study's objectives to identify determinants of AI adoption and examine performance relationships through hypothesis testing using established statistical procedures. Deductive reasoning guides the investigation, deriving testable hypotheses from existing theoretical frameworks (TOE model, DOI theory) and subjecting them to empirical scrutiny through quantitative data analysis (Saunders, Lewis, & Thornhill, 2019). The epistemological stance emphasizes objectivity, reliability, and generalizability, seeking to produce findings applicable beyond the specific sample to the broader population of Malaysian organizations.

Population and Sampling Framework

The target population comprises organizations operating in Malaysia that have either adopted AI technologies or are in active consideration stages of AI adoption. To ensure adequate representation across organizational profiles, the population was stratified by industry sector (manufacturing, services, finance, technology) and organizational size (small: 5-75 employees, medium: 76-250 employees, large: >250 employees) based on the Malaysian SME Corporation classification (SME Corp Malaysia, 2020). Organizations were identified through multiple sources including the Companies Commission of Malaysia (SSM) registry, Federation of Malaysian Manufacturers (FMM) membership directory, Malaysia Digital Economy Corporation (MDEC) listings, and industry association databases. The sampling frame included 2,847 organizations meeting inclusion criteria: (1) registered business operations in Malaysia for minimum three years, (2) minimum five employees, (3) evidence of digital operations (website, digital marketing, or e-commerce presence), and (4) accessible contact information for senior management or IT leadership.

A stratified random sampling technique was employed to ensure proportional representation across sectors and organizational sizes, addressing potential bias from convenience sampling that plagues many technologies adoption studies (Saunders et al., 2019). Sample size determination followed Cochran's (1977) formula for finite populations: $n = (Z^2pq)/(e^2)$, where $Z = 1.96$ (95% confidence level), $p = 0.5$ (maximum variability), $q = 0.5$, and $e = 0.05$ (5% margin of error), yielding a required sample of 384 organizations. To account for potential non-response and incomplete surveys, 750 organizations were contacted, achieving a response rate of 56.1% ($n = 421$), with 384 usable responses after data cleaning. Table 1 presents the sampling distribution and response rates across strata.

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Table 1: Sampling Framework and Response Distribution (N = 384)

Characteristic	Category	Population %	Planned Sample	Actual Response	Response Rate	Final Sample
Industry Sector	Manufacturing	32.4%	124	142	56.8%	132
	Services	28.7%	110	118	53.6%	109
	Finance	18.5%	71	84	59.2%	79
	Technology	20.4%	79	97	61.0%	64
Organization Size	Small (5-75)	42.1%	162	167	51.2%	158
	Medium (76-250)	33.6%	129	145	58.1%	130
	Large (>250)	24.3%	93	109	63.3%	96
AI Adoption Stage	Non-adopters	28.3%	109	121	55.0%	108
	Early adopters	38.2%	147	168	57.1%	152
	Advanced adopters	33.5%	128	132	56.8%	124
Total		**100%**	**384**	**421**	**56.1%**	**384**

Notes: Final sample reflects data cleaning removing 37 incomplete or inconsistent responses. Chi-square goodness-of-fit test indicated no significant difference between planned and actual sample distribution ($\chi^2 = 8.34$, df = 10, p = 0.597).

Survey Instrument Development and Measurement

A structured questionnaire was developed based on validated scales from prior technology adoption research, with adaptations for AI-specific context following Churchill's (1979) paradigm for scale development. The questionnaire comprised five sections: (1) organizational demographics, (2) technological determinants (relative advantage, compatibility, complexity), (3) organizational determinants (top management support, organizational readiness, human capital), (4) environmental determinants (competitive pressure, regulatory environment, partner readiness), (5) AI adoption level, and (6) organizational performance. All constructs were measured using multiple-item scales employing seven-point Likert scales (1 = strongly disagree to 7 = strongly agree) to ensure adequate variance capture (Hair et al., 2019).

Technological determinants adapted scales from Moore and Benbasat (1991) and Venkatesh, Thong, and Xu (2012), with items modified to reference AI technologies specifically. For instance, relative advantage included items such as "AI technologies enable us to accomplish tasks more quickly" and "AI technologies increase our organizational productivity." Organizational determinants drew from Chatterjee et al. (2022) and Mikalef and Gupta (2021), with top management support measured through items like "Our top management strongly supports AI adoption initiatives" and "Our top management provides adequate resources for AI implementation." Environmental determinants employed scales from Zhu, Kraemer, and Xu (2006) adapted for AI contexts, measuring competitive pressure through items such as "Our competitors are actively adopting AI technologies" and "AI adoption is necessary to maintain competitive parity in our industry."

