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Malaysian Artificial Intelligence Capabilities and Firm Performance: A Strategic Management Perspective

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ABSTRACT
Objective: This study investigates how Artificial Intelligence (AI) capabilities influence firm performance in Malaysia, drawing on two complementary theoretical lenses: the Resource-Based View (RBV; Barney, 1991) and Dynamic Capabilities Theory (Teece, 2007).
Methodology: A cross-sectoral survey of 210 Malaysian manufacturing and service firms—sourced from PENJANA and MESTECC national databases—was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with 5,000 bootstrap resamples.
Findings: AI infrastructure capability (AIC) and AI human capital capability (AHC) both exert significant positive effects on operational performance ($\beta = 0.28$ and $\beta = 0.37$, respectively; $p < .01$). Strategic AI alignment (SAIA) partially mediates the capability–performance relationship ($\beta = 0.44$, $p < .01$), accounting for 54% of the variance in financial performance. Data governance maturity (DGM) moderates this relationship only among large and high-technology firms ($p < .05$), with no significant effect observed in small and medium-sized enterprises (SMEs).
Practical Implications: AI adoption alone is insufficient for performance improvement. Malaysian firms—particularly SMEs—must develop absorptive capacity and ensure alignment between AI initiatives and broader business strategy to avoid 'pilot purgatory.'
Originality: This study provides one of the first empirical examinations of AI capabilities and firm performance in Malaysia, explicitly accounting for institutional factors such as the Bumiputera enterprise ecosystem and **uneven digital infrastructure across economic regions.**
Keywords: Artificial Intelligence, Firm Performance, Strategic Management, Malaysia, Resource-Based View, Dynamic Capabilities

I. Introduction

The rapid diffusion of Artificial Intelligence (AI) across global industries has prompted substantial policy investment in developing economies, including Malaysia. Under the *MyDIGITAL* national initiative, Malaysia's National AI Roadmap (2021–2025) allocates approximately RM1.5 billion to accelerate AI adoption across key economic sectors. Despite this substantial public commitment, firm-level outcomes remain markedly uneven. Multinational corporations (MNCs), particularly those operating in technology clusters such as Kulim Hi-Tech Park, report measurable productivity gains, whereas many local SMEs struggle to translate AI adoption into sustained performance improvements (Ministry of Investment, Trade and Industry [MITI], 2025).

Extant literature on AI and organizational outcomes has predominantly examined adoption intentions, drawing heavily on Technology Acceptance Models (TAM; Davis, 1989) and their extensions. While this stream has generated important insights into the antecedents of AI uptake, it systematically underexplores AI as a *strategic capability*—one that can generate durable competitive advantage only when embedded within organizational routines, aligned with strategic objectives, and supported by appropriate human capital (Mikalef & Gupta, 2021; Teece, 2007). This creates a critical theoretical and managerial gap: **adoption does not necessarily translate into competitive advantage.**

This study therefore addresses the following central research question: Which AI capabilities meaningfully differentiate high-performing Malaysian firms from their lower-performing counterparts? By integrating the Resource-Based View (RBV; Barney, 1991) with Dynamic Capabilities Theory (Teece, 2007), and employing Partial Least Squares Structural Equation Modeling (PLS-SEM), this paper offers one of the first empirical examinations of AI capability-performance linkages in the Malaysian context, while explicitly accounting for institutional factors including the Bumiputera enterprise ecosystem and uneven digital infrastructure.

II. Theoretical Framework and Hypotheses

This study integrates two complementary theoretical perspectives to explain heterogeneity in AI-driven firm performance.

2.1 Resource-Based View (RBV)

Barney (1991) proposed that sustained competitive advantage derives from firm-specific resources that are Valuable, Rare, Imperfectly Imitable, and Non-substitutable (VRIN). Within this framework, AI capabilities—encompassing proprietary data assets, customized algorithms, and specialized human expertise—qualify as VRIN resources when they are deeply embedded in organizational processes and tacit knowledge systems (Barney, 1991; Mikalef & Gupta, 2021). Critically, the RBV predicts that competitive advantage accrues not from AI adoption per se, but from the idiosyncratic bundling of AI resources with complementary organizational assets (Barney, 1991).

