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When Readiness Is Not Enough: Explaining the AI Adoption Paradox in Organisations from a Developing Economy

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Abstract

Artificial intelligence (AI) adoption is increasingly recognised as a strategic driver of productivity growth, innovation efficiency, resource optimisation, and sustainable economic competitiveness in knowledge-intensive organisations. Particularly in developing economies, firms invest in AI technologies to enhance operational performance, strengthen strategic decision-making, and create long-term economic value. However, organisational readiness does not always translate into successful implementation. This study examines the determinants of AI adoption and introduces the concept of the AI Adoption Paradox, where readiness conditions fail to produce corresponding adoption outcomes. Using survey data from 410 professionals across knowledge-intensive sectors in Sri Lanka, Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied. The model explained 51.3% of the variance in AI adoption. The findings reveal that AI awareness, technological infrastructure, and top management support positively influence AI adoption, while digital skills readiness demonstrates a significant inverse relationship. Organisational culture significantly moderates the relationship between digital skills readiness and AI adoption. The paradox framing offers a novel theoretical contribution by challenging the linear assumption that readiness automatically leads to adoption. The findings suggest that sustainable AI adoption depends not only on readiness, but on an organisation's ability to convert readiness into behavioural acceptance and strategic economic value.

Keywords: AI adoption, Artificial intelligence, Digital skills readiness, Organisational culture, Technological infrastructure, Top management support

Introduction

The rapid advancement of artificial intelligence (AI) technologies has significantly transformed organisational and economic systems, reshaping how firms allocate resources, manage productivity, and sustain strategic competitiveness in an increasingly digital economy (Rashid & Kausik, 2024; Murire, 2024). Across industries, organisations are investing heavily in AI-driven systems to improve operational efficiency, enhance data-driven decision-making, and generate sustainable economic value through innovation and long-term performance improvement. AI is increasingly viewed not only as a technological tool but also as a strategic economic asset capable of influencing labour transformation, cost optimisation, and firm-level competitiveness. Within this evolving landscape, the concept of organisational readiness has emerged as a central determinant of successful technology adoption, reflecting the extent to which firms possess the technological infrastructure, human capabilities, and managerial commitment necessary to implement advanced digital systems effectively (Silva et al., 2024; Nawaz et al., 2024).

Theoretical perspectives on technology adoption consistently emphasise the importance of readiness in enabling successful implementation outcomes and strengthening firm performance. The Technology–Organisation–Environment (TOE) framework highlights how technological capability, organisational structure, and environmental conditions jointly influence adoption decisions and innovation efficiency (Awa et al., 2017; Faiz et al., 2024). From an economic perspective, organisations with stronger infrastructure and strategic alignment are better positioned to convert technological investments into productivity gains and sustainable competitive advantage. Complementing this, organisational readiness for change theory underscores the role of collective commitment and shared efficacy in supporting the transition towards new technologies and improving the efficient utilisation of organisational resources (Budi Santoso Syarif et al., 2024). Empirical studies further suggest that factors such as AI awareness, technological infrastructure, digital skills readiness, and top management support are critical drivers of organisational preparedness for digital transformation initiatives and long-term value creation (Venugopal et al., 2024; Uren & Edwards, 2023; Kraus et al., 2022). These perspectives collectively assume a relatively linear relationship, whereby higher levels of readiness are expected to facilitate greater adoption, stronger innovation outcomes, and more effective utilisation of AI technologies.

Despite these theoretical expectations, emerging evidence indicates that the relationship between organisational readiness and AI adoption is more complex than previously assumed. In many organisational contexts, particularly within developing economies, investments in digital infrastructure and workforce capabilities have not consistently translated into measurable productivity improvements or successful adoption outcomes (Machucho & Ortiz, 2025; Michelotto & Joia, 2024). This discrepancy raises important economic concerns regarding inefficient resource allocation, underutilised

technological investments, and weakened strategic competitiveness. The presence of readiness conditions alone may therefore be insufficient to ensure implementation success or sustainable firm performance. Instead, the process of AI adoption may be influenced by additional behavioural, cultural, and contextual factors that determine whether readiness can be converted into actual organisational and economic value.