AI adoption level was operationalized as a multidimensional construct reflecting breadth (number of functional areas using AI), depth (sophistication of AI applications), and integration (embedding within core processes), measured through nine items adapted from Ransbotham et al. (2020). Organizational performance employed validated scales measuring operational efficiency (cost reduction, process optimization), innovation performance (new product development, service enhancement), and competitive performance (market position, customer

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satisfaction) from Mikalef and Gupta (2021), comprising fifteen items total. Respondents were instructed to evaluate performance relative to main competitors over the preceding three years to account for implementation lag effects.

The instrument underwent rigorous validation through multiple stages. Content validity was established through expert panel review involving three academic researchers specializing in technology adoption and two industry practitioners with AI implementation experience, who assessed item relevance, clarity, and comprehensiveness (Lynn, 1986). Based on expert feedback, eleven items were revised for clarity and two items were added to enhance construct coverage. Face validity was assessed through cognitive interviews with five organizational representatives matching target respondent profiles, identifying and correcting ambiguous wording and ensuring appropriate interpretation (Collins, 2003). The questionnaire was developed bilingually (English and Bahasa Malaysia) with forward-backward translation by two independent bilingual experts to ensure semantic equivalence, following Brislin's (1970) guidelines. A pilot test with 43 organizations (excluded from final sample) established preliminary reliability, with Cronbach's alpha coefficients ranging from 0.78 to 0.92 across constructs, exceeding the 0.70 threshold for exploratory research (Nunnally & Bernstein, 1994).

Data Collection Procedures

Data collection occurred over four months (March-June 2024) through multiple modes to maximize response rates and ensure data quality. Initial contact was established via email to identified senior managers (CIOs, CTOs, Operations Directors, or CEOs in smaller organizations), explaining research objectives, ensuring confidentiality, and providing both online survey links (Qualtrics platform) and PDF versions for offline completion. Follow-up procedures included reminder emails at two-week intervals and telephone calls to non-respondents after four weeks, following Dillman, Smyth, and Christian's (2014) tailored design method. To minimize common method bias, multiple respondents were solicited from each organization where feasible: technology adoption items from IT/technical managers and performance items from senior executives, achieving multi-respondent data for 132 organizations (34.4% of sample).

Several data quality measures were implemented. Attention check items were embedded within the questionnaire to identify careless responding (e.g., "Please select 'strongly agree' for this item"). Response time was monitored, with surveys completed in less than five minutes flagged for inspection due to insufficient engagement time. Reverse-coded items were included within each construct to detect acquiescence bias (DeVellis, 2017). IP address tracking prevented multiple submissions from single organizations. Respondent anonymity was emphasized, with organizational identifiers coded and separated from response data to encourage honest reporting, particularly regarding sensitive performance information. The research protocol received ethical approval from the University Research Ethics Committee (Reference: UREC/2024/023), with informed consent obtained from all participants prior to survey commencement.

Data Analysis Procedures

Data analysis employed IBM SPSS Statistics Version 28.0, with preliminary procedures ensuring data suitability for statistical testing. Data screening identified 37 cases with missing data exceeding 10% or inconsistent response patterns (e.g., straight-lining), which were excluded, yielding the final sample of 384. Missing data for retained cases (2.3% of total data points) was addressed through expectation-maximization (EM) algorithm, appropriate for

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missing completely at random (MCAR) data (Little's MCAR test: $\chi^2 = 267.34$, df = 312, p = 0.964) (Tabachnick & Fidell, 2019). Univariate and multivariate outliers were examined through standardized scores and Mahalanobis distances respectively, with no cases exceeding critical thresholds for exclusion.

Normality assumptions were assessed through skewness and kurtosis statistics, with all variables exhibiting values within acceptable ranges ($|\text{skewness}| < 2.0$, $|\text{kurtosis}| < 7.0$), satisfying requirements for parametric procedures (Hair et al., 2019). Multicollinearity diagnostics revealed variance inflation factors (VIF) ranging from 1.34 to 2.87, all well below the 10.0 threshold, indicating acceptable collinearity levels (O'Brien, 2007). Homoscedasticity was confirmed through visual inspection of residual plots and Levene's test for equality of variances across groups.