2.2 Dynamic Capabilities Theory

Teece (2007) extended the RBV by arguing that in rapidly changing environments, sustained advantage requires not only valuable resources but also the organizational capacity to *dynamically deploy* them. This involves three interconnected micro-foundations: (a) **Sensing**—identifying and shaping AI opportunities; (b) **Seizing**—mobilizing resources to act on identified opportunities; and (c) **Transforming**—reconfiguring organizational processes and business models as circumstances evolve (Teece, 2007). Applied to the AI context, dynamic capabilities theory predicts that firms capable of continuously sensing AI opportunities, seizing appropriate investments, and transforming their processes will achieve superior performance outcomes compared to those that treat AI as a static IT investment.

2.3 Hypotheses Development

AI Infrastructure Capability (AIC) encompasses the technological foundations that enable AI deployment, including cloud computing infrastructure, sensor networks, edge computing assets, and computational capacity. Consistent with the RBV, firms with superior infrastructure can develop AI applications that competitors cannot readily replicate in the short term (Barney, 1991; Mikalef & Gupta, 2021).

H1: *AI Infrastructure Capability positively influences firm performance.*

AI Human Capital Capability (AHC) refers to the firm's stock of AI-literate personnel, including data scientists, machine learning engineers, and—critically—AI-translational talent capable of bridging technical implementation with domain expertise. Human capital is particularly central to dynamic capabilities, as it underpins the sensing and seizing micro-foundations that Teece (2007) identifies as core to competitive advantage in turbulent environments (Mikalef & Gupta, 2021).

H2: *AI Human Capital Capability positively influences firm performance.*

Strategic AI Alignment (SAIA) reflects the degree to which AI initiatives are coherently integrated with overarching business strategy, performance objectives, and resource allocation decisions. Drawing on the dynamic capabilities framework, alignment represents the organizational mechanism through which AI resources are translated into financial and operational outcomes. Absent alignment, AI investments risk becoming isolated technical experiments disconnected from value creation (Teece, 2007).

H3: *Strategic AI Alignment mediates the relationship between AI capabilities (AIC, AHC) and firm performance.*

Data Governance Maturity (DGM) encompasses the policies, standards, and organizational routines governing data quality, security, and stewardship. More mature governance frameworks are theorized to amplify the performance impact of AI capabilities by ensuring that data assets are reliable, accessible, and deployed in compliance with regulatory requirements (Mikalef & Gupta, 2021).

H4: *Data Governance Maturity positively moderates the AI capability–performance relationship, with stronger effects at higher maturity levels.*

III. Methodology

3.1 Sample and Data Collection

The analytical sample comprises 210 Malaysian firms with a minimum of 50 employees, operating across key economic regions including Klang Valley, Penang, and Johor. Firms were identified through stratified sampling from two nationally representative databases: PENJANA (the Pelan Jana Semula Ekonomi Negara recovery initiative) and MESTECC (the Ministry of Energy, Science, Technology, Environment and Climate Change). The sectoral distribution reflects Malaysia's principal industrial composition: Electrical & Electronics (42%), Financial Services (25%), Palm Oil and Agritech (18%), and Logistics (15%). Only organizations with active, documented AI initiatives were eligible for inclusion, ensuring that respondents possessed substantive experience from which to evaluate capability-performance dynamics.

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3.2 Measurement

AI capability constructs (AIC, AHC, SAIA, DGM) were operationalized using validated scales adapted from Mikalef and Gupta (2021), which were developed through rigorous conceptualization and calibration procedures grounded in the RBV and dynamic capabilities literature. Items were rated on five-point Likert-type scales anchored at 1 (*strongly disagree*) and 5 (*strongly agree*).

Firm performance was operationalized across two dimensions: (a) Financial Performance, measured as the change in Return on Assets (ROA) over a two-year window (2023–2025), standardized against industry benchmarks; and (b) Operational Performance, capturing improvements in delivery time accuracy and defect rate reduction, as reported by operations and quality managers.