This study addresses this gap by examining the relationship between organisational readiness and AI adoption within knowledge-intensive firms in Sri Lanka, a context characterised by growing digital transformation efforts alongside structural and institutional constraints (Perera et al., 2025; Dedunu et al., 2025). Knowledge-intensive sectors such as information technology, higher education, financial services, and consulting are particularly relevant, as they rely heavily on intellectual capital and data-driven decision-making processes (Lee & Miozzo, 2019). While these sectors demonstrate increasing exposure to AI technologies, variations in organisational culture, workforce capabilities, and strategic alignment may influence the extent to which readiness translates into actual adoption.

This study, based on a survey of 410 professionals across these sectors, introduces the concept of the "AI Adoption Paradox." The AI adoption paradox is defined in this study as a theoretically unexpected condition in which organisational readiness factors, particularly digital skills readiness, do not translate into stronger AI adoption despite established adoption theories predicting a positive relationship (Awa et al., 2017; Kumar & Mittal, 2024). It is not assumed in advance, but operationalised and tested empirically through the structural model, where the paradox is evidenced by the significant inverse effect of digital skills readiness on AI adoption and the significant moderating role of organisational culture (Ali et al., 2022; Zhang et al., 2023). The findings indicate that while AI awareness, technological infrastructure, and top management support demonstrate significant positive relationships with AI adoption, digital skills readiness exhibits a significant inverse relationship, suggesting that readiness alone may not ensure successful implementation. This creates a theoretically meaningful contradiction, as one of the most expected readiness factors produces the opposite outcome. Furthermore, organisational culture significantly moderates the relationship between digital skills readiness and AI adoption, reinforcing the importance of contextual alignment (Ali et al., 2022; Zhang et al., 2023).

By framing these findings through a paradox lens, the study contributes theoretically, empirically, and managerially. First, it challenges the linear assumptions embedded in dominant technology adoption frameworks by demonstrating that readiness is necessary but not sufficient for AI adoption. Second, it extends existing research by introducing a behavioural and context-sensitive perspective that emphasises the role of organisational culture and socio-technical alignment in digital transformation processes. Third, it provides empirical evidence from a developing economy context, thereby addressing the limited availability of firm-level studies on AI adoption in Global South settings. These findings are particularly relevant for policymakers seeking to improve digital competitiveness and strategic AI investment in developing economies.

The remainder of this paper is structured as follows. The next section reviews the relevant literature on AI adoption and organisational readiness, with particular attention to behavioural and contextual influences. This is followed by the research methodology, including data collection and analytical techniques. The subsequent sections present the empirical findings and discuss their implications in relation to the AI adoption paradox. The paper concludes with theoretical and practical implications, along with directions for future research.

Literature review

Artificial intelligence (AI) has evolved from a set of computational tools supporting automation into a strategic organisational capability that shapes decision-making, innovation, productivity, and long-term competitiveness (Romeo & Lacko, 2025; Rashid & Kausik, 2024; Murire, 2024). Contemporary organisations increasingly deploy AI across functions to enhance efficiency, enable predictive analytics, improve resource allocation, and generate sustainable economic value. In knowledge-intensive environments, where firms rely heavily on intellectual capital and data-driven processes, AI technologies play a critical role in supporting organisational performance, innovation efficiency, and strategic competitiveness (Lee & Miozzo, 2019; Venugopal et al., 2024).

Despite its potential, AI adoption is not purely a technological process. Rather, it represents a broader organisational transformation involving structural, behavioural, and strategic changes (Madanchian & Taherdoost, 2025). Studies have emphasised that successful AI implementation requires not only technological infrastructure but also organisational alignment, workforce competencies, and managerial support (Faiz et al., 2024; Kraus et al., 2022). Consequently, the economic value created through AI depends heavily on whether organisations are prepared to accommodate these multidimensional changes.

However, empirical findings across contexts indicate that AI adoption remains uneven and often slower than anticipated, particularly in developing economies (Machucho & Ortiz, 2025). Many firms invest in digital technologies expecting productivity gains and competitive advantage, yet these investments do not always translate into effective organisational practices or measurable firm performance. This inconsistency highlights the need to examine AI adoption beyond technological determinants and to consider broader organisational and contextual influences.