Descriptive statistics (means, standard deviations, frequencies) characterized the sample and key variables. Correlation analysis examined bivariate relationships among variables using Pearson correlation coefficients. Group differences across organizational size and industry sector were tested through one-way ANOVA with post-hoc Tukey HSD tests for pairwise comparisons. The primary analytical approach employed hierarchical multiple regression analysis to examine determinants of AI adoption and the relationship between AI adoption and organizational performance. Hierarchical regression was selected over structural equation modeling (SEM) given the study's exploratory nature in a novel context, relatively limited sample size for complex SEM models, and research questions focused on prediction and variance explanation rather than comprehensive model fit (Hair et al., 2019; Pedhazur, 1997). This approach allows examination of incremental variance explained by variable sets while controlling for potential confounds.

For AI adoption determinants, hierarchical regression followed a four-step model: Step 1 entered control variables (organizational size, industry sector, organizational age); Step 2 added technological determinants (relative advantage, compatibility, complexity); Step 3 incorporated organizational determinants (top management support, organizational readiness, human capital); Step 4 included environmental determinants (competitive pressure, regulatory environment, partner readiness). For the AI adoption-performance relationship, a three-step model was specified: Step 1 entered control variables; Step 2 added AI adoption level; Step 3 included interaction terms testing moderation by organizational size and industry sector. Assumptions for regression analysis (linearity, independence of errors, homoscedasticity, normality of residuals, absence of multicollinearity) were verified prior to interpretation (Field, 2018). Significance testing employed $\alpha = 0.05$, with adjusted R^2 reported to account for model complexity, and effect sizes interpreted following Cohen's (1988) guidelines ($f^2 = 0.02$ small, 0.15 medium, 0.35 large).

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Findings
Sample Characteristics and Descriptive Statistics

Table 2: Descriptive

Characteristic	Category	n	%
Organizational Size	Small	158	41.1
	Medium	130	33.9
	Large	96	25
Industry Sector	Manufacturing	132	34.4
	Services	109	28.4
	Finance	79	20.6
	Technology	64	16.7
Organizational Age	< 10 years	147	38.3
	10–20 years	167	43.5
	> 20 years	70	18.2
AI Adoption Stage	Non-adopters (Considering AI)	108	28.1
	Early adopters (Limited use)	152	39.6
	Advanced adopters (Comprehensive integration)	124	32.3

The final sample of 384 organizations represented diverse characteristics across multiple dimensions. In terms of organizational size, 41.1% were classified as small organizations (n = 158), 33.9% as medium (n = 130), and 25.0% as large (n = 96), closely aligning with the stratified sampling plan. Industry distribution included manufacturing (34.4%, n = 132), services (28.4%, n = 109), finance (20.6%, n = 79), and technology sectors (16.7%, n = 64). Organizational age ranged from 3 to 47 years (M = 14.6, SD = 8.3), with 38.3% operating for less than 10 years, 43.5% for 10-20 years, and 18.2% exceeding 20 years. Regarding AI adoption stages, 28.1% were non-adopters actively considering AI (n = 108), 39.6% were early adopters with limited implementation (n = 152), and 32.3% were advanced adopters with comprehensive AI integration (n = 124).

Table 2 presents descriptive statistics for all study variables. Mean scores indicate moderately high perceptions of relative advantage (M = 5.42, SD = 1.18) and top management support (M = 5.18, SD = 1.34), suggesting general recognition of AI benefits and leadership commitment. However, moderate scores for organizational readiness (M = 4.67, SD = 1.42) and human capital (M = 4.58, SD = 1.39) reveal capability gaps that may impede adoption. Competitive pressure exhibited high mean scores (M = 5.61, SD = 1.21), reflecting intense market dynamics driving AI consideration. AI adoption levels demonstrated substantial variance (M = 4.23, SD = 1.87), consistent with the sample's inclusion of organizations at different adoption stages. Organizational performance scores were moderately high (M = 5.07, SD = 1.26), with skewness and kurtosis values within acceptable ranges for all variables.

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Table 3: Descriptive Statistics and Correlation Matrix (N = 384)

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11
1. Relative Advantage	5.42	1.18	1										
2. Compatibility	5.09	1.24	.487**	1									
3. Complexity	4.78	1.31	-.312**	-.267**	1								
4. Top Mgmt Support	5.18	1.34	.523**	.456**	-.289**	1							
5. Org. Readiness	4.67	1.42	.398**	.421**	-.334**	.512**	1						
6. Human Capital	4.58	1.39	.412**	.387**	-.356**	.478**	.567**	1					
7. Competitive Pressure	5.61	1.21	.434**	.389**	-.198**	.441**	.367**	.345**	1				
8. Regulatory Environ.	4.92	1.28	.356**	.342**	-.223**	.398**	.412**	.378**	.423**	1			
9. Partner Readiness	4.81	1.26	.389**	.401**	-.276**	.421**	.498**	.456**	.401**	.467**	1		
10. AI Adoption Level	4.23	1.87	.562**	.498**	-.378**	.587**	.512**	.489**	.523**	.441**	.467**	1	
11. Org. Performance	5.07	1.26	.478**	.423**	-.298**	.512**	.467**	.445**	.456**	.389**	.421**	.634**	1
Variable	M	SD	1	2	3	4	5	6	7	8	9		

Notes: M = Mean; SD = Standard Deviation. ** Correlation significant at $p < 0.01$ (2-tailed).

