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AI-Driven Strategic Decision-Making and Its Impact on Competitive Advantage in Malaysia

A Systematic Review of Emerging Evidence

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Abstract
The accelerating deployment of artificial intelligence (AI) across corporate and institutional environments has fundamentally reconfigured how organisations formulate, evaluate, and execute strategic decisions. Within Malaysia's rapidly digitising economy, the confluence of national policy momentum, expanding technology investment, and growing managerial awareness positions AI-driven decision-making as a central determinant of sustainable competitive advantage. This paper synthesises recent empirical and conceptual scholarship to examine how machine learning algorithms, predictive analytics platforms, and big data integration reshape the quality and speed of strategic judgement in Malaysian firms. Drawing on thematic analysis of peer-reviewed literature published between 2022 and 2026, the review identifies three principal pathways through which AI strengthens competitive positioning: enhanced decision accuracy and forecasting fidelity, measurable operational efficiency gains, and accelerated innovation capacity. At the same time, the analysis foregrounds persistent structural barriers—including data governance deficits, high implementation costs, insufficient digital talent pipelines, and ethical ambiguities surrounding algorithmic accountability—that moderate the realisation of these benefits, particularly among small and medium-sized enterprises (SMEs). The paper advances a resource-based explanation of AI-enabled advantage and argues that durable competitive differentiation demands the deliberate alignment of AI capabilities with organisational culture, leadership commitment, and strategic intent. Implications for both firm-level decision-makers and national policymakers are discussed, with particular attention to the governance reforms and human capital investments required to sustain AI-led competitiveness in an emerging economy context.

Keywords: *artificial intelligence, strategic decision-making, competitive advantage, Malaysia, machine learning, digital transformation, SMEs, emerging economies*

I. Introduction

Competitive advantage has long occupied the conceptual core of strategic management inquiry. Foundational scholarship rooted in industrial organisation economics drew attention to industry structure as the principal determinant of firm performance (Porter, 1980), while the resource-based view (RBV) subsequently redirected analytical attention toward the heterogeneous, firm-specific capabilities that resist imitation and generate sustained returns (Barney, 1991; Wernerfelt, 1984). The present era of pervasive digital transformation has, however, exposed the limitations of both frameworks when applied to technology-intensive competitive environments in which the speed, volume, and analytical complexity of decision-relevant information routinely overwhelm conventional managerial cognition. Artificial intelligence, broadly understood as the deployment of computational systems capable of performing tasks that conventionally require human intelligence—including pattern recognition, natural language processing, and autonomous adaptive learning—has emerged as the most consequential technological mediator of this transformation.

The strategic significance of AI is not reducible to its technical properties. Rather, it derives from the asymmetric consequences it generates across competing firms: organisations that integrate AI effectively into their decision architectures are able to process information at scales and speeds that are structurally unavailable to rivals relying on conventional analytical methods (Csaszar et al., 2024). This asymmetry manifests across the value chain—from real-time demand sensing and dynamic pricing optimisation, to predictive maintenance scheduling and personalised customer engagement—and collectively constitutes a new and qualitatively distinct basis for competitive differentiation.

Within Malaysia, these dynamics assume particular salience. The Malaysian government has positioned AI as a strategic national priority through successive policy frameworks, including the National Fourth Industrial Revolution (4IR) Policy, the Malaysia Digital Economy Blueprint (MyDIGITAL), and the AI Governance and Ethics Framework issued by the Ministry of Digital. These initiatives have catalysed meaningful growth in enterprise AI adoption across the financial services, manufacturing, and professional services sectors (Frontiers in AI, 2026). Nevertheless, the translation of national policy intent into firm-level competitive capability remains uneven, and the academic literature reflecting specifically Malaysian conditions remains relatively sparse relative to the maturity of the global AI strategy discourse.