Organisational readiness is widely recognised as a key determinant of successful technology adoption. It refers to the extent to which an organisation is prepared to implement and utilise new technologies effectively, encompassing both structural capabilities and psychological preparedness (Silva et al., 2024). The concept integrates multiple dimensions, including technological infrastructure, workforce competencies, leadership commitment, and organisational alignment (Nawaz et al., 2024).

From a theoretical perspective, organisational readiness for change theory emphasises that successful implementation depends on collective commitment and shared belief in the organisation's ability to execute change (Budi Santoso Syarif et al., 2024). This perspective suggests that readiness is not merely a function of resources, but

also reflects organisational attitudes, confidence, and willingness to transform. In digital environments, this becomes particularly important because AI adoption often requires significant adjustments in workflows, decision-making structures, and organisational routines (Michelotto & Joia, 2024).

Empirical research identifies several determinants of readiness in the context of AI adoption. These include awareness of AI technologies (Lachaiah & Hajdu Barat, 2026; Wang et al., 2025), robust technological infrastructure (Chen et al., 2023; Petrescu et al., 2022), workforce digital skills (Kumar & Mittal, 2024; Radhakrishnan et al., 2022; Sharma et al., 2021), and support from top management (Uren & Edwards, 2023; Venugopal et al., 2024; Radhakrishnan et al., 2022). Collectively, these factors are expected to improve innovation efficiency, productivity, and long-term value creation through digital transformation.

The Technology–Organisation–Environment (TOE) framework provides a comprehensive theoretical lens for analysing technology adoption at the organisational level (Awa et al., 2017). According to this framework, adoption decisions are influenced by technological, organisational, and environmental contexts. The technological context includes infrastructure and system compatibility; the organisational context includes resources, leadership, and internal processes; and the environmental context includes competition and regulatory pressures.

Within the TOE framework, technological infrastructure is considered a fundamental requirement for AI adoption. Organisations with advanced digital systems, integrated databases, and analytical capabilities are better positioned to implement AI-driven solutions and convert technological investments into productivity gains (Faiz et al., 2024; Uren & Edwards, 2023). Similarly, top management support and strategic vision play a critical role in legitimising innovation initiatives and ensuring effective resource allocation for sustainable competitive advantage (Kraus et al., 2022).

Workforce capabilities, particularly digital skills readiness, represent another important determinant. AI systems require employees who can interpret data, interact with digital platforms, and adapt to new technological environments (Rabie et al., 2026; Deepa et al., 2024). Without adequate human capital, technological investments may fail to generate expected outcomes. Additionally, awareness of AI technologies shapes organisational perceptions of benefits and risks, influencing openness to adoption (Machucho & Ortiz, 2025).

While the TOE framework provides a structured understanding of adoption determinants, it assumes that favourable technological and organisational conditions will naturally lead to successful implementation. This assumption may overlook organisational realities where available resources do not automatically produce adoption outcomes, particularly when behavioural resistance or weak cultural alignment interferes with implementation.

Beyond structural determinants, behavioural and contextual factors significantly shape AI adoption. Organisational behaviour literature suggests that individuals and groups may resist technological change due to uncertainty, perceived risks, or disruption

of established practices (Scholes, 2025). These responses can reduce the practical value of technological investments and weaken innovation efficiency.

In the context of AI adoption, uncertainty is especially relevant due to concerns regarding job displacement, ethical implications, and the reliability of algorithmic decision-making (Machucho & Ortiz, 2025). Such concerns may create cautious or resistant attitudes among employees, even in organisations that appear structurally prepared. This demonstrates that readiness must be supported by psychological acceptance and trust.

Organisational culture, defined as the shared values and norms guiding behaviour within firms, has been identified as a major contextual factor influencing adoption outcomes (Zhang et al., 2023). Cultures that promote innovation, learning, and collaboration are more likely to support successful implementation and sustainable value creation (Ali et al., 2022). Conversely, rigid or risk-averse cultures may hinder adoption by limiting engagement and flexibility.