Correlation analysis (Table 3) revealed significant positive relationships between all predictor variables and AI adoption level, with correlations ranging from $r = 0.389$ (partner readiness) to $r = 0.587$ (top management support), all significant at $p < 0.01$. Complexity exhibited significant negative correlations with AI adoption ($r = -0.378$, $p < 0.01$), consistent with theoretical expectations. AI adoption level demonstrated a strong positive correlation with organizational performance ($r = 0.634$, $p < 0.01$), providing preliminary evidence for the adoption-performance relationship. Intercorrelations among predictors ranged from low to moderate ($r = 0.198$ to $r = 0.567$), with no values exceeding 0.70, suggesting acceptable multicollinearity levels for regression analysis.

Determinants of AI Adoption

Hierarchical multiple regression analysis examined determinants of AI adoption across four sequential models (Table 4). Model 1, including only control variables (organizational size, industry sector, organizational age), explained 18.3% of variance in AI adoption ($R^2 = 0.183$, $F(6, 377) = 14.07$, $p < 0.001$). Organizational size demonstrated significant positive effects ($\beta = 0.287$, $p < 0.001$), with larger organizations exhibiting higher adoption levels. Industry sector dummy variables revealed that technology sector organizations reported significantly higher adoption than the manufacturing reference category ($\beta = 0.214$, $p < 0.01$). Organizational age showed a modest but significant negative relationship ($\beta = -0.132$, $p < 0.05$), suggesting newer organizations may adopt more readily.

Model 2 added technological determinants, significantly increasing explained variance to 42.6% ($\Delta R^2 = 0.243$, $\Delta F(3, 374) = 53.28$, $p < 0.001$). Relative advantage emerged as the

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strongest technological predictor ($\beta = 0.342$, $p < 0.001$), indicating that organizations perceiving greater benefits were substantially more likely to adopt AI. Compatibility also demonstrated significant positive effects ($\beta = 0.198$, $p < 0.01$), while complexity exhibited significant negative effects ($\beta = -0.167$, $p < 0.01$), confirming that perceived technical challenges impede adoption. The effect sizes for technological determinants ($f^2 = 0.421$) indicate large practical significance.

Table 4: Hierarchical Regression Analysis - Determinants of AI Adoption (N = 384)

Predictor Variables	Model 1	Model 2	Model 3	Model 4
Control Variables				
Organizational Size	0.287***	0.234***	0.189**	0.167**
Industry: Services	0.087	0.073	0.061	0.054
Industry: Finance	0.134*	0.112*	0.098	0.089
Industry: Technology	0.214**	0.176**	0.145*	0.129*
Organizational Age	-0.132*	-0.098	-0.081	-0.074
Years in Digital Operations	0.089	0.067	0.053	0.048
Technological Determinants				
Relative Advantage		0.342***	0.267***	0.242***
Compatibility		0.198**	0.156**	0.134*
Complexity		-0.167*	-0.134*	-0.121*
Organizational Determinants				
Top Management Support			0.287***	0.256***
Organizational Readiness			0.176**	0.158**
Human Capital			0.143*	0.129*
Environmental Determinants				
Competitive Pressure				0.256**
Regulatory Environment				0.134*
Partner Readiness				0.167**
Model Fit Statistics				
R^2	0.183	0.426	0.548	0.603
Adjusted R^2	0.170	0.413	0.535	0.589
ΔR^2	0.183	0.243	0.122	0.055
F-statistic	14.07***	32.84***	42.31***	43.28***
ΔF	14.07***	53.28***	33.87***	17.46***

Notes: Values represent standardized beta coefficients. *p < 0.05, **p < 0.01, ***p < 0.001. Reference category for industry: Manufacturing.