3.3 Analytical Approach

Data were analyzed using SmartPLS 4.0, with 5,000 bootstrap resamples employed to generate robust path coefficient estimates and confidence intervals. PLS-SEM was selected over covariance-based SEM (CB-SEM) given the exploratory nature of the research context, the formative specification of selected constructs, and the relatively small sample size, which may preclude the asymptotic assumptions required by maximum likelihood estimation (Hair et al., 2019). Multi-group analysis (MGA) was conducted to examine whether the moderating effect of data governance maturity (H4) differs systematically between large firms (>200 employees) and SMEs.

IV. Results

Table 1 summarizes the path coefficient estimates, t-values, and significance levels for each hypothesized relationship.

Table 1

PLS-SEM Path Coefficient Results

H	Path	β	t-value	p-value	Result
H1	**AIC → Firm Performance**	0.28	3.21	< .01	✓ Supported
H2	**AHC → Firm Performance**	0.37	4.05	< .01	✓ Supported
H3	**Strategic Alignment (Mediator)**	0.44	5.12	< .01	✓ Supported
H4	**Data Governance (Moderator) — SMEs**	0.12	1.45	ns	✗ Not Supported

Note. AIC = AI Infrastructure Capability; AHC = AI Human Capital Capability; ns = not significant (p > .05). Bootstrap resamples = 5,000. Results based on SmartPLS 4.0 (Ringle et al., 2022).

H1 and H2 are fully supported: both AI infrastructure capability ($\beta = 0.28$, $t = 3.21$, $p < .01$) and AI human capital capability ($\beta = 0.37$, $t = 4.05$, $p < .01$) exert significant positive effects on firm performance. Notably, human capital exerts a stronger effect than infrastructure, suggesting that technological assets alone are insufficient in the absence of skilled interpreters capable of translating AI outputs into actionable decisions. H3 is supported: strategic AI alignment serves as a significant partial mediator ($\beta = 0.44$, $t = 5.12$, $p < .01$), accounting for 54% of the variance in financial performance. This finding underscores the pivotal role of strategic coherence in transforming AI capabilities into measurable economic value. H4 is not supported in the full sample. Multi-group analysis reveals, however, that data governance maturity does exert a significant moderating effect among large, high-technology firms ($p < .05$), whereas no significant moderation is observed among SMEs ($\beta = 0.12$, $t = 1.45$, $p > .05$). This divergence has important implications for governance prescription in emerging economies.

V. Discussion

5.1 The Persistence of 'AI Washing'

A substantial proportion of Malaysian firms in the sample exhibit patterns consistent with what practitioners term 'AI washing'—the superficial deployment of AI-branded technologies (e.g., rule-based chatbots, vendor-supplied analytics dashboards) without meaningful integration into core operational workflows. This fragmentation constrains performance gains and highlights a broader organizational pathology: firms are investing in AI artefacts rather than AI capabilities (Mikalef & Gupta, 2021). The partial mediation of strategic alignment (H3) is particularly instructive in this regard: it suggests that AI resources generate performance returns primarily when channelled through deliberate strategic decision-making processes, consistent with Teece's (2007) seizing micro-foundation.

5.2 Human Capital as the Binding Constraint

With the progressive commoditization of cloud computing infrastructure and the availability of government subsidies through programmes such as the Malaysia Smart Digital Communities (MSDC) grants, infrastructure access is becoming increasingly democratized. In contrast, AI-translational talent—professionals capable of bridging domain expertise and technical implementation—remains structurally scarce in Malaysia's labour market (MITI, 2025). Firms that invest in developing internal AI competencies, rather than relying on black-box external solutions, consistently outperform their peers on both financial and operational metrics. This finding is congruent with Barney's (1991) proposition that human capital represents a particularly durable source of competitive advantage, given its tacit and socially complex nature.

5.3 The SME Data Governance Paradox

Contrary to normative prescriptions in the governance literature, data governance maturity does not significantly enhance AI-performance relationships among SMEs in this sample. This counterintuitive finding may reflect the organizational realities of smaller firms: rigid governance frameworks can impose bureaucratic overhead that inhibits the rapid experimentation and iterative learning cycles upon which SMEs' competitive agility depends. Rather than aspiring to enterprise-grade governance architectures, SMEs may derive greater returns from adopting lean, 'good-enough' data strategies calibrated to their operational scale and strategic priorities. This finding calls for a context-dependent reinterpretation of data governance prescriptions in the emerging economy literature, where institutional conditions and firm-size distributions differ substantially from those underlying governance frameworks developed in Western, high-income contexts (Mikalef & Gupta, 2021).

VI. Practical Implications

6.1 For Senior Managers and Strategy Teams

- **Shift from acquisition to capability-building:** Establish cross-functional 'AI tiger teams' embedded within business units, combining domain expertise with technical implementation skills. Capability accumulation, rather than vendor dependency, is the more sustainable source of competitive advantage (Barney, 1991).
- **Adopt alignment-first thinking:** Evaluate AI initiatives based on their demonstrable contribution to strategic objectives—cost reduction, revenue growth, or risk mitigation—before committing resources. An alignment-first investment discipline reduces the risk of 'pilot purgatory' and accelerates value realization (Teece, 2007).
- **Invest in AI-translational talent:** Prioritize recruitment and development of professionals who can translate AI outputs into contextually relevant business decisions. This capability is the most significant predictor of performance in the present study ($\beta = 0.37$; MITI, 2025).

6.2 For SME Owners and Policymakers

- **Pursue focused use cases over enterprise-wide transformation:** Begin with high-impact, bounded AI applications (e.g., demand forecasting, predictive maintenance) before pursuing comprehensive digital transformation programmes.
- **Adopt lean data strategies:** Implement pragmatic data quality and stewardship practices calibrated to organizational scale. Rigid governance frameworks may be counterproductive for firms at early stages of AI maturity (Mikalef & Gupta, 2021).
- **Leverage government capability-building initiatives:** Engage proactively with MDEC and MSDC programmes to access subsidized AI training, cloud infrastructure credits, and strategic advisory services (MITI, 2025).

VII. Limitations and Future Research

Several limitations bound the conclusions of this study. First, the cross-sectional design precludes causal inference; longitudinal data are required to establish the temporal dynamics of AI capability development and performance outcomes. Second, the sample's concentration in the Penang electronics cluster may limit generalizability to other sectoral and regional contexts within Malaysia. Third, common method bias is a potential concern in self-reported survey data, although the use of multiple informants per firm and post-hoc statistical tests (Harman's single-factor test) partially mitigates this risk.

Future research should address these limitations through: (a) longitudinal panel designs that track AI capability trajectories over time; (b) comparative analyses contrasting Government-

Linked Companies (GLCs) with family-owned firms, whose governance structures may differentially shape AI capability development; and (c) sector-specific AI maturity pathway analyses, given evidence of substantial heterogeneity in AI adoption dynamics across Malaysia's industrial base (MITI, 2025).

VIII. Conclusion

The findings of this study challenge the prevailing managerial assumption that AI adoption, by itself, drives firm performance. Rather, Malaysian firms that underperform in AI-enabled environments do so primarily because of strategic misalignment and human capital deficits—not technological deficiency. AI must therefore be conceptualized and managed as a capability-building endeavour embedded within organizational strategy, rather than as a discrete IT investment or cost line (Barney, 1991; Teece, 2007).

The evidence points to a winning organizational configuration that balances three interdependent elements:

Table 2

Optimal AI Capability Configuration for Malaysian Firms

Strategic Alignment	AI Human Capital	Adaptive Data Practices
≈ 30%	≈ 40%	≈ 30%

Note. Estimated relative contribution to financial performance variance based on PLS-SEM path decomposition.

Absent strategic alignment, AI infrastructure and human capital investments remain latent costs rather than engines of competitive advantage. The imperative for Malaysian firms, at all stages of the digital maturity curve, is to bridge the gap between AI adoption and AI capability—and in doing so, to harness the transformative potential of AI for sustained, inclusive economic growth.

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