Research further indicates that organisational culture often acts as a moderating variable, influencing the strength of relationships between technological determinants and adoption outcomes (Kwong et al., 2021). This means that even when organisations possess strong digital skills and infrastructure, the effectiveness of these resources depends on whether the cultural environment supports experimentation and change.

The dynamics of AI adoption in developing economies differ significantly from those in developed contexts. While many developing countries have improved digital infrastructure and workforce capabilities, institutional constraints, limited strategic resources, and organisational maturity challenges remain significant (Perera et al., 2025; Dedunu et al., 2025). These limitations can reduce the ability of firms to convert readiness into measurable productivity improvements and sustainable competitive advantage.

Sri Lanka represents a particularly relevant context for examining these dynamics. The country has experienced growth in knowledge-intensive sectors such as information technology, business process outsourcing, and financial services, with a workforce exceeding 120,000 professionals engaged in ICT-related activities (ICT Industry Information - Service Providers in Sri Lanka - EDB, 2022). Despite this growth, uneven digital transformation practices and cultural misalignment continue to influence AI adoption (Perera et al., 2025).

A particularly important unresolved issue concerns digital skills readiness. Prior studies generally assume that stronger workforce digital capability should improve AI adoption. However, limited research has examined situations where higher digital readiness may produce inverse or contradictory outcomes. Skilled employees may become more critical of poorly implemented systems, more aware of operational risks, or more resistant to technologies that threaten autonomy and professional judgment. Existing literature rarely explains why a theoretically positive readiness factor may generate negative adoption outcomes.

This creates a major research gap. Most studies focus on identifying determinants of readiness rather than explaining why these determinants fail to produce expected

implementation results. There is also limited attention to null or contradictory findings, particularly in developing economies where contextual constraints are stronger.

This study conceptualises this inconsistency as the "AI Adoption Paradox." The paradox arises when organisations demonstrate moderate to high readiness but fail to achieve corresponding levels of AI adoption. Rather than treating readiness as sufficient, this perspective explains adoption as the result of interaction between structural capability, behavioural responses, and organisational culture.

By introducing the AI adoption paradox, this study extends existing literature on technology adoption and digital transformation. It shifts the focus from determinant-based explanations toward understanding the conditions under which readiness fails to translate into adoption. This is particularly important for firms seeking productivity improvement, innovation efficiency, and sustainable economic value through AI investment.

Accordingly, this study moves beyond traditional readiness models to examine how organisational culture moderates the relationship between digital skills readiness and AI adoption, offering a more comprehensive explanation of adoption outcomes in developing economy contexts.

Based on the reviewed literature and identified theoretical contradiction, the following hypotheses are proposed.

H1: AI awareness has a positive effect on AI adoption in organisations.

Prior studies suggest that awareness of AI technologies enhances understanding of potential benefits and reduces uncertainty, thereby encouraging adoption decisions (Lachaiah & Hajdu Barat, 2026; Wang et al., 2025). Awareness shapes organisational perceptions and readiness for digital transformation (Machucho & Ortiz, 2025).

H2: Technological infrastructure has a positive effect on AI adoption in organisations.

The TOE framework highlights infrastructure as a critical enabler of technology adoption, as organisations with advanced digital systems are better positioned to implement AI solutions (Awa et al., 2017; Chen et al., 2023). Adequate infrastructure supports integration and scalability of AI applications (Faiz et al., 2024).

H3: Digital skills readiness has a positive effect on AI adoption in organisations.

Workforce capabilities are essential for AI implementation, as employees must possess the skills required to operate and adapt to digital systems (Kumar & Mittal, 2024; Radhakrishnan et al., 2022). Skilled employees facilitate effective utilisation of AI technologies (Deepa et al., 2024).

H4: Top management support has a positive effect on AI adoption in organisations.

Leadership commitment plays a crucial role in technology adoption by ensuring resource allocation and strategic direction (Kraus et al., 2022; Venugopal et al., 2024). Top management support legitimises innovation initiatives and drives organisational change (Uren & Edwards, 2023).

H5: Organisational culture moderates the relationship between digital skills readiness and AI adoption, such that the relationship is stronger in supportive organisational cultures.

Organisational culture influences how employee capabilities are translated into actual behaviour, particularly in technology adoption contexts (Ali et al., 2022; Zhang et al., 2023). Cultures that promote learning and innovation enhance the effectiveness of workforce skills in driving adoption outcomes (Kwong et al., 2021).

Variable Operationalization

Table 1: Variable Operationalization

Variable Type	Variable	Definition	Measurement Indicators (Sample Items)	Scale	Key References
Independent Variable	**AI Awareness**	The extent to which employees and organisations understand AI technologies, their applications, and potential benefits	Awareness of AI tools; understanding of AI applications; familiarity with AI-driven decision-making; perceived usefulness of AI	5-point Likert Scale	Lachaiah & Hajdu Barat (2026); Wang et al. (2025); Machucho & Ortiz (2025)
Independent Variable	**Technological Infrastructure**	The availability and adequacy of technological systems, digital platforms, and IT capabilities required to support AI implementation	Availability of digital systems; data integration capability; IT system compatibility; access to AI-related tools	5-point Likert Scale	Chen et al. (2023); Petrescu et al. (2022); Uren & Edwards (2023)

Independent Variable	**Digital Skills Readiness**	The level of employee competency in using digital technologies and adapting to AI-based systems	Employee technical skills; ability to use digital tools; adaptability to new technologies; data interpretation skills	5-point Likert Scale	Kumar & Mittal (2024); Radhakrishnan et al. (2022); Deepa et al. (2024)
Independent Variable	**Top Management Support**	The degree of commitment, support, and strategic involvement of leadership in AI adoption initiatives	Leadership encouragement; resource allocation; strategic vision for AI; managerial support for innovation	5-point Likert Scale	Kraus et al. (2022); Venugopal et al. (2024); Uren & Edwards (2023)
Moderating Variable	**Organisational Culture**	The shared values, beliefs, and norms that influence employee behaviour and openness to technological change	Innovation-oriented culture; openness to change; collaboration; support for learning and experimentation	5-point Likert Scale	Ali et al. (2022); Zhang et al. (2023); Kwong et al. (2021)
Dependent Variable	**AI Adoption**	The extent to which organisations implement and utilise AI technologies in their operational and decision-making processes	Use of AI in operations; integration of AI systems; frequency of AI usage; perceived effectiveness of AI implementation	5-point Likert Scale	Faiz et al. (2024); Kraus et al. (2022); Venugopal et al. (2024)

Source: Developed based on the Literature Review

Research Methodology

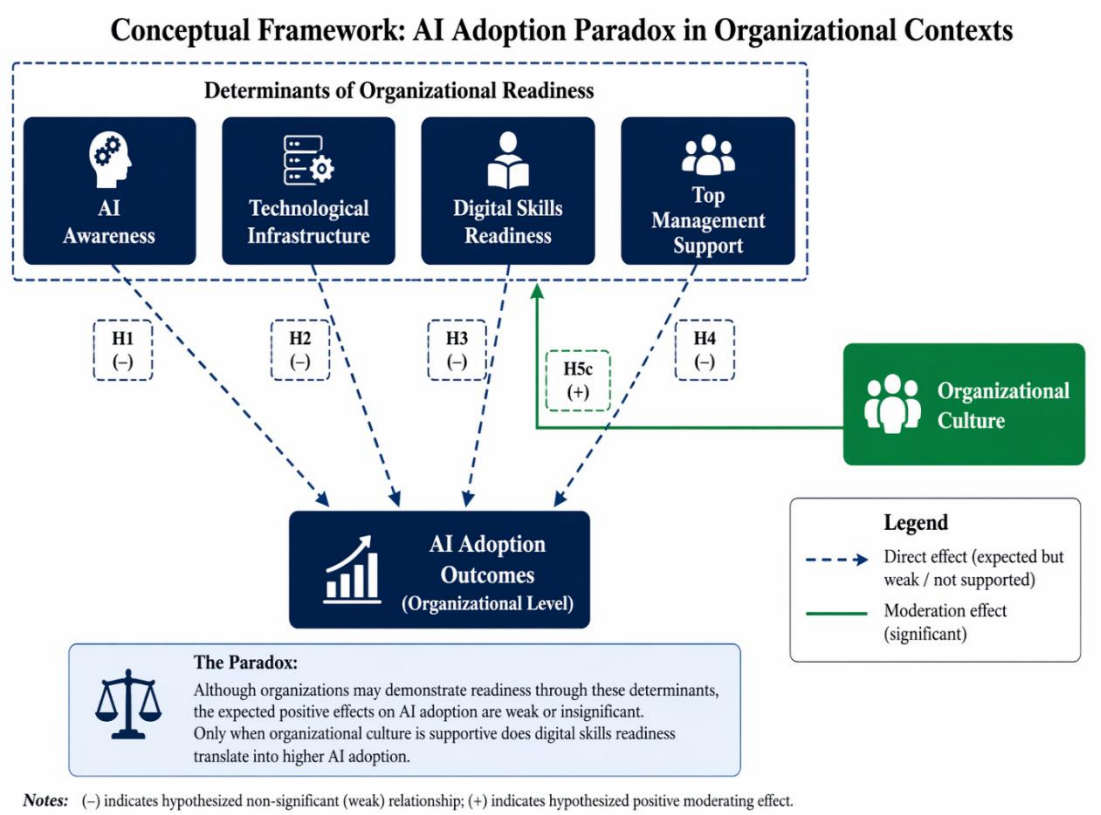

Figure 1: AI Adoption Paradox Conceptual Framework in Organisational Contexts
Source: Developed based on the Literature Review

This framework illustrates the AI adoption paradox, where key organisational determinants; AI awareness, technological infrastructure, digital skills, and top management support; exhibit weak direct effects on adoption outcomes. Organisational culture acts as a critical moderating factor, enabling digital skills readiness to translate into adoption, highlighting the importance of behavioural and contextual alignment in Organisations.

This study adopts a quantitative cross-sectional explanatory research design to examine the determinants of artificial intelligence (AI) adoption in organisational contexts within a developing economy. A deductive approach is employed, drawing on established theoretical frameworks such as the Technology–Organisation–Environment (TOE) model while extending them through a paradox-oriented interpretation.

The target population comprises professionals working in knowledge-intensive sectors in Sri Lanka, including information technology, financial services, higher education, consulting, and knowledge process outsourcing. These sectors represent a significant portion of the country's digitally engaged workforce and are considered appropriate contexts for examining AI adoption dynamics.

A non-probability convenience sampling approach was adopted due to the difficulty of obtaining a complete sampling frame of professionals working across

multiple knowledge-intensive sectors. Given the exploratory nature of organisational AI adoption research and the need to access experienced professionals directly involved in digital transformation processes, convenience sampling was considered appropriate and practically feasible. The final sample consisted of 410 respondents, which is considered adequate for PLS-SEM analysis. The sample size exceeds the commonly recommended minimum requirements for structural equation modelling, including the 10-times rule, which suggests that the sample should be at least ten times the largest number of structural paths directed at any endogenous construct. Since AI adoption is predicted by multiple direct and moderating relationships, a larger sample strengthens statistical power, improves model stability, and enhances the reliability of bootstrapping results. Therefore, the sample size of 410 is sufficient for assessing the proposed structural model and testing the hypothesised relationships. Primary data were gathered through a structured self-administered questionnaire distributed electronically. The questionnaire used a five-point Likert scale to measure all constructs.

The study examines AI awareness, technological infrastructure, digital skills readiness, and top management support as independent variables, organisational culture as a moderating variable, and AI adoption at the organisational level as the dependent variable.

Data analysis was conducted in two stages. First, SPSS was used to generate descriptive statistics and demographic profiles of respondents. Second, Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed using SmartPLS software to evaluate the measurement and structural models. Reliability and validity of the measurement model were assessed using Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and Heterotrait–Monotrait Ratio (HTMT) to ensure internal consistency, convergent validity, and discriminant validity of the constructs. Structural relationships and moderation effects were analysed using bootstrapping techniques.

Finally, a paradox-oriented interpretive approach was applied to examine the discrepancy between theoretically expected relationships and empirical findings. This enabled the identification of the AI adoption paradox, where key organisational determinants exhibit weak or statistically insignificant direct effects on adoption outcomes, while organisational culture demonstrates a selective moderating influence.

Ethical Considerations

Ethical considerations were carefully maintained throughout the study. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. Confidentiality and anonymity were assured, and responses were used solely for academic purposes. No personal identifiers were collected, ensuring participant privacy and research integrity.

Theory-driven Paradox Interpretation

Although H1–H4 are theoretically proposed as positive relationships based on established technology adoption literature, this study recognises that organisational readiness does not always translate into successful AI adoption. In developing economy contexts, readiness determinants such as awareness, infrastructure, skills, and

management support may produce weak, insignificant, or even negative effects due to behavioural resistance, cultural barriers, and contextual constraints. This theoretical contradiction forms the basis of the AI Adoption Paradox, where readiness alone is insufficient unless supported by enabling organisational conditions, particularly organisational culture.

Results and Analysis

Table 2: Demographic Analysis

Demographics		**Frequency**	**Percent** (%)
Gender	Male	224	54.6
	Female	178	43.4
	Prefer not to say	8	2.0
Age Group	Below 25	43	10.5
	25–34	168	41.0
	35–44	102	24.9
	45–54	68	16.6
	Above 55	29	7.1
Highest Education	Diploma	36	8.8
	Bachelor's Degree	195	47.6
	Master's Degree	135	32.9
	Other	25	6.1
	Doctorate	19	4.6
Sector of Employment	Higher Education	75	18.3
	KPO/BPO	55	13.4
	Financial Services	80	19.5
	Information Technology	151	36.8
	Consulting	49	12.0
Work Experience	Less than 2 years	54	13.2
	2–5 years	121	29.5
	6–10 years	112	27.3
	More than 10 years	123	30.0
	Total	410	100.0
Position Level	Middle Management	142	34.6
	Executive	126	30.7
	Operational Staff	56	13.7
	Senior Management	86	21.0

Source: Data Analysis Results, 2026

The demographic profile indicates a well-balanced and relevant sample drawn from knowledge-intensive sectors. A slight male majority (54.6%) is observed, with a predominantly young and mid-career workforce, as 41.0% fall within the 25–34 age group. The sample is highly educated, with over 80% holding bachelor's or postgraduate qualifications, supporting data reliability. Sector-wise, strong representation from information technology (36.8%) and financial services reflects digital exposure. Work experience is evenly distributed, with a notable proportion exceeding 10 years (30.0%). Additionally, the presence of middle and senior management respondents enhances the study's credibility, indicating informed organisational perspectives on AI adoption dynamics.

Table 3: Descriptive Statistics

	AI Awareness	Technological Infrastructure	Digital Skills Readiness	Top Management Support	Organisational Culture	AI Adoption
Mean	3.32	3.44	3.39	3.45	3.31	3.51
Median	3.00	3.43	3.14	3.29	3.00	3.43
Std. Deviation	0.58	0.63	0.60	0.60	0.61	0.67

Source: Data Analysis Results, 2026

The descriptive statistics indicate moderate perceptions across all constructs, with AI adoption recording the highest mean (3.51), suggesting relatively stronger agreement. Other variables show balanced responses around the midpoint. Standard deviations below 1.0 reflect consistent responses, indicating reliability and stability in respondents' perceptions regarding AI adoption determinants within organisations.

Table 4: Reliability

Construct	Cronbach's Alpha
AI Awareness	0.865
Digital Skills Readiness	0.893
Technological Infrastructure	0.905
Top Management Support	0.866
Organisational Culture	0.892
AI Adoption	0.914

Source: Data Analysis Results, 2026

The results indicate strong internal consistency, as all Cronbach's alpha values exceed 0.70. This confirms that the measurement items reliably capture their respective constructs, supporting the reliability of the measurement model.

Table 5: Convergent Validity Results

Construct	AVE	Threshold (≥ 0.50)	Convergent Validity
AI Awareness	0.552	Above Threshold	Established
Digital Skills Readiness	0.608	Above Threshold	Established
Technological Infrastructure	0.637	Above Threshold	Established
Top Management Support	0.555	Above Threshold	Established
Organisational Culture	0.606	Above Threshold	Established
AI Adoption	0.661	Above Threshold	Established

Source: Data Analysis Results, 2026

All constructs exceed the AVE threshold of 0.50, indicating adequate convergent validity. This confirms that the indicators effectively represent their respective constructs, supporting the validity of the measurement model.

Table 6: HTMT Discriminant Validity Assessment

Construct	AI Adoption	AI Awareness	Digital Skills Readiness	Organisational Culture	Technological Infrastructure	Top Management Support
AI Awareness	0.504	-				
Digital Skills Readiness	0.439	0.368	-			
Organisational Culture	0.533	0.264	0.394	-		
Technological Infrastructure	0.606	0.407	0.382	0.391	-	
Top Management Support	0.511	0.220	0.308	0.362	0.406	-
Organisational Culture × Digital Skills	0.566	0.360	0.862	0.872	0.445	-

Source: Data Analysis Results, 2026

The HTMT values are below the recommended threshold of 0.90, indicating acceptable discriminant validity. Higher values for the interaction construct are expected, reflecting its composite nature, yet remain within acceptable limits.

Table 7: Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Awareness -> AI Adoption	0.286	0.287	0.046	6.180	0.000
Digital Skills Readiness -> AI Adoption	-0.722	-0.714	0.320	2.255	0.024
Organisational Culture -> AI Adoption	-0.565	-0.560	0.326	1.736	0.083
Technological Infrastructure -> AI Adoption	0.303	0.301	0.049	6.212	0.000
Top Management Support -> AI Adoption	0.273	0.273	0.048	5.688	0.000
Organisational Culture x Digital Skills Readiness -> AI Adoption	0.247	0.245	0.094	2.629	0.009

Source: Data Analysis Results, 2026

The structural model results indicate that AI Awareness (β = 0.286, p = 0.000), Technological Infrastructure (β = 0.303, p = 0.000), and Top Management Support (β = 0.273, p = 0.000) have significant positive effects on AI Adoption. Digital Skills Readiness shows a significant negative effect (β = -0.722, p = 0.024). This reveals a paradox where higher digital readiness may create resistance, unmet expectations, or implementation complexity unless supported by a conducive organisational culture. Organisational Culture has no significant direct effect (p = 0.083). However, its moderating effect on Digital Skills Readiness is significant (β = 0.247, p = 0.009), strengthening AI adoption. Organisational culture alone does not directly drive adoption, but functions as an enabling condition.

Table 8: R Square

Endogenous Construct	R^2 (Original Sample)	Adjusted R^2	Sample Mean	Std. Deviation	T-value	p-value	95% CI Lower	95% CI Upper
AI Adoption	0.513	0.502	0.528	0.033	15.445	0.000	0.448	0.579

Source: Data Analysis Results, 2026

The model explains 51.3% of the variance in AI Adoption (R^2 = 0.513), indicating moderate explanatory power. The significant p-value confirms that the structural model demonstrates acceptable predictive relevance and overall adequacy.

Table 9: Effect Size (f^2)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Awareness -> AI Adoption	0.085	0.089	0.029	2.963	0.003
Digital Skills Readiness -> AI Adoption	0.014	0.017	0.014	1.050	0.294
Organisational Culture -> AI Adoption	0.009	0.012	0.011	0.795	0.426
Technological Infrastructure -> AI Adoption	0.115	0.119	0.039	2.971	0.003
Top Management Support -> AI Adoption	0.084	0.088	0.030	2.782	0.005
Organisational Culture x Digital Skills Readiness -> AI Adoption	0.019	0.022	0.016	1.241	0.214

Source: Data Analysis Results, 2026

The effect size (f^2) results indicate that Technological Infrastructure ($f^2 = 0.115$), AI Awareness ($f^2 = 0.085$), and Top Management Support ($f^2 = 0.084$) have small but meaningful effects on AI Adoption, as they exceed the 0.02 threshold. Digital Skills Readiness ($f^2 = 0.014$) and Organisational Culture ($f^2 = 0.009$) show negligible effects, indicating limited individual contribution. The moderating effect of Organisational Culture × Digital Skills Readiness ($f^2 = 0.019$) also has a negