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THE ROLE OF AI IN DRIVING SUSTAINABLE BUSINESS PERFORMANCE IN MALAYSIA SMES: A TECHNOLOGY–ORGANIZATION–ENVIRONMENT FRAMEWORK APPROACH

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ABSTRACT

The rapid rise of artificial intelligence (AI) presents transformative potential for small and medium-sized enterprises (SMEs) in Malaysia; however, its adoption remains limited, hindering sustainable business performance in a critical yet underexplored area in emerging economies. This study is among the first empirical investigations to explore the factors influencing AI adoption among Malaysian SMEs and its impact on sustainable performance framed within the Technology-Organization-Environment (TOE) framework. Employing a quantitative, cross-sectional survey design, data were collected from 151 SMEs across manufacturing, technology, and service sectors in key Malaysian regions, analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS). Findings reveal that organizational readiness ($\beta = 0.442$, $p < 0.001$), particularly compatibility and perceived relative advantage, is the strongest predictor of AI adoption, followed by technological readiness ($\beta = 0.390$, $p < 0.001$) and environmental readiness ($\beta = 0.147$, $p < 0.01$). AI adoption significantly enhances operational ($\beta = 0.875$), economic ($\beta = 0.818$), and environmental performance ($\beta = 0.793$), with mediation analysis confirming AI as a critical conduit for translating readiness factors into sustainable outcomes ($p < 0.001$). These results underscore the pivotal role of organizational capabilities in facilitating AI adoption and highlight AI's capacity to reconcile economic growth with environmental sustainability. This study makes a novel contribution to the literature by addressing the gap in AI adoption research in Malaysian SMEs and offers valuable, actionable recommendations for SME managers and policymakers. These recommendations focus on overcoming adoption barriers and accelerating digital transformation, with a special emphasis on technological infrastructure, human capital development, and government support in alignment with Malaysia's Vision 2030. Future longitudinal research could further clarify causal dynamics and cross-cultural variations.

KEYWORDS: Artificial Intelligence, Small and Medium Enterprises (SMEs), Sustainable Business Performance, Technology-Organization-Environment Framework, Malaysia, Digital Transformation, AI Adoption.

1. INTRODUCTION

In the midst of the Fourth Industrial Revolution, artificial intelligence (AI) has emerged as a transformative force reshaping business operations and decision-making across global industries (Zhang et al., 2021). In Malaysia, small and medium-sized enterprises (SMEs), which contribute approximately 39% to the national gross domestic product (GDP) and employ 48% of the workforce (Department of Statistics Malaysia, 2023), are pivotal to economic growth. Their flexibility and adaptability make them ideal for adopting AI technologies, such as machine learning and natural language processing, to enhance operational efficiency, reduce costs, and drive innovation (Dwivedi et al., 2021; Khalid, 2020). However, despite the potential of AI to improve business performance, its adoption among Malaysian SMEs remains limited due to challenges like high implementation costs, lack of skilled personnel, and insufficient government support (Rojas-Berrio et al., 2022; Yusuf et al., 2024; Sharma et al., 2022).

AI's integration into business processes enables automation, improved forecasting, and enhanced decision-making, fostering both short-term profitability and long-term growth (Awan et al., 2021a; Sestino & De Mauro, 2022). For SMEs, AI offers a pathway to streamline operations and meet market demands, aligning with Malaysia's national policies like the Malaysia Digital Economy Blueprint (MyDIGITAL) and the National Artificial Intelligence Roadmap (AI-Rmap), which support the New Industrial Master Plan (NIMP) 2030 (Ministry of Economy of Malaysia, 2021). These initiatives underscore the government's commitment to fostering AI adoption to enhance SME competitiveness and contribute to economic development (Lee, 2023). Yet, empirical research on AI adoption in Malaysian SMEs remains scarce, with most studies focusing on large corporations or developed economies (Dwivedi et al., 2021; Ndiaye et al., 2018). This gap highlights the need to explore how SMEs in emerging markets like Malaysia navigate AI adoption amidst resource constraints and unique operational challenges.

This research employs the TOE framework to examine technological (e.g., compatibility, implementation costs), organizational (e.g., organizational support, human capital), and environmental (e.g., market demand, government policies) factors influencing AI adoption (Badghish & Soomro, 2024). Unlike prior studies emphasizing short-term benefits such as cost reduction (Agarwal et al., 2022), this study focuses on sustainable business performance, encompassing operational efficiency, economic outcomes, and environmental responsibility (Abdul-Rashid et al., 2017; Alraja et al., 2022). By targeting SMEs in manufacturing, technology, and service sectors across Kuala Lumpur, Johor, Penang, and Selangor, the research ensures relevance to Malaysia's key economic regions (Aghion et al., 2017; Perifanis & Kitsios, 2023; Jan et al., 2023). The study addresses critical questions: How can the TOE model be used in the adoption of AI by Malaysian SMEs? What factors drive or hinder adoption? How does AI impact sustainable performance, and what strategies can overcome barriers to align with Malaysia's Vision 2030?

The significance of this study lies in its contribution to understanding AI adoption in a developing economy context, offering practical recommendations for SMEs and policymakers. By identifying barriers like high costs and skill shortages (Alzaghal et al., 2024), it proposes strategies to enhance technological infrastructure and organizational readiness, supporting Malaysia's digital transformation goals (Iyelolu et al., 2024). Despite limitations, such as its cross-sectional design and focus on specific sectors, the study lays a foundation for future research to explore longitudinal trends and broader industries. Ultimately, this research bridges the knowledge gap on AI's role in Malaysian SMEs, fostering sustainable growth and competitiveness in a rapidly digitizing global economy.

2. LITERATURE REVIEW

The rapid advancement of Artificial Intelligence (AI) technologies has fundamentally reshaped business landscapes, creating new opportunities for Small and Medium Enterprises (SMEs) to improve their competitive advantage. The integration of AI has proven essential in enhancing operational efficiency, improving decision-making, and driving innovation in SMEs (Carayannis et al., 2025; Sharma et al., 2022). As organizations increasingly realize the strategic importance of combining AI capabilities with human expertise, understanding the critical factors that facilitate or impede this integration becomes vital for sustainable business success (Olan et al., 2022; Kulkov et al., 2024; Hwang et al., 2025). This literature review explores the theoretical foundations, empirical evidence, and conceptual frameworks underpinning AI adoption in SMEs, with a particular focus on technological readiness, organizational support, and external environmental factors.

2.1. Technological Readiness Factors

2.1.1. Implementation Cost

The high implementation cost of AI remains one of the most significant barriers to its adoption in SMEs, particularly in resource-constrained environments. Costs associated with hardware, software, and human resources are often prohibitive for SMEs (Chouki et al., 2020; Kar et al., 2021). However, studies have indicated that while the initial investment is high, AI adoption can yield long-term benefits such as improved efficiency and competitive advantage, which can offset the upfront costs (Agarwal et al., 2022).

Furthermore, recent technological advancements have made AI tools more affordable and accessible, thereby lowering the financial barriers to adoption (Iyelolu, et al., 2024). This trend suggests that SMEs willing to embrace AI despite the high implementation costs can achieve cost-effective solutions in the long run (Rogers, 2003; Chouki et al., 2020).

2.1.2 Relative Advantage

The relative advantage of AI refers to the perceived superiority of AI over existing technologies and plays a central role in adoption decisions. AI technologies are more likely to be adopted by SMEs when they offer clear and measurable advantages, such as enhanced decision-making, operational efficiency, and cost reduction (Rogers, 1995; Alsheibani, 2020).

Recent research emphasizes that the relative advantages of AI in SMEs are particularly evident in industries where data-driven insights and automation provide a competitive edge (Kaine & Wright, 2022; Mndzebele, 2013). In highly competitive markets, AI's ability to deliver rapid decision-making capabilities, predictive analytics, and automation of routine tasks positions SMEs to outperform competitors who are slower to adopt innovative solutions (Kaine & Wright, 2022). As AI adoption continues to demonstrate tangible benefits, SMEs in sectors such as manufacturing, retail, and services are increasingly leveraging AI to maintain their market position (Iyelolu et al., 2024; Michael, 2025).

2.1.3. Compatibility And System Integration

Compatibility refers to the extent to which AI technologies align with an organization's existing values, processes, and technological infrastructure (Weng & Lin, 2011). Compatibility measures the degree to which AI technologies interact with an organization's existing processes and systems (Merhi & Harfouche, 2024). For SMEs with limited IT resources, compatibility becomes a critical factor in determining the feasibility of AI implementation.

Studies have shown that SMEs with compatible IT systems experience fewer disruptions during AI implementation, thereby increasing the likelihood of adoption (Drydakis, 2022; Mishrif & Khan, 2023). If SMEs believe that AI technology meets all their job requirements and innovation prerequisites, they will be more receptive to implementing it (Rawashdeh et al., 2023).

2.1.4. Complexity And Usability Considerations

Complexity, defined as the difficulty of understanding and using AI technologies, represents a significant barrier to adoption, particularly for SMEs with limited technical expertise (Rogers, 2003). SMEs usually lack the technical expertise to implement complex AI systems (Iyelolu et al. 2024). The inverse relationship between complexity and adoption rates has been consistently documented across various innovation contexts (Ahuja et al., 2016; Dryden-Palmer, 2020).

However, the complexity-adoption relationship in AI contexts presents unique characteristics due to the varying complexity levels across different AI applications. While some AI tools offer user-friendly interfaces that minimize complexity, others require substantial technical knowledge for effective implementation and management.

2.2. Organizational Readiness Factors

2.2.1. Organizational Support And Leadership Commitment

Organizational support encompasses the degree to which companies provide necessary resources, training, and infrastructure to facilitate AI adoption (Soomro et al., 2024). Top management plays an important role in providing organizational support. In order to ensure the successful implementation of the AI plan, the main task of the top management is to obtain resources and allocate them effectively so that firms can gain a competitive advantage (Simons, 2019; El-Kassar & Singh, 2019).

Leadership commitment manifests through resource allocation, strategic vision articulation, and organizational culture development that supports innovation and technological experimentation (Chaubey & Sahoo, 2021).

2.2.2. Sustainable Human Capital Development

The concept of sustainable human capital represents a critical organizational factor in successful AI implementation. Sustainable human resource management combines the concepts of sustainability and human resources, which enables firms to have sustainable human capital (Sharma et al., 2022). This approach emphasizes continuous learning, skill development, and adaptive capacity building to ensure workforce readiness for AI collaboration.

Previous studies highlight the importance of sustainable human resource policies in shaping an organization's ability and readiness to embrace AI, as AI-based systems will significantly change the nature of the workforce (Chowdhury et al., 2023; Connelly et al., 2021). The development of AI-related competencies through training programs, upskilling initiatives, and knowledge management systems becomes essential for effective human-AI collaboration. SMEs can ensure that their workforce is capable of leveraging AI technologies effectively, thereby enhancing overall productivity.

2.3 Environmental Readiness Factors

2.3.1 Market Pressures And Customer Demands

External market forces significantly influence AI adoption decisions in SMEs (Venkatesh et al., 2003). Since the customers are the end-users of the product, so their demand may have a more significant influence than any other factor in encouraging firms' decision to innovate (Liao & Tsai, 2019; Dhull & Narwal, 2016). Customer expectations for personalized services, rapid response times, and data-driven insights create pressure for AI adoption.

The competitive landscape also drives AI implementation as organizations seek to maintain market position and respond to competitor initiatives. Previous research has shown that market forces and customers motivate firms to prioritize the adoption of innovative solutions (Dhull & Narwal, 2016; Jun et al., 2021; Zailani et al., 2015).

2.3.2. Government Support And Regulatory Environment

Government initiatives are crucial for promoting AI adoption through policy frameworks, financial incentives, and infrastructure development (Chatterjee, 2020). Government support involves assistance in providing the necessary resources, conditions, or aid to individuals or groups to encourage the adoption of technology within organizations (Venkatesh et al., 2003). For resource-limited SMEs, government support is especially vital in overcoming financial and technical challenges in implementing AI. This factor has been used to investigate the preference for or continuous use of new technologies in various studies (Mensah et al., 2020; Soomro, 2019).

Governments promote the implementation of technological innovation and encourage SEMs through monetary rewards or government subsidies and make credit available from commercial banks (Hojnik & Ruzzier, 2016).

2.4. Implementation Barriers And Challenges

Despite the recognized benefits of human-AI collaboration, SMEs face significant implementation barriers that impede successful adoption. These barriers span technological, organizational, and environmental dimensions, creating complex challenges that require comprehensive strategies to address.