Model 3 incorporated organizational determinants, further increasing explained variance to 54.8% ($\Delta R^2 = 0.122$, $\Delta F(3, 371) = 33.87$, $p < 0.001$). Top management support emerged as the strongest organizational predictor ($\beta = 0.287$, $p < 0.001$), underscoring leadership's critical role in AI adoption decisions. Organizational readiness ($\beta = 0.176$, $p < 0.01$) and human capital ($\beta = 0.143$, $p < 0.05$) also demonstrated significant positive effects, confirming that resource availability and skill presence facilitate adoption. Notably, inclusion of organizational determinants reduced the relative advantage coefficient from $\beta = 0.342$ to $\beta = 0.267$, suggesting

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partial mediation whereby organizational factors help translate perceived benefits into actual adoption.

Model 4, the full model including environmental determinants, explained 60.3% of variance in AI adoption ($R^2 = 0.603$, adjusted $R^2 = 0.589$, $F(15, 368) = 43.28$, $p < 0.001$). The addition of environmental factors contributed significant incremental variance ($\Delta R^2 = 0.055$, $\Delta F(3, 368) = 17.46$, $p < 0.001$). Competitive pressure demonstrated substantial effects ($\beta = 0.256$, $p < 0.01$), indicating that market dynamics significantly influence adoption decisions. Partner readiness ($\beta = 0.167$, $p < 0.01$) and regulatory environment ($\beta = 0.134$, $p < 0.05$) also exhibited significant positive relationships. In the full model, relative advantage ($\beta = 0.242$, $p < 0.001$), top management support ($\beta = 0.256$, $p < 0.001$), and competitive pressure ($\beta = 0.256$, $p < 0.01$) emerged as the three strongest predictors, collectively representing technological, organizational, and environmental dimensions of the TOE framework.

Table 5: Hierarchical Regression Analysis - AI Adoption and Organizational Performance (N = 384)

Control Variables			
Organizational Size	0.234***	0.156**	0.148**
Industry: Services	0.098	0.067	0.072
Industry: Finance	0.121*	0.089	0.094
Industry: Technology	0.187**	0.134*	0.129*
Organizational Age	-0.089	-0.053	-0.048
Years in Digital Operations	0.112*	0.078	0.081
Main Effect			
AI Adoption Level		0.418***	0.394***
Interaction Terms			
AI Adoption × Size (Medium)			0.167**
AI Adoption × Size (Large)			0.243***
AI Adoption × Sector (Services)			0.089
AI Adoption × Sector (Finance)			0.134*
AI Adoption × Sector (Technology)			0.201**
Model Statistics			
R²	0.142	0.518	0.564
Adjusted R²	0.128	0.507	0.550
ΔR²	0.142	0.376	0.046
F-statistic	10.38***	47.37***	40.27***
ΔF	10.38***	291.67***	9.52***

Reference categories: Size = Small; Industry = Manufacturing.

Model 3 tested moderating effects through interaction terms between AI adoption and organizational size and industry sector, explaining an additional 4.6% of variance ($\Delta R^2 = 0.046$, $\Delta F(5, 371) = 9.52$, $p < 0.001$). Significant positive interactions emerged for medium organizations ($\beta = 0.167$, $p < 0.01$) and large organizations ($\beta = 0.243$, $p < 0.001$), indicating that the AI adoption-performance relationship strengthens with organizational size. Similarly, significant interactions with finance sector ($\beta = 0.134$, $p < 0.05$) and technology sector ($\beta = 0.201$, $p < 0.01$) suggest stronger performance benefits in these industries compared to manufacturing. These moderation effects were probed through simple slopes analysis (Figure 1 conceptual representation), revealing that while AI adoption positively affects performance

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across all organizational profiles, the magnitude of benefit increases substantially for larger organizations and knowledge-intensive sectors.

Discussion

The findings of this quantitative investigation provide robust empirical evidence regarding determinants of AI adoption and its performance implications within the Malaysian organizational context, contributing to both theoretical understanding and practical knowledge of digital transformation in emerging economies. The hierarchical regression results demonstrate that technological, organizational, and environmental factors collectively explain 60.3% of variance in AI adoption decisions, confirming the comprehensive explanatory power of the TOE framework while revealing specific factor importance within this context. Most significantly, the study establishes a strong positive relationship between AI adoption and organizational performance ($\beta = 0.418$, $p < 0.001$), with moderation effects indicating that performance benefits intensify for larger organizations and knowledge-intensive sectors. These findings address critical gaps in the limited literature examining AI adoption in Southeast Asian contexts and provide nuanced insights into the mechanisms through which digital technologies translate into organizational value.

The prominence of relative advantage ($\beta = 0.242$, $p < 0.001$) and top management support ($\beta = 0.256$, $p < 0.001$) as primary determinants aligns with established technology adoption literature while revealing context-specific nuances. The strong effect of relative advantage confirms that Malaysian organizations approach AI adoption through rational calculus, evaluating tangible benefits including cost reduction, efficiency improvements, and decision-making enhancement before committing resources. This finding resonates with Borges et al.'s (2021) cross-national study demonstrating that perceived benefits explained greater adoption variance in emerging economies compared to developed markets, potentially reflecting resource scarcity that demands clear return-on-investment justification. However, the relatively moderate score for organizational readiness ($M = 4.67$, $SD = 1.42$) despite high relative advantage perceptions ($M = 5.42$, $SD = 1.18$) reveals an intention-behavior gap wherein organizations recognize AI value but lack capabilities for effective implementation. This gap manifests most acutely in human capital constraints, with 67% of surveyed organizations reporting insufficient data science and AI expertise, consistent with broader Southeast Asian patterns documented by Chatterjee et al. (2022). Top management support emerges as a critical bridging factor that translates perceived benefits into actual adoption, suggesting that leadership commitment helps organizations mobilize resources, overcome resistance, and sustain implementation efforts despite capability limitations. The finding that management support effects remained substantial even when controlling for organizational readiness and resources ($\beta = 0.256$ in full model) indicates that leadership influence operates through mechanisms beyond resource allocation, possibly including vision articulation, cultural change facilitation, and political capital deployment to overcome organizational inertia.

Competitive pressure demonstrated unexpectedly strong effects ($\beta = 0.256$, $p < 0.01$), rivaling technology-push factors in magnitude, suggesting that market dynamics serve as powerful adoption drivers in the Malaysian context. This finding extends Wamba-Taguimdje et al.'s (2020) observations regarding competitive isomorphism in technology adoption, indicating that organizations pursue AI not solely for efficiency gains but to maintain competitive parity and signal market sophistication to stakeholders. The interview data from respondents (collected informally during survey administration) revealed that many organizations, particularly in finance and technology sectors, viewed AI adoption as essential for customer retention and

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brand positioning rather than purely operational improvement. This market-driven adoption motivation carries implications for implementation approaches: organizations adopting primarily due to competitive pressure may pursue visible, customer-facing AI applications (chatbots, recommendation systems) rather than fundamental operational transformation, potentially limiting performance benefits. The moderating effect of industry sector on the adoption-performance relationship (with stronger effects in finance and technology) partially supports this interpretation, suggesting that organizations in knowledge-intensive sectors derive greater value from AI adoption, possibly due to better alignment between AI capabilities and core value creation activities.

The significant negative effect of complexity ($\beta = -0.121$, $p < 0.05$) confirms that technical challenges impede AI adoption, though the relatively modest coefficient compared to facilitating factors suggests complexity acts more as a barrier to be overcome than an insurmountable obstacle. Interestingly, complexity effects were substantially stronger among non-adopters ($\beta = -0.298$) compared to adopters ($\beta = -0.134$), indicating that actual implementation experience may reduce complexity perceptions, consistent with learning-by-doing effects documented in innovation diffusion research (Rogers, 2003). This pattern suggests that pilot projects and experimentation opportunities may help organizations overcome initial complexity barriers by building confidence and familiarity. The finding that compatibility demonstrated significant but moderate effects ($\beta = 0.134$, $p < 0.05$) challenges assumptions in some technology adoption literature regarding the primacy of technical fit. In the Malaysian context, organizations may pursue AI adoption despite imperfect compatibility with legacy systems, viewing integration challenges as manageable through phased implementation or parallel operations. This pragmatic approach reflects resource constraints and limited technological alternatives available to organizations in emerging markets compared to developed economy counterparts with more mature technology ecosystems.

The robust positive relationship between AI adoption and organizational performance ($\beta = 0.418$, $p < 0.001$, explaining 37.6% incremental variance) provides compelling evidence that AI technologies deliver tangible value to organizations, addressing skepticism in some literature regarding technology-performance linkages (Verma et al., 2021). This effect size substantially exceeds those reported in prior studies examining big data analytics adoption ($\beta = 0.28$ in Wamba-Taguimdje et al., 2020) and cloud computing adoption ($\beta = 0.31$ in Gupta et al., 2008), suggesting that AI may offer superior performance enhancement potential, possibly due to its broader applicability across operational domains and strategic decision-making processes. However, several caveats warrant consideration. First, the cross-sectional design precludes definitive causal inference; high-performing organizations may possess characteristics (resource availability, management quality, strategic orientation) that simultaneously enable AI adoption and drive performance, creating spurious associations. The study attempted to address this through statistical controls and by measuring performance relative to competitors rather than absolute metrics, but longitudinal investigation remains necessary to establish causality conclusively. Second, the reliance on self-reported performance measures introduces potential bias, though the multi-respondent design for 34.4% of the sample and the strong convergence between IT managers' adoption reports and executives' performance assessments ($r = 0.89$ for organizations with multiple respondents) provides some confidence in measurement validity.

The significant moderation effects whereby larger organizations and knowledge-intensive sectors derive greater performance benefits from AI adoption reveal important boundary

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conditions for the adoption-performance relationship. The interaction between AI adoption and organizational size (β = 0.243 for large organizations) suggests that performance benefits increase with scale, consistent with resource-based theory predictions that larger organizations possess complementary assets (data infrastructure, analytical capabilities, change management experience) that enhance AI value extraction (Mikalef & Gupta, 2021). This finding carries concerning implications for small and medium enterprises (SMEs), which represent 98.5% of Malaysian businesses: if SMEs face both greater adoption barriers and reduced performance benefits, digital divides may widen, potentially concentrating economic value among large corporations. However, the significant positive AI-performance relationship even for small organizations (β = 0.394 - 0.243 = 0.151, still substantial) indicates that SMEs can achieve meaningful benefits, suggesting that targeted support programs addressing capability gaps may help realize AI's democratizing potential rather than its concentrating effects. Industry sector moderation, with strongest performance effects in technology (β = 0.201) and finance (β = 0.134) sectors, likely reflects better alignment between AI capabilities and industry value drivers in knowledge-intensive domains where data processing, pattern recognition, and predictive modeling directly enhance core operations. Manufacturing organizations may face greater challenges translating AI adoption into performance gains due to integration complexities with physical operations, legacy equipment constraints, and workforce adaptation requirements, suggesting sector-specific implementation approaches may optimize outcomes.

Conclusion

This quantitative investigation of 384 Malaysian organizations provides comprehensive empirical evidence regarding determinants of AI adoption and its impact on organizational performance, addressing critical gaps in the limited literature examining digital transformation in Southeast Asian contexts. The study confirms that the Technology-Organization-Environment framework offers robust explanatory power for AI adoption decisions, with technological characteristics (particularly relative advantage and compatibility), organizational factors (especially top management support and human capital), and environmental pressures (notably competitive dynamics) collectively explaining 60.3% of adoption variance. Among these determinants, top management support, relative advantage, and competitive pressure emerge as the three strongest predictors, highlighting the interplay between leadership vision, perceived benefits, and market forces in driving organizational AI integration. Significantly, the research establishes a substantial positive relationship between AI adoption and organizational performance, with effect sizes suggesting that AI technologies deliver meaningful value across multiple performance dimensions including operational efficiency, innovation capacity, and competitive positioning. The moderation analyses revealing stronger performance benefits for larger organizations and knowledge-intensive sectors indicate important boundary conditions, suggesting that organizational characteristics and industry contexts shape value realization from AI investments.

The findings carry important implications for both theoretical development and management practice in the digital economy. Theoretically, this study validates the applicability of established technology adoption frameworks to AI contexts while revealing context-specific factors particularly salient in emerging economies, including competitive isomorphism effects and human capital constraints that may operate differently than in developed markets. The demonstrated strength of the AI adoption-performance relationship provides empirical support for resource-based arguments that AI technologies constitute strategic resources capable of generating sustainable competitive advantages, though moderation effects caution against universal performance expectations and highlight the importance of complementary

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organizational capabilities and industry alignment. For practitioners, the research offers actionable insights regarding factors deserving management attention and resource allocation during AI transformation initiatives. The prominence of top management support underscores that successful AI adoption requires active leadership engagement beyond mere resource provision, encompassing vision articulation, cultural change facilitation, and sustained commitment throughout implementation challenges. The significant effects of human capital and organizational readiness indicate that capability building, through training investments and systematic change management, represents a prerequisite rather than parallel activity to technological deployment. Organizations should approach AI adoption as comprehensive transformation requiring alignment across technical systems, human capabilities, organizational processes, and strategic objectives rather than isolated technology acquisition. The finding that competitive pressure drives adoption but sector membership moderates' performance outcomes suggests that organizations should evaluate AI opportunities through strategic fit lenses rather than purely following market trends, prioritizing applications that align with core value creation activities and distinctive competencies.

However, several limitations qualify these conclusions and suggest directions for future research refinement. The cross-sectional design, while efficient for examining relationships across diverse organizations, precludes definitive causal inferences regarding both determinants of adoption and adoption effects on performance. Longitudinal investigations tracking organizations through AI adoption journeys would clarify causal mechanisms, reveal temporal dynamics including learning curves and delayed performance effects, and enable more robust testing of mediating processes through which determinants influence adoption and adoption influences performance. The reliance on self-reported measures, particularly for performance outcomes, introduces potential bias despite efforts to enhance validity through multi-respondent data collection and comparative rather than absolute metrics. Future research employing objective performance indicators (financial data, productivity metrics, innovation outputs) would strengthen confidence in performance effect conclusions. The sample, while representative of organizational diversity within Malaysia, limits generalizability to other Southeast Asian contexts with different institutional environments, digital infrastructure maturity, and cultural characteristics. Comparative studies across ASEAN nations would illuminate the extent to which findings reflect Malaysian specificities versus broader regional patterns. The study's focus on aggregate AI adoption levels, while providing overall insights, obscures heterogeneity in AI applications, implementation approaches, and specific technologies adopted. Future research disaggregating AI into distinct capability domains (machine learning, natural language processing, computer vision, robotics) and examining their differential determinants and performance implications would provide more granular guidance for organizational decision-making. The identified moderation effects by organizational size and industry sector suggest other potential contingencies—organizational culture, strategic orientation, regulatory contexts—that warrant investigation to develop comprehensive understanding of boundary conditions for AI value realization. Finally, the TOE framework, while validated, represents one theoretical lens; future research integrating alternative perspectives including institutional theory, organizational learning theory, and stakeholder theory could enrich understanding of the complex social, political, and cognitive processes underlying AI adoption and implementation.

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Recommendations for Future Research

The findings and limitations of this study suggest several promising directions for advancing scholarly understanding of AI adoption and its organizational implications. First, longitudinal research designs tracking organizations through multiple stages of AI maturity would address causality concerns and reveal temporal dynamics insufficiently captured in cross-sectional investigations. Such studies could examine how determinants vary across adoption stages (awareness, evaluation, trial, implementation, expansion), whether successful early implementations create path dependencies influencing subsequent decisions, and how performance effects evolve over time potentially exhibiting J-curve patterns with initial disruption followed by improvement. Panel data approaches employing fixed effects models would enable stronger causal inference by controlling for time-invariant organizational characteristics that may confound adoption-performance relationships. Second, qualitative investigations employing in-depth case studies would complement quantitative findings by illuminating mechanisms, contextual nuances, and organizational processes through which determinants operate and through which AI adoption translates (or fails to translate) into performance improvements. Comparative case designs examining successful versus unsuccessful implementation efforts within similar organizational contexts could identify critical success factors and common failure patterns inadequately captured in survey research. Third, research examining specific AI applications rather than aggregate adoption would provide more actionable insights for practitioners facing decisions about which AI capabilities to pursue given resource constraints and strategic priorities. Comparative studies examining determinants and outcomes across machine learning for operational optimization, natural language processing for customer service, predictive analytics for decision support, and computer vision for quality control would reveal application-specific adoption patterns and value drivers.

Fourth, investigations of the dark side of AI adoption, including implementation failures, unintended consequences, employee resistance, and ethical challenges, would provide balanced understanding acknowledging that technology adoption involves risks and potential negative outcomes alongside benefits. Research examining organizational and technological factors that distinguish successful from failed implementations would offer valuable guidance for risk mitigation. Fifth, studies examining AI adoption from multi-stakeholder perspectives, including not only organizational leadership but also employees affected by AI implementation, customers experiencing AI-enhanced services, and partners participating in AI ecosystems, would illuminate diverse impacts and potentially conflicting interests requiring navigation during digital transformation. Employee acceptance, skill development needs, and concerns regarding job security and autonomy represent critical factors inadequately addressed in organization-level adoption research. Sixth, comparative international research examining AI adoption across diverse institutional, economic, and cultural contexts would establish boundary conditions for theoretical frameworks predominantly developed and tested in Western settings. Such research could illuminate how regulatory environments, data governance regimes, education systems, digital infrastructure, and cultural values shape adoption decisions and implementation approaches. Finally, interdisciplinary research integrating insights from information systems, strategic management, organizational behavior, economics, and sociology would develop more comprehensive theoretical understanding of AI adoption as a complex sociotechnical phenomenon involving technological, organizational, economic, social, and ethical dimensions that cannot be adequately understood through single disciplinary lenses.

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