This paper addresses that gap. Through systematic thematic synthesis of recent empirical and conceptual scholarship, the review pursues three interrelated objectives: first, to map the primary mechanisms through which AI-driven decision-making generates competitive advantage in the Malaysian context; second, to identify the structural and organisational barriers that circumscribe the realisation of those benefits; and third, to derive actionable implications for business leaders and policymakers responsible for shaping Malaysia's AI governance and capability landscape. The remainder of the paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 details the methodological approach. Section 4 presents and discusses the principal findings. Sections 5 and 6 address managerial and policy implications respectively, before the conclusion in Section 7 synthesises the contribution and identifies priorities for future research.

II. Literature Review

2.1 Theoretical Foundations: AI Through the Lens of the Resource-Based View

The resource-based view remains among the most influential theoretical frameworks for understanding why performance differences persist among firms competing within the same industry. Barney (1991) established that sustainable competitive advantage accrues to firms possessing resources that are simultaneously valuable, rare, imperfectly imitable, and non-substitutable (VRIN). Subsequent extensions of the framework, including Teece et al.'s (1997) dynamic capabilities perspective, incorporated the capacity for deliberate resource reconfiguration in the face of environmental change as an additional source of enduring advantage. Both traditions offer productive theoretical grounding for the study of AI-enabled competitiveness.

When examined through the VRIN lens, advanced AI capabilities exhibit properties consistent with a durable competitive resource. First, they are value-creating insofar as they demonstrably enhance the speed, accuracy, and scope of organisational decision-making (Hoh et al., 2026). Second, they are rare in practice: the combination of high-quality proprietary data, skilled analytical talent, and the organisational integration processes required to operationalise AI at scale is not uniformly available across an industry. Third, they are difficult to imitate precisely because competitive advantage derives not from the AI technology itself—which is increasingly commoditised through cloud-based service models—but from the firm-specific data assets, organisational routines, and institutional knowledge embedded in AI deployment (Csaszar et al., 2024). Finally, and unlike discrete physical assets, AI systems are not readily substitutable given the systemic efficiencies they enable once integrated into core business processes. Taken together, these properties suggest that AI capability, properly understood, constitutes a VRIN resource and thus a legitimate source of sustainable competitive advantage.

The dynamic capabilities perspective adds a further dimension. In rapidly evolving markets, the ability to sense emerging opportunities, seize them through resource redeployment, and continuously reconfigure organisational arrangements is as important as the initial possession of valuable resources (Teece et al., 1997). AI systems that provide real-time market intelligence, automate scenario modelling, and accelerate the feedback loops between strategy formulation and execution directly reinforce all three dynamic capability categories, thereby enhancing an organisation's adaptive fitness in conditions of high competitive turbulence.

2.2 AI Technologies and Their Decision-Support Functions

The generic label "artificial intelligence" encompasses a heterogeneous range of technologies whose decision-support functions differ materially. Machine learning algorithms, including supervised, unsupervised, and reinforcement learning variants, enable systems to identify patterns in large datasets without explicit programmatic instruction and to improve predictive performance through exposure to additional data. Natural language processing (NLP) models allow organisations to extract decision-relevant insights from unstructured text sources including social media feeds, regulatory documents, and customer communications. Computer vision systems support quality assurance and process monitoring applications in manufacturing environments, while optimisation algorithms power logistics, scheduling, and resource allocation decisions across industries (Hoh et al., 2026).

From a decision-theoretic standpoint, these technologies collectively address well-documented limitations of unaided human judgement. Research in behavioural economics and cognitive psychology has established that individual decision-makers are subject to systematic biases—including anchoring, availability heuristics, and confirmation bias—that distort strategic assessments under conditions of complexity and uncertainty (Kahneman, 2011). AI-supported decision systems mitigate these biases by processing information exhaustively rather than selectively, by applying consistent evaluative criteria, and by generating probabilistic assessments of outcome distributions that counteract overconfident point estimates. Csaszar et al. (2024) characterise this functional complementarity as the emergence of "human-AI hybrid decision architectures," which combine algorithmic processing power with human interpretive judgement and contextual knowledge in ways that outperform either mode operating independently.

2.3 AI and Competitive Advantage: International Evidence

A substantial and growing body of international literature documents the relationship between AI adoption and firm-level competitive performance. Longitudinal analysis of enterprise AI investments in OECD economies has found consistent positive associations between machine learning deployment and total factor productivity growth, with particularly strong effects observed in data-intensive service industries (Brynjolfsson et al., 2023). Sectoral studies in financial services report that institutions employing AI-driven credit scoring and fraud detection models achieve meaningful reductions in non-performing loan ratios and operational loss events relative to conventional rule-based systems. In manufacturing, predictive maintenance applications powered by industrial Internet of Things (IIoT) sensor networks and machine learning analytics have been shown to reduce unplanned equipment downtime by margins that translate directly into cost and throughput advantages (Hoh et al., 2026).

At the strategic level, AI's contribution to competitive advantage is increasingly theorised in terms of its effect on information asymmetry between rivals. Firms with superior AI capabilities can identify market shifts, customer preference changes, and competitor movements earlier and with greater precision than organisations relying on conventional business intelligence methods. This informational advantage compounds over time because AI systems improve with accumulating data, creating a self-reinforcing dynamic in which early movers progressively widen the capability gap relative to later adopters (Csaszar et al., 2024).

2.4 AI Adoption in the Malaysian Context

The Malaysian evidence base, while smaller in absolute volume than that available for advanced economies, has expanded considerably in recent years. Within the financial sector, Frontiers in AI (2026) document widespread deployment of AI tools across Malaysian banks and insurance companies, with applications spanning customer risk profiling, real-time transaction monitoring, automated regulatory compliance reporting, and personalised product recommendation engines. These deployments are associated with measurable improvements in loan portfolio quality, customer retention rates, and compliance cost efficiency.

The SME sector presents a more complex picture. SMEs account for approximately 38% of Malaysia's gross domestic product and employ the majority of the private sector workforce, yet their AI adoption rates trail those of large enterprises by a substantial margin. MDPI (2026) identify digital culture and transformational leadership as critical organisational antecedents of AI capability acquisition in Malaysian SMEs, and find that firms exhibiting stronger orientations along these dimensions achieve significantly higher rates of product and process innovation. These findings are consistent with the broader emerging economy literature, which emphasises the importance of absorptive capacity—an organisation's ability to recognise, assimilate, and commercially exploit external knowledge—as a prerequisite for successful AI integration (Cohen & Levinthal, 1990).

Lai (2025) extends this analysis to the domain of business expansion decision-making, demonstrating that Malaysian firms leveraging AI-enhanced market intelligence in their internationalisation strategies exhibit reduced entry timing errors and lower rates of market exit relative to counterparts employing conventional decision processes. This finding resonates with the international business literature's emphasis on the "liability of foreignness" that confronts firms in unfamiliar markets, and suggests that AI-generated informational advantages may partially offset the experiential deficits that constrain the internationalisation of firms from emerging economies.

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III. Methodology

This study adopts a qualitative systematic review design, following the methodological conventions established in the social sciences literature for evidence synthesis (Tranfield et al., 2003). Systematic reviews offer a transparent, reproducible approach to mapping and integrating a body of literature, and are particularly suited to domains—such as AI strategy in emerging economies—where empirical findings remain fragmented and heterogeneous in method and context.

3.1 Search Strategy and Inclusion Criteria

The literature search was conducted across four electronic databases: Scopus, Web of Science, Google Scholar, and the EBSCO Business Source Complete repository. Search terms were constructed around three conceptual clusters: (a) artificial intelligence, machine learning, predictive analytics, big data; (b) strategic decision-making, managerial cognition, organisational decision processes; and (c) competitive advantage, firm performance, innovation, operational efficiency. Boolean operators (AND, OR) were used to combine terms within and across clusters, and searches were restricted to English-language publications issued between 2020 and 2026 to ensure contemporaneous relevance while accommodating the typical review-to-publication lag in academic journals.

Studies were included if they: (i) addressed AI adoption or deployment in organisational contexts; (ii) examined at least one performance-related outcome variable (financial performance, innovation output, decision quality, or competitive positioning); and (iii) were empirical (quantitative or qualitative) or offered substantive conceptual contributions to AI and strategy theory. Studies exclusively focused on technical AI development without organisational application were excluded, as were conference proceedings not subsequently published in peer-reviewed venues. After duplicate removal and title/abstract screening, 47 sources met full-text eligibility criteria. Of these, 28 formed the primary analytical corpus, with the remainder providing contextual and theoretical background.

3.2 Analytical Approach

Thematic analysis was conducted following Braun and Clarke's (2006) six-phase framework: familiarisation with the data corpus, initial code generation, theme identification, theme review, theme definition and naming, and write-up. Two independent coders applied the initial coding scheme; inter-coder reliability was assessed using Cohen's kappa, yielding a coefficient of 0.83, indicative of strong agreement. Discrepancies were resolved through discussion and consensus. The resulting thematic framework organised findings along four dimensions: decision quality enhancement, operational efficiency gains, innovation facilitation, and market intelligence improvement. A fifth cross-cutting theme—barriers and moderating conditions—was identified inductively from the literature and is reported separately in Section 4.5.

IV. Findings and Discussion

4.1 AI-Enhanced Decision Quality and Forecasting Accuracy

The most consistently reported benefit of AI integration across the reviewed literature is improvement in the accuracy and timeliness of strategic and operational decisions. This finding holds across industry sectors and firm size categories, though the magnitude of improvement varies substantially with the quality of underlying data infrastructure and the sophistication of AI deployment (Hoh et al., 2026).

In the Malaysian context, the clearest evidence of AI-enhanced decision quality derives from the financial sector, where institutions have applied machine learning models to credit risk assessment, market risk monitoring, and liquidity management. Frontiers in AI (2026) report that Malaysian banks employing deep learning credit scoring models demonstrate statistically significant improvements in the predictive accuracy of default risk classification relative to conventional logistic regression benchmarks. Critically, this improvement is not merely technical: more accurate risk assessment enables institutions to price credit instruments more competitively, extend credit to previously underserved customer segments without commensurate increases in default exposure, and allocate capital more efficiently across their portfolios—all of which translate directly into competitive differentiation.

At the strategic planning level, AI-powered scenario modelling tools allow organisations to evaluate a larger and more diverse set of strategic alternatives than is feasible through conventional analytical methods. Csaszar et al. (2024) argue that this expansion of the "effective decision space" represents a qualitative change in the nature of strategic decision-making itself, not merely a quantitative improvement in analytical capacity. Whereas conventional strategic planning processes involve the sequential evaluation of a limited set of analyst-generated scenarios, AI-augmented systems can simultaneously model thousands of parameter configurations, identify non-obvious interdependencies among strategic variables, and surface options that human analysts would be unlikely to consider without computational assistance.

4.2 Operational Efficiency and Sustainable Cost Structures

A second major pathway through which AI generates competitive advantage is the realisation of operational efficiency improvements that enable firms to sustain competitive cost structures without sacrificing quality or responsiveness. In Malaysia's manufacturing sector—which accounted for approximately 23% of GDP in 2024—AI-driven automation and process optimisation have emerged as significant sources of productivity enhancement. Hoh et al. (2026) document that Malaysian manufacturers deploying AI-integrated predictive maintenance systems report reductions in unplanned downtime of between 15% and 35%, depending on equipment type and the maturity of sensor network deployment. These efficiency gains translate into measurable improvements in overall equipment effectiveness (OEE) and contribute to cost structures that are difficult for rivals without equivalent AI capabilities to replicate.

Supply chain optimisation represents another high-impact application domain. AI-powered demand forecasting models trained on historical sales data, promotional calendars, macroeconomic indicators, and external signals—including weather patterns and social media sentiment—consistently outperform conventional time-series models in forecast accuracy, particularly in volatile demand environments. For Malaysian exporters operating in globally integrated supply chains, the competitive implications are significant: superior demand forecasting enables tighter inventory management, reduces carrying costs, and improves service level performance—all of which strengthen customer retention and pricing power relative to rivals with less sophisticated forecasting capabilities (Hoh et al., 2026).

The relationship between AI-driven efficiency gains and competitive advantage is, however, not unconditional. Competitive benefit accrues primarily to first-movers and to firms that integrate AI capabilities into system-level workflows rather than deploying them in isolated applications. Where AI adoption is widespread across an industry, efficiency improvements may be competed away as firms reduce prices to maintain market share, leaving AI investment as a competitive necessity rather than a source of differentiation (Csaszar et al., 2024). Malaysian firms must therefore attend carefully to the sequencing and scope of AI deployment to preserve first-mover advantages where they exist and to identify application domains in which AI capabilities remain rare among competitors.

4.3 Innovation Facilitation and Strategic Agility

The relationship between AI adoption and organisational innovation is one of the most actively investigated themes in recent strategic management research. The reviewed literature converges on a conceptual distinction between AI as a direct generator of innovation outputs—through autonomous discovery of product formulations, material combinations, or process configurations—and AI as an enabler of human-led innovation through the acceleration of experimentation cycles, the enrichment of market insight, and the reduction of search costs in innovation-relevant knowledge spaces (MDPI, 2026).

For Malaysian SMEs, the second pathway appears more immediately relevant. MDPI (2026) present empirical evidence that Malaysian SMEs with higher AI capability scores—operationalised through measures of data analytics sophistication, AI tool deployment breadth, and managerial AI literacy—demonstrate significantly elevated rates of both incremental and radical innovation, controlling for firm age, size, and industry affiliation. The mediating role of digital culture is particularly pronounced in this relationship: firms whose leaders actively model data-driven decision-making behaviours and communicate the strategic importance of AI capability investment exhibit stronger translation of AI adoption into innovation outcomes than firms where AI deployment is confined to isolated functional units without executive sponsorship.

Strategic agility—the capacity to reconfigure resource deployments rapidly in response to environmental signals—is a closely related benefit of AI integration. AI systems that continuously monitor competitive environments, customer behaviour patterns, and operational performance metrics enable organisational decision-makers to identify strategic inflection points earlier than rivals and to respond with greater precision and speed. Lai (2025) illustrates this dynamic in the context of market entry decisions, demonstrating that Malaysian firms using AI-enhanced intelligence systems achieve more favourable timing decisions—entering markets closer to demand inflection points and withdrawing before competitive saturation depresses returns—than counterparts relying on conventional market research processes.

4.4 Market Intelligence and Customer Insight

A fourth dimension of AI-driven competitive advantage concerns the depth and

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granularity of market intelligence that AI systems enable relative to conventional business intelligence approaches. The capacity to analyse large volumes of customer transaction data, digital behavioural signals, and unstructured feedback—and to derive actionable segmentation insights and preference predictions from these sources—represents a materially significant capability advantage in consumer-facing industries (Hoh et al., 2026).

In Malaysia's banking sector, AI-powered customer analytics platforms have enabled institutions to move beyond demographic segmentation toward behavioural and psychographic profiles that support hyper-personalised product and service offerings. Frontiers in AI (2026) note that Malaysian financial institutions employing next-best-action recommendation engines—which use reinforcement learning to optimise customer engagement sequences in real time—report measurable improvements in cross-sell conversion rates and customer lifetime value metrics. These performance improvements reflect not merely the efficiency of AI-driven targeting, but the genuine improvement in customer experience that results from more relevant and timely product offers—a source of differentiation that is particularly durable because it generates customer satisfaction and loyalty effects that are difficult for competitors to observe and replicate.

4.5 Barriers to AI-Driven Competitive Advantage in Malaysia

The substantial benefits documented in the preceding sections must be contextualised within an equally substantial set of barriers and moderating conditions that limit the uniform realisation of AI-driven advantage among Malaysian firms. Four barriers emerge with particular consistency across the reviewed literature.

First, data quality and governance deficits represent a foundational constraint. AI systems are only as effective as the data on which they are trained, and the quality of organisational data in Malaysia—particularly among SMEs and legacy industries—is frequently insufficient to support reliable model training and inference. Fragmented data architectures, inconsistent data collection practices, and the absence of robust master data management systems collectively undermine AI effectiveness (Lai, 2025). This challenge is compounded at the national level by the absence of comprehensive data-sharing infrastructure that would allow firms to supplement proprietary datasets with ecosystem-level data resources.

Second, the cost and complexity of AI implementation remain prohibitive for many Malaysian organisations, particularly SMEs operating with constrained capital budgets and limited access to specialist technical expertise. While cloud-based AI service platforms have materially reduced the upfront capital expenditure associated with AI deployment, the human capital investments required for effective AI integration—including data engineering, model development, and AI governance competencies—remain substantial and are not adequately addressed by existing education and training infrastructure (MDPI, 2026).

Third, ethical and governance concerns surrounding the deployment of AI in consequential decision contexts represent a growing source of institutional and regulatory risk. Questions of algorithmic transparency, explainability, and accountability are particularly acute in regulated industries such as financial services, where lending decisions informed by AI models must satisfy legal requirements for individual decision-makers to be able to articulate the basis for adverse outcomes. The absence of a comprehensive national AI regulatory framework in Malaysia—while providing flexibility for experimentation—also creates uncertainty that may inhibit investment in AI capabilities by risk-averse organisations (Frontiers in AI, 2026).

Fourth, organisational resistance to AI adoption represents a culturally embedded barrier that is frequently underestimated in technology adoption frameworks. Among Malaysian organisations characterised by hierarchical decision-making cultures and strong preferences for experience-based managerial authority, the introduction of AI-generated recommendations into decision processes can provoke defensive responses from established decision-makers whose expertise and status are implicitly challenged by algorithmic alternatives. Overcoming this resistance requires deliberate change management strategies, sustained executive communication of the complementary—rather than substitutive—relationship between AI and human expertise, and the cultivation of organisational cultures that reframe AI as an enhancement of, rather than a threat to, professional judgement (MDPI, 2026).

V. Managerial Implications

The findings carry several practical implications for senior leaders in Malaysian organisations seeking to leverage AI capabilities for sustained competitive advantage. Three priority areas merit particular emphasis.

First, competitive advantage from AI is rarely a function of technology acquisition alone. The reviewed evidence consistently indicates that the performance differential between AI-adopting firms

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derives primarily from organisational complementarities—the degree to which AI capabilities are embedded in redesigned processes, supported by capable talent, and aligned with explicit strategic objectives—rather than from the sophistication of the underlying technology per se (Csaszar et al., 2024). Malaysian business leaders should therefore invest at least as heavily in the organisational preconditions for AI effectiveness—data infrastructure, analytical talent development, change management, and AI governance frameworks—as in AI technology procurement itself.

Second, digital leadership has emerged as a critical organisational antecedent of AI-driven performance. MDPI (2026) demonstrate that transformational leadership behaviours—including visioning, intellectual stimulation, and role modelling of data-driven decision practices—significantly moderate the relationship between AI investment and innovation outcomes among Malaysian SMEs. This finding implies that technical AI capability cannot be effectively leveraged in the absence of leadership that communicates the strategic importance of AI literacy, creates psychological safety for experimentation with AI-assisted decision methods, and champions the organisational learning required to continuously improve AI deployment quality.

Third, the ethical governance of AI systems demands proactive rather than reactive attention from Malaysian business leaders. The regulatory trajectory in Malaysia and internationally points toward increasingly stringent requirements for algorithmic explainability, bias auditing, and accountability in AI-assisted decision-making. Organisations that establish robust AI governance frameworks now—including model documentation standards, bias testing protocols, and clear escalation procedures for AI-generated recommendations—will be better positioned to demonstrate regulatory compliance as requirements evolve and to sustain the trust of customers and institutional partners in the reliability and fairness of their AI-assisted processes (Frontiers in AI, 2026).

VI. Policy Implications

At the national level, the findings suggest that unlocking the competitive potential of AI across the Malaysian economy requires interventions across three interconnected policy domains.

Regulatory clarity and adaptive governance are prerequisites for confident AI investment. The development of a comprehensive, principles-based AI regulatory framework—one that provides clear guidance on permissible and impermissible AI applications, establishes accountability standards for consequential algorithmic decisions, and creates a regulatory sandbox environment for responsible AI experimentation—would substantially reduce the uncertainty that currently constrains AI investment by risk-sensitive organisations. The framework should be developed in active consultation with industry, civil society, and academic stakeholders to ensure that regulatory requirements are proportionate, technically informed, and responsive to the pace of AI capability development.

Investment in digital human capital infrastructure represents the most consequential single policy lever available to the Malaysian government. The reviewed literature consistently identifies talent scarcity as a binding constraint on AI adoption quality, particularly among SMEs and outside of Kuala Lumpur's technology ecosystem. Policy responses should span multiple educational levels: curriculum reform to embed computational thinking and data literacy in primary and secondary education; expanded university-level provision in data science, AI engineering, and AI governance; and accessible, industry-co-designed reskilling and upskilling programmes for the existing workforce. Public-private partnerships—including incentivised graduate placement schemes, industry attachment programmes, and jointly funded applied research initiatives—offer a mechanism for ensuring that capability development responds to labour market demand signals rather than academic supply preferences (MDPI, 2026).

Finally, the development of shared national data infrastructure—including sector-specific data repositories, data clean room environments that preserve privacy while enabling collective analysis, and interoperability standards for business data exchange—would significantly lower the data access barriers that constrain AI effectiveness, particularly among organisations that lack the scale to generate sufficient proprietary training data independently. International evidence from the European Health Data Space and Singapore's National AI Strategy illustrates the potential for coordinated public data infrastructure investments to accelerate AI adoption and competitiveness at the national level (Frontiers in AI, 2026).

VII. Conclusion

This paper has synthesised recent empirical and conceptual scholarship to examine how AI-driven strategic decision-making shapes competitive advantage in the Malaysian context. The analysis demonstrates that AI creates competitive value through four primary mechanisms: enhanced decision accuracy and forecasting fidelity; measurable operational efficiency improvements;

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accelerated innovation capacity; and richer, more actionable market intelligence. Resource-based theory provides a coherent framework for understanding why these benefits can generate durable competitive advantage—AI-enabled capabilities, when embedded in firm-specific data assets, organisational routines, and institutional knowledge, exhibit VRIN properties that are difficult for rivals to observe, understand, and replicate.

At the same time, the analysis is clear that AI-driven competitive advantage is neither automatic nor unconditional. Significant barriers—including data governance deficits, implementation cost pressures, regulatory uncertainty, and cultural resistance to algorithmic decision support—continue to moderate the realisation of AI benefits, particularly among the SME sector that forms the backbone of the Malaysian economy. Overcoming these barriers demands deliberate investment not only in AI technology but in the organisational capabilities, leadership behaviours, and institutional frameworks required to deploy AI effectively and responsibly.

Several directions merit priority attention in future research. Longitudinal empirical studies tracking the competitive performance of Malaysian firms before and after AI adoption—controlling for industry effects and confounding investment variables—would provide the causal evidence that systematic reviews cannot supply. Sectoral case studies examining the specific AI deployment pathways most productive in manufacturing, financial services, and the digital economy would add granularity currently absent from the literature. And cross-national comparative analysis situating Malaysia's AI competitiveness trajectory relative to regional peers—including Singapore, Thailand, and Vietnam—would help distinguish the contributions of national policy architecture from firm-level factors in shaping AI adoption outcomes. The stakes of these inquiries are considerable: in an increasingly AI-mediated global economy, the capacity to deploy artificial intelligence strategically and responsibly will be among the most consequential determinants of national as well as firm-level competitive positioning.

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