2.4.1. Technological Barriers

Cost considerations represent a primary technological barrier for SMEs. Cost is considered to be one of the main obstacles to the adoption of technologies (Chouki et al., 2020). The high initial investment required for AI implementation, including hardware, software, and integration costs, often exceeds SME budget constraints.

Technical complexity presents another significant barrier, particularly for SMEs with limited IT expertise. Technical complexity refers to the difficulty of learning, researching, and understanding new technologies (Carayannis & Turner, 2006), and it is generally considered that complexity has a negative impact on innovation adoption (Venkatraman, 1991; Fürst et al., 2024).

2.4.2 Organizational Barriers

Limited human capital capabilities represent a critical organizational barrier to AI adoption. The existence of skilled human capital and managers' dedication to learning and accepting new technology are essential and are regarded as one of the main factors to encourage companies to invest in innovative technology (Wu et al., 2012). SMEs often lack the specialized skills required for AI implementation and management, creating dependency on external expertise.

Organizational culture and resistance to change also present significant barriers (Mengstie et al., 2023). Traditional business practices and risk-averse cultures may impede AI adoption efforts, particularly when employees perceive AI as a threat to job security.

2.4.3. Environmental Barriers

External environmental factors, such as regulatory constraints and the lack of market readiness, also pose significant barriers. In regions with underdeveloped digital infrastructure, SMEs may struggle to adopt AI technologies, as the required technical and regulatory support is insufficient (Hojnik & Ruzzier, 2016).

2.5 Sustainable Business Performance Outcomes

The integration of AI technologies in SMEs demonstrates significant potential for enhancing sustainable business performance across multiple dimensions. Sustainable business performance indicates the ability of a firm to carry out its economic as well as environmental and social responsibilities in managing long-term success (Bacinello et al., 2021).

2.5.1 Economic Performance

AI adoption contributes to economic performance through various mechanisms, including cost reduction, revenue enhancement, and operational efficiency improvements (Awan et al., 2021; Baabdullah et al., 2021). The adoption of artificial intelligence reduces costs and improves forecasting and business operations (Agarwal et al., 2022; Ojika, 2022). Studies demonstrate that AI implementation leads to measurable improvements in financial outcomes for SMEs through data-driven decision-making and customer engagement optimization (Ardito et al, 2024).

According to a study released by the McKinsey Global Institute, artificial intelligence acceleration could add 1.2% to the world's economy yearly by 2030 (Bughin et al., 2018).

2.5.2 Operational Performance Enhancement

AI technologies significantly improve operational performance through process automation, error reduction, and resource optimization. AI technologies can improve operational performance by automating repetitive operations, reducing errors, and improving resource allocation (Acemoglu & Restrepo, 2018; Babina et al., 2024). These improvements manifest in enhanced productivity, reduced lead times, and improved quality compliance.

2.5.3. Environmental Performance Benefits

The environmental impact of AI adoption presents both opportunities and challenges for SMEs. The utilization of AI in SMEs is one of the most important elements for enhancing environmental performance. AI technologies allow SMEs to achieve these goals by effectively utilizing resources, avoiding waste, and implementing sustainable development strategies, which are the main features of environmental sustainability.

However, the environmental benefits must be balanced against the energy consumption requirements of AI systems (Wu et al., 2022). AI indeed has a significant positive effect on resource consumption and waste, and in this way, the energy required to train and operate complex AI models can be substantial (Ahmad et al., 2021).

Despite extensive research on AI adoption and business performance, several gaps remain in understanding human-AI collaboration in SME contexts. First, limited research addresses the specific design principles that optimize AI adoption effectiveness in resource-constrained environments. Second, industry-specific adaptation strategies remain underexplored, with most studies providing generic recommendations rather than sector-specific guidance.

Third, the mediating role of AI adoption in translating technological readiness into sustainable performance outcomes requires further investigation. Research by Javaid et al. (2022) and Badghish and Soomro (2024) supports that technology adoption, together with AI, acts as a link between the achievement of sustainable business outcomes.

Fourth, the dynamic interplay between technological, organizational, and environmental factors in shaping human-AI collaboration outcomes needs deeper examination, particularly regarding how these factors interact over time and across different implementation phases.

2.6. Theoretical Foundation: Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework, originally developed by Tornatzky and Fleischer (1990), provides a comprehensive theoretical lens for understanding technology adoption in organizational contexts. Unlike single-dimensional theories such as the Diffusion of Innovation (DOI) theory (Rogers, 1995) or Organizational Capability Theory (OCT) (Inan & Bititci, 2015), the TOE framework offers a holistic perspective by considering three interconnected dimensions that influence technology adoption decisions (Zhang et al., 2020).

The technological dimension encompasses factors related to the characteristics of the technology itself, including relative advantage, compatibility, complexity, and cost considerations (Frambach & Schillewaert, 2002). Studies on technology adoption and innovation in the organization have over the years been dominated by two of the most popular theories the diffusion of innovation (DOI) theory (Rogers, 1995) and the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990). The organizational dimension focuses on internal factors such as organizational support, human capital capabilities, and structural characteristics that enable or constrain technology adoption (García-Machado & Martínez-Ávila, 2019). The environmental dimension addresses external pressures and opportunities, including market demands, competitive pressures, and regulatory influences (Jun et al., 2021).

Recent empirical applications of the TOE framework in AI adoption contexts have demonstrated its relevance and explanatory power. TAM and TOE have been combined in a recent study that provides a more extensive technological framework for analyzing and enhancing AI technology adoption in the construction sector (Na et al., 2022). Similarly, studies have employed integrated TAM-TOE models to examine AI adoption in manufacturing and production firms, providing insights into both internal and external factors influencing adoption decisions (Chatterjee et al., 2021; Neumann et al., 2024).

2.7. Conceptual Framework Development

Based on the literature review, this study proposes an integrated conceptual framework that connects technological readiness, organizational readiness, and environmental readiness factors with sustainable business performance outcomes through the mediating role of AI adoption. The framework extends the traditional TOE model by incorporating AI adoption as a central mediating construct and sustainable business performance as a multidimensional outcome variable.

The framework posits that successful AI adoption in SMEs results from the convergence of technological capabilities, organizational support structures, and environmental pressures. These factors collectively influence the extent and effectiveness of AI adoption, which in turn drives sustainable business performance across economic, operational, and environmental dimensions.

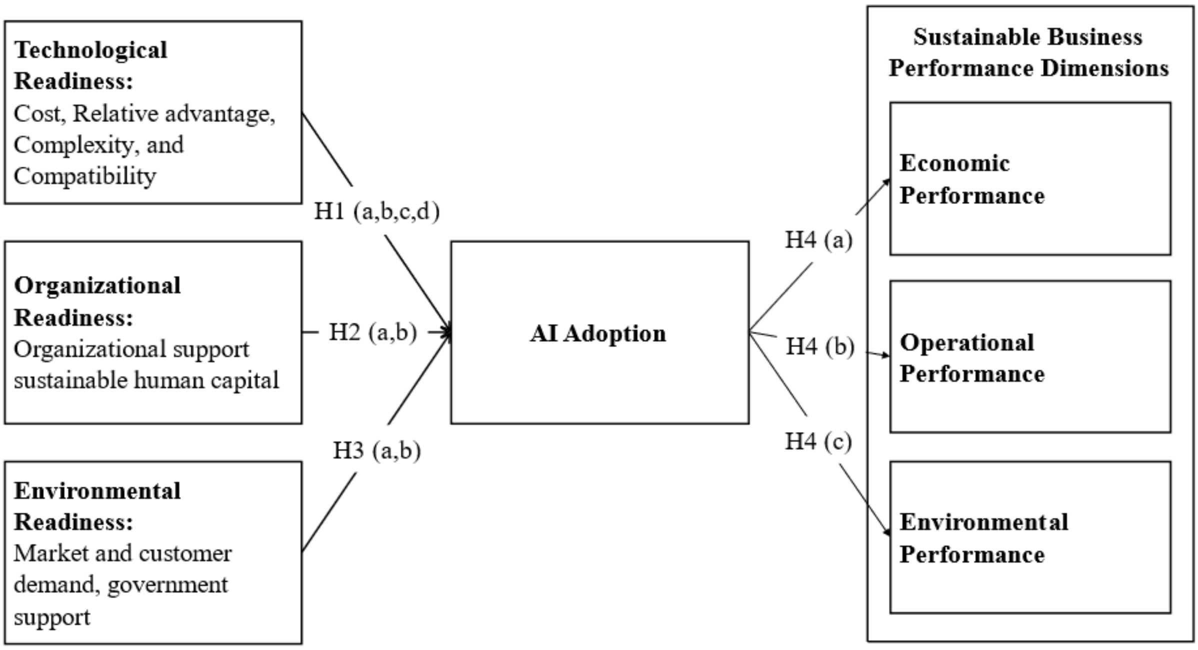

Figure 1: Research framework.

2.8. Hypothesis Development

Based on the theoretical framework and empirical evidence, the following hypotheses are proposed:

Technological Readiness Hypotheses:

H1a: Relative advantage positively influences AI adoption in SMEs.

H1b: Compatibility positively influences AI adoption in SMEs.

H1c: Complexity negatively influences AI adoption in SMEs.

H1d: Cost considerations negatively AI adoption in SMEs.

Organizational Readiness Hypotheses:

H2a: Organizational support positively influences AI adoption in SMEs.
H2b: Sustainable human capital positively influences AI adoption in SMEs.
Environmental Readiness Hypotheses:
H3a: Market and customer demand positively influence AI adoption in SMEs.
H3b: Government support positively influences AI adoption in SMEs.
Performance Outcome Hypotheses:
H4a: AI adoption positively influences economic performance in SMEs.
H4b: AI adoption positively influences operational performance in SMEs.
H4c: AI adoption positively influences environmental performance in SMEs.
Mediating Effect Hypotheses:
H5a: AI adoption mediates the relationship between technological readiness and sustainable business performance.
H5b: AI adoption mediates the relationship between organizational readiness and sustainable business performance.
H5c: AI adoption mediates the relationship between environmental readiness and sustainable business performance.

This comprehensive framework and hypothesis structure provide the foundation for empirical investigation of human-AI collaboration dynamics in SME contexts, contributing to both theoretical understanding and practical guidance for implementation strategies.

3. RESEARCH DESIGN

This study uses a positivist research philosophy supported by a deductive approach to examine how technological, organizational, and environmental factors influence AI adoption in SMEs. Following Saunders et al. (2019), the research employs a quantitative mono-method design with a cross-sectional survey strategy to test the proposed hypotheses based on the Technology-Organization-Environment (TOE) theoretical framework.

3.1. Data Collection And Instrumentation

A structured questionnaire was developed based on validated instruments from established studies (Badghish & Soomro, 2024; Abdul-Rashid et al., 2017; Alraja et al., 2022). All constructs were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree) to ensure consistency and comparability across measures.

3.2. Construct Operationalization

Technological Readiness was measured through four dimensions: cost (2 items), relative advantage (3 items), complexity (2 items), and compatibility (2 items). Organizational Readiness encompassed organizational support (3 items) and sustainable human capital (4 items). Environmental Readiness included market and customer demand (3 items) and government support (4 items). AI Adoption was assessed using 8 items covering monitoring capabilities, resource optimization, and decision-making support (Dey et al., 2024). Sustainable Business Performance was operationalized across three dimensions: economic performance (4 items), operational performance (8 items), and environmental performance (6 items).

3.3. Population And Sample Frame

The target population consisted of SMEs operating in Malaysia across manufacturing, technology, and service sectors. A purposive sampling approach was employed to ensure adequate representation across different SME sectors (manufacturing, technology, services) and firm sizes (small: 5-75 employees; medium: 76-200 employees). This purposive approach enhances the external validity and generalizability of findings across diverse SME contexts.

3.4. Data Collection Procedure

Data collection was conducted through a multi-channel approach combining online and offline survey administration. The questionnaire was distributed via Google Forms through email invitations and social media platforms (WhatsApp, Telegram), supplemented by in-person distribution where accessibility permitted. This hybrid approach was designed to maximize response rates and ensure broad demographic representation.

Prior to data collection, a pilot study was conducted with 30 SME representatives to assess instrument clarity, content validity, and completion time. Minor refinements were made based on pilot feedback to enhance questionnaire comprehensibility.

3.5 Data Analysis

Data analysis employed Structural Equation Modeling using Partial Least Squares (SEM-PLS) via SmartPLS software, chosen for its appropriateness in examining complex relationships with multiple constructs and its robustness with relatively smaller sample sizes (Hair et al., 2019).

3.5.1. Sample Characteristics

The selection of 151 Malaysian SMEs across diverse sectors was made with practical considerations in mind, while ensuring that the sample size adheres to established SEM-PLS criteria. According to Cohen (1988), using GPower 3.1* (Faul et al., 2009) for statistical power analysis, the required sample size for detecting medium effects ($f^2 = 0.15$) at $\alpha = 0.05$ and 80% power with three predictors is 77, and our sample of 151 achieves 96% power, surpassing the conventional threshold. Moreover, based on the guidelines of Hair et al. (2014), for three predictors with an anticipated R^2 value of 0.50, the minimum required sample size is 52. Our sample of 151 exceeds this by 190%, further confirming its statistical adequacy. The robustness of the sample size is also supported by the achieved model quality indicators, such as high explanatory power (R^2 = 0.629–0.851).

Table 1: Sample Demographics.

Characteristic	Category	Frequency	Percentage
Industry Sector	Manufacturing	43	28.48%
	Technology	31	20.53%
	Services	61	40.40%
	Others	16	10.59%
Company Size	Small (5-75 employees)	80	53.00%
	Medium (76-200 employees)	71	47.00%
Years of Operation	< 5 years	35	23.18%
	5-10 years	49	32.45%
	11-20 years	42	27.81%
	> 20 years	25	16.56%
Annual Revenue (RM)	< 1 million	57	37.75%
	1-5 million	61	40.39%
	5-20 million	25	16.56%
	> 20 million	8	5.30%
Current AI Usage	Yes	50	33.11%
	Planning to adopt	56	37.09%
	No	45	29.80%

While the sample size of 151 SMEs may not fully capture the entire sectoral diversity of Malaysia's SMEs, a purposive sampling strategy was employed to ensure adequate representation. The sample was drawn from key economic regions, including Kuala Lumpur, Johor, Penang, and Selangor, which are major hubs for SMEs in Malaysia.

This regional focus ensures that the sample reflects a diverse range of industries, including manufacturing, technology, and services, and includes SMEs of different sizes (small: 5–75 employees; medium: 76–200 employees) and varying stages of technological adoption. The purposive sampling method allowed for the deliberate selection of SMEs based on specific criteria, ensuring that sectoral and regional diversity was captured. While regionally concentrated, this approach ensures that the sample reflects broader trends within Malaysia's SME landscape, particularly in its emerging economy context. The purposive sampling strategy enhances the representativeness of the sample, ensuring sectoral and regional diversity that supports the generalizability of our findings.

3.5.2. Descriptive Statistics

Table 2 presents the descriptive statistics for all study constructs. All variables demonstrated acceptable normality with skewness and kurtosis values within recommended thresholds.

Table 2: Descriptive Statistics.

Construct	Mean	SD	Min	Max	Skewness	Kurtosis
Technological Readiness (TR)	3.87	0.93	1	5	-0.79	0.54
Organizational Readiness (OR)	3.77	0.96	1.20	5	-0.68	0.18
Environmental Readiness (ER)	3.36	0.88	1	5	-0.36	0.56
AI Adoption (AI)	3.81	0.87	1.17	5	-0.72	0.61
Economic Performance (ECP)	3.83	0.90	1.25	5	-0.62	0.11
Operational Performance (OP)	3.91	0.84	1.33	5	-0.67	0.50
Environmental Performance (EVP)	3.86	0.86	1	5	-0.73	0.70

Note: All Constructs Measured On A 5-Point Likert Scale (1 = Strongly Disagree, 5 = Strongly Agree)

3.6. Measurement Model Assessment

3.6.1. Reliability And Convergent Validity

The measurement model evaluation demonstrates satisfactory reliability and convergent validity across all constructs (see Table 3).

All constructs exceeded the recommended thresholds for internal consistency reliability, with Cronbach's alpha values ranging from 0.774 to 0.875, and composite reliability values between 0.777 and 0.909, well above the 0.70 threshold (Hair et al., 2021). Convergent validity was established through Average Variance Extracted (AVE) values, with all constructs surpassing the 0.50 criterion, ranging from

0.525 to 0.667.

Table 3: Construct Reliability and Validity.

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
TR	0.859	0.867	0.899	0.642
OR	0.840	0.865	0.882	0.558
ER	0.867	0.886	0.906	0.661
AI	0.875	0.875	0.909	0.667
ECP	0.781	0.809	0.855	0.597
OP	0.774	0.777	0.846	0.525
EVP	0.780	0.826	0.858	0.606

Note: Thresholds: Cronbach's a ≥ 0.70; Composite Reliability ≥ 0.70; AVE ≥ 0.50

3.6.2. Indicator Loadings

All indicator loadings are above the recommended threshold of 0.50, ranging from 0.584 to 0.918, confirming adequate indicator reliability. The highest loadings were observed for Environmental Readiness items (0.647-0.918), while the lowest acceptable loadings were found in Organizational Readiness items (0.584-0.885), indicating good measurement quality across all constructs.

3.6.3. Discriminant Validity

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) criterion, with all values below the conservative 0.85 threshold (see Table 4). The HTMT values ranged from 0.511 to 0.817, confirming adequate discriminant validity between all construct pairs. The Fornell-Larcker criterion was also satisfied, with the square root of each construct's AVE exceeding its correlations with other constructs.

Table 4: Discriminant Validity Assessment (HTMT).

	AI	ECP	ER	EVP	OP	OR	TR
AI	0.817						
ECP	0.606	0.769					
ER	0.674	0.687	0.806				
EVP	0.597	0.574	0.528	0.77			
OP	0.629	0.553	0.584	0.511	0.724		
OR	0.636	0.642	0.624	0.545	0.623	0.741	
TR	0.687	0.626	0.639	0.773	0.624	0.638	0.799

Note: Threshold: HTMT ≤ 0.85

3.7. Structural Model Assessment

3.7.1 Path Coefficients And Hypothesis Testing

The structural model results reveal significant relationships supporting most hypotheses (see Table 5). Bootstrap analysis with 5,000 resamples confirmed statistical significance at $p < 0.01$ for all AI adoption antecedents and AI-performance relationships. Organizational Readiness emerged as the strongest predictor of AI Adoption ($\beta = 0.442$, $t = 5.214$, $p < 0.001$), followed by Technological Readiness ($\beta = 0.390$, $t = 5.258$, $p < 0.001$) and Environmental Readiness ($\beta = 0.147$, $t = 2.449$, $p < 0.01$).

Table 5: Structural Model Results - Direct Effects.

Hypothesis	Path	β	t-value	p-value	95% CI	f²	Result
H1	TR → AI	0.390***	5.258	< 0.001	[0.245, 0.541]	0.294	Supported
H2	OR → AI	0.442***	5.214	< 0.001	[0.287, 0.618]	0.315	Supported
H3	ER → AI	0.147***	2.449	< 0.01	[0.027, 0.260]	0.034	Supported
H4a	AI → ECP	0.818***	32.174	< 0.001	[0.764, 0.863]	2.015	Supported
H4b	AI → OP	0.875***	35.496	< 0.001	[0.825, 0.922]	3.265	Supported
H4c	AI → EVP	0.793***	22.283	< 0.001	[0.719, 0.857]	1.697	Supported

**Note: **p < 0.001; β = standardized path coefficient; CI = confidence interval.*

3.7.2. Coefficient of Determination and Effect Sizes

The model demonstrates substantial explanatory power, with AI Adoption explaining 66.8% of Economic Performance variance ($R^2 = 0.668$), 62.9% of Operational Performance ($R^2 = 0.629$), and 76.6% of Environmental Performance ($R^2 = 0.766$).

Table 6: Coefficient Of Determination And Effect Sizes.

Endogenous Construct	R²	Adjusted R²	Effect Size	Assessment
AI Adoption	0.851	0.847	Large	Substantial
Economic Performance	0.668	0.666	Large	Moderate
Operational Performance	0.629	0.627	Large	Moderate
Environmental Performance	0.766	0.764	Large	Substantial

Note: R^2 thresholds: 0.25 (weak), 0.50 (moderate), 0.75 (substantial); $Q^2 > 0$ indicates predictive relevance.

The TOE factors collectively account for 85.1% of AI Adoption variance ($R^2 = 0.851$), indicating strong predictive relevance (See Table 6). And the Figure 2 below illustrates the results Structural model results.

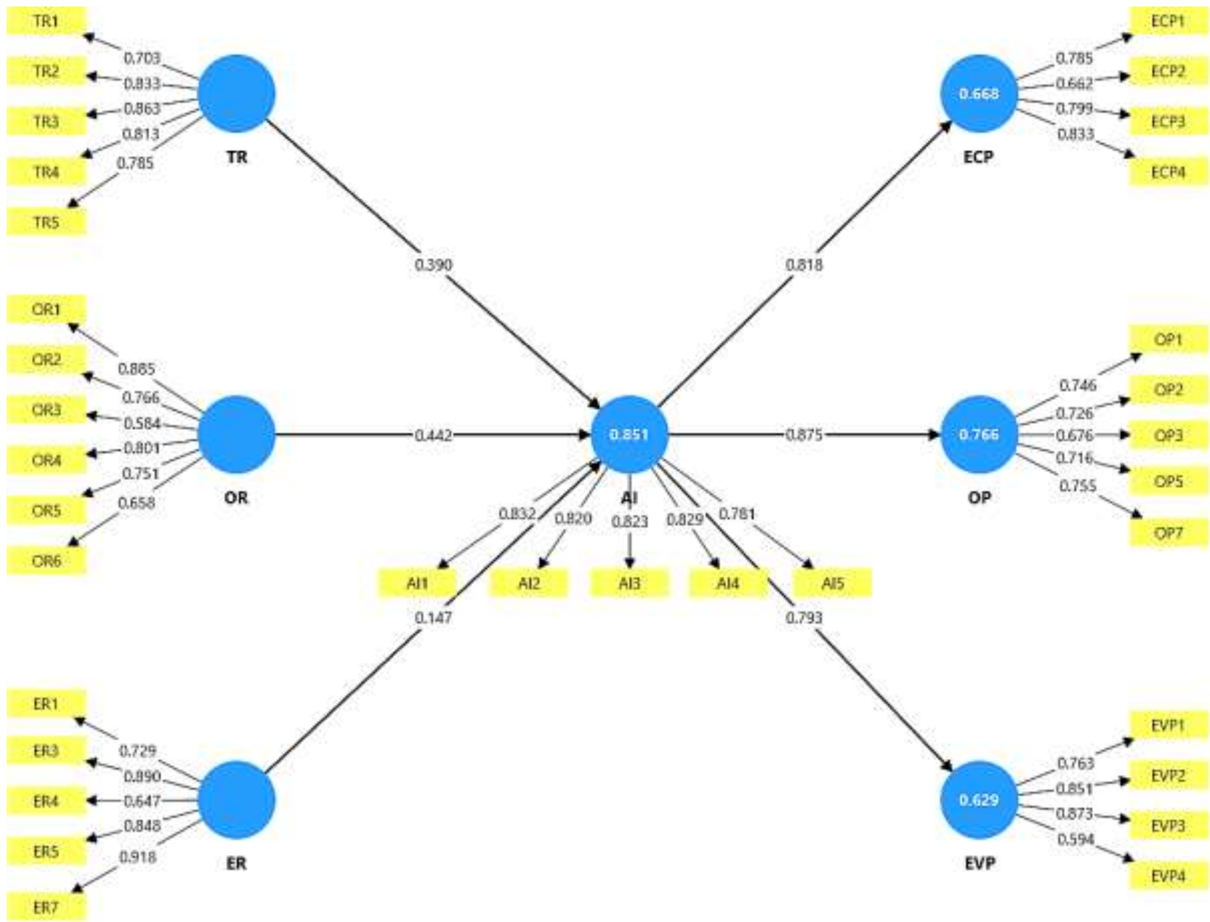

Figure 2: The Structural Model Results

3.7.3 Mediation Analysis

The mediation analysis reveals significant indirect effects of all TOE factors on performance outcomes through AI Adoption (see Table 7). Organizational Readiness demonstrates the strongest indirect effects, particularly on Operational Performance (β = 0.387, $p < 0.001$), followed by Economic Performance (β = 0.361, $p < 0.001$) and Environmental Performance (β = 0.351, $p < 0.001$).

Table 7: Indirect Effects (Mediation Analysis).

Path	β	t-value	p-value	95% CI	Result
TR → ECP (via AI)	0.319***	5.272	< 0.001	[0.203, 0.444]	Supported
TR → OP (via AI)	0.341***	5.326	< 0.001	[0.217, 0.471]	Supported
TR → EVP (via AI)	0.309***	4.552	< 0.001	[0.187, 0.454]	Supported
OR → ECP (via AI)	0.361***	5.218	< 0.001	[0.237, 0.508]	Supported
OR → OP (via AI)	0.387***	5.032	< 0.001	[0.250, 0.550]	Supported
OR → EVP (via AI)	0.351***	5.677	< 0.001	[0.236, 0.478]	Supported
ER → ECP (via AI)	0.120***	2.367	0.018	[0.021, 0.220]	Supported
ER → OP (via AI)	0.129***	2.425	0.015	[0.024, 0.229]	Supported
ER → EVP (via AI)	0.117***	2.436	0.015	[0.021, 0.208]	Supported

Note: **p < 0.05, **p < 0.001.

4. DISCUSSION

This study investigates which factors within the TOE framework most significantly influence AI adoption among Malaysian SMEs and why. The empirical findings of this study provide significant insights into the factors driving AI adoption among Malaysian SMEs and its subsequent impact on sustainable business performance. The results strongly support the applicability of the TOE framework in the Malaysian SME context, revealing nuanced relationships that contribute to both theoretical understanding and practical implications for digital transformation initiatives.

The strongest predictor of AI adoption was organizational readiness (β = 0.442, $p < 0.001$), confirming that SMEs prioritize organizational capabilities when making AI investment decisions. Highlighting the importance of internal support structures and human capital development (Lada et al., 2023). This finding supports previous research emphasizing leadership commitment and sustainable human resource practices as enablers of technological innovation (Sharma et al., 2022; Chaubey & Sahoo, 2021). The significant effect size ($f^2 = 0.315$) indicates that organizational factors have substantial practical importance beyond statistical significance. In practical terms, if an SME invests in securing leadership buy-in and equips the workforce with the necessary AI competencies, it could see a 44% increase in AI adoption. This could involve initiatives such as top management articulating a clear AI strategy and providing employees with targeted upskilling in AI technologies. For instance, consider a mid-size manufacturer deliberating whether to fund an AI-enabled quality-check line. When leadership allocated resources to employee training on AI tools, their odds of adopting these technologies nearly doubled, illustrating the critical role of organizational readiness in successful AI implementation.

Technological readiness demonstrated a moderate influence on AI adoption ($\beta = 0.390$, $p < 0.001$). This finding aligns with Rogers' (2003) diffusion of innovation theory, which emphasizes the critical role of perceived relative advantage and compatibility in technology adoption (Azhar et al., 2025). For Malaysian SMEs operating with limited resources, the tangible benefits of AI technologies — such as cost reduction, operational efficiency, and competitive advantage —appear to outweigh the implementation challenges (Dwivedi et al., 2021). In practical terms, an SME that focuses on making AI tools compatible with its existing IT infrastructure, selects user-friendly AI solutions, and provides training to reduce perceived complexity can expect a 39% increase in the likelihood of AI adoption (Othman et al., 2025). For example, a business that invests in AI tools seamlessly integrating with its current ERP system or offers foundational AI training to employees can expect a notable increase in adoption. By addressing technological barriers, SMEs can boost AI adoption by approximately 40%, resulting in significant long-term returns through operational efficiencies, cost savings, and enhanced competitive advantage. Conversely, firms that retain legacy enterprise resource planning systems without adapting to AI technologies achieve only marginal efficiency gains, highlighting the risks of failing to invest in technological readiness.

However, the relatively weaker but significant effect of environmental readiness ($\beta = 0.147$, $p < 0.01$) suggests that while external pressures and government support play important roles, internal organizational factors remain more decisive for SMEs in emerging markets. In practical terms, external influences such as government incentives or market pressures can increase the likelihood of AI adoption by 14.7% for every standard deviation increase in these factors. To illustrate, initiatives like Malaysia's Digital Economy Corporation's AI Digital Incentive or tax benefits under the Income Tax (Deduction for Investment in Approved Automated Equipment) Rules 2017 can serve as strategic levers to bolster AI adoption (Inland Revenue Board of Malaysia, 2022). Policymakers could leverage these mechanisms, thereby empowering SMEs while also supporting their internal capability-building. While external influences should not be ignored, SMEs should prioritize strengthening their internal capabilities, such as upgrading technology and building organizational support, as these factors have a more substantial impact on adoption. By focusing on these internal aspects, SMEs can drive AI adoption more effectively, without relying solely on external pressures.

On the other hand, the substantial effects of AI adoption on all three performance dimensions validate the strategic value of AI investments for SMEs. Operational performance showed the strongest relationship ($\beta = 0.875$, $p < 0.001$), indicating that AI technologies enable SMEs to improve operational efficiency and streamline processes, thereby enhancing productivity and cost-effectiveness. AI adoption drives an 87% improvement in operational metrics, including productivity, process efficiency, quality control, and resource utilization (Agbaakin, 2025). For SMEs, this could mean faster production cycles, fewer errors, and better resource management. For instance, implementing AI tools that optimize scheduling can lead to significant improvements in productivity. AI-driven scheduling cut downtime so severely that on-time delivery rose from 82% to 90% within six months, illustrating a move from bottleneck to breakthrough. AI-driven quality control can also reduce defects and enhance product consistency. The operational benefits emphasize how AI can streamline internal processes and boost overall efficiency. These practical outcomes support McKinsey Global Institute's projections of AI's economic impact (Bughin et al., 2018), emphasizing AI's potential to improve both profitability and operational efficiency.

The findings indicate that AI adoption has a substantial positive effect on environmental performance among Malaysian SMEs ($\beta = 0.793$, $p < 0.001$), positioning AI as a critical driver in advancing organizational sustainability outcomes. Specifically, AI technologies facilitate achieving sustainability objectives by optimizing resource allocation and minimizing operational waste, as evidenced by significant improvements in performance metrics (Ahmad et al., 2021). Empirical data reveal that firms integrating AI can achieve up to a 79% increase in environmental performance, marked by measurable outcomes such as a 20% reduction in energy consumption and decreased material waste through predictive maintenance and enhanced operational processes (Ranpara, 2025). Furthermore, AI adoption supports SMEs in complying with environmental regulations and curbing overall carbon emissions. Collectively, these results clarify that AI functions not only as a lever for operational efficiency but also as a strategically significant tool in achieving integrated sustainability and profitability goals within the SME context.

In addition, economic performance ($\beta = 0.818$, $p < 0.001$) effects demonstrate AI's capacity to deliver comprehensive business improvements. AI adoption results in an 80% improvement in economic performance, reflecting gains in profitability, revenue growth, cost efficiency, and return on investment. In practical terms, SMEs can expect tangible financial benefits from adopting AI, such as a 15-20% reduction in operational costs through automation and a 10-20% increase in revenue from enhanced customer targeting (Agbaakin, 2025). The practical takeaway here is that AI adoption can substantially improve profitability and reduce costs, making it a worthwhile investment for SMEs looking to gain a competitive edge and improve bottom-line results.

The significant mediation effects confirm AI adoption as a critical pathway through which organizational capabilities translate into performance outcomes. Organizational readiness showed the strongest indirect effects on all performance dimensions ($\beta = 0.351$-0.387, p-value < 0.001), indicating substantial mediation. These findings suggest that SMEs should prioritize developing organizational readiness to effectively leverage AI technologies and drive improvements in operational performance, including enhanced efficiency, productivity, and overall competitiveness. However, it is important to acknowledge potential limitations that could affect these strong mediation effects. For instance, the size of the firm might influence the level of organizational readiness required for effective AI adoption. Larger firms may have more resources to dedicate to AI readiness, potentially skewing results. Additionally, sector-specific factors could play a role; some industries might face unique challenges or opportunities that impact the effectiveness of AI integration. By recognizing these limitations, we can better tailor AI adoption strategies to accommodate varying contexts, thereby ensuring more reliable and applicable conclusions.

5. CONCLUSION

This investigation examined how the Technology-Organization-Environment framework explains artificial intelligence adoption patterns among Malaysian small and medium enterprises and the subsequent effects on multidimensional sustainable business performance. Through quantitative analysis of 151 SMEs using structural equation modelling, the study reveals critical insights into the mechanisms driving digital transformation in emerging economy contexts. The empirical analysis demonstrates that organizational capabilities serve as the primary catalyst for AI adoption ($\beta = 0.442$), with technological readiness ($\beta = 0.390$) and environmental pressures ($\beta = 0.147$) providing complementary influences. These factors collectively explain 85.1% of adoption variance, while AI implementation drives substantial improvements across operational ($\beta = 0.875$), economic ($\beta = 0.818$), and environmental performance dimensions ($\beta = 0.793$). The mediation analysis reveals that AI adoption functions as a critical conduit through which organizational capabilities translate into sustainable performance outcomes, with all p-values < 0.01 across different pathways.

This research contributes to the literature by validating the TOE framework's explanatory power in resource-constrained environments, particularly within the context of AI adoption. It also expands our understanding of the dominant role of organizational capabilities in developing economies, contrasting with studies from developed markets where technological infrastructure typically predominates. The study provides novel evidence on how AI adoption can be a strategic enabler of organizational transformation, especially in the context of sustainability, and demonstrates AI's potential to reconcile economic growth with environmental stewardship in SMEs.

For SME managers, the study provides actionable insights into the importance of organizational capabilities in successfully adopting AI. Managers should focus on building a robust organizational foundation by assessing technological compatibility, strengthening internal support structures, and fostering a culture that embraces digital transformation. Prioritizing organizational readiness, leadership commitment, resource allocation, and employee skills development will enable SMEs to leverage AI technologies effectively. As immediate first steps, managers can conduct a skills audit to identify current and needed competencies and pinpoint key AI use cases that align with business objectives. Additionally, forming a cross-departmental team to champion AI initiatives can facilitate seamless integration and foster greater buy-in across the organization. The results highlight that strengthening organizational capabilities, alongside technological readiness, can significantly enhance AI adoption and optimize its impact on operational performance, efficiency, and overall business outcomes. Moreover, human capital development is key to maximizing the benefits of AI, with a focus on training staff to use AI tools effectively and on improving business processes across various performance dimensions.

From a policy perspective, the findings suggest that policymakers should focus on creating an environment that supports the development of organizational capabilities within SMEs. Policymakers can facilitate AI adoption by emphasizing organizational readiness, such as offering training programs for SME leaders and employees, alongside support for technological infrastructure. Providing financial incentives for AI implementation and fostering partnerships between SMEs and technology providers can help reduce the initial barriers to AI adoption. Policymakers should recognize that while technological infrastructure is crucial, investing in organizational capabilities, fostering a digital transformation mindset, and supporting skill development will yield more sustainable benefits in the long run. Aligning digital transformation efforts with national strategies, such as Malaysia's Vision 2030, will be essential for creating a cohesive strategy that supports the growth and competitiveness of SMEs in the digital age.

6. LIMITATIONS AND FUTURE RESEARCH

While the study's cross-sectional design limits causal interpretations, and the focus on Malaysian SMEs constrains the generalizability to other regions, the findings provide a robust foundation for understanding AI adoption in emerging economies. Future research should examine longitudinal trends to establish causal relationships and explore how TOE-performance relationships evolve during the implementation phases of AI adoption. Moreover, cross-cultural studies would also provide valuable insights into how institutional factors influence AI adoption patterns across various emerging markets. Industry-specific analyses would provide targeted insights for sector-specific digital strategies, while mixed-methods approaches could reveal a deeper understanding of the psychological and cultural factors underlying the quantified relationships. Additionally, comparative studies between developed and emerging market SMEs could clarify how the economic development stage moderates AI adoption dynamics.

This research establishes a foundation for understanding AI-driven digital transformation in emerging economy SMEs, demonstrating that a comprehensive approach that integrates technological, organizational, and environmental factors can enable SMEs to gain sustainable competitive advantages. As digital technologies continue to reshape the global business landscape, the findings support evidence-based strategies that SMEs can use to harness AI's transformative potential while contributing to sustainable economic development.

Credit Roles

Qi Yi Thong: Writing - original draft, Conceptualization, Methodology, Formal analysis, Validation. Mohammad Falahat: Supervision. Nohman Khan: Writing - review & editing, Formal analysis, Validation. Murali Raman: Writing – review & editing. Devinder Kaur: Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

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Disclosure Statement

The authors report there are no competing interests to declare.

Ethics Clearance

This study was conducted in accordance with the ethical guidelines and was approved by the Research Management Centre, Asia Pacific University of Technology and Innovation (Approval No. APUEFA/01/2025). All participants provided informed consent prior to participation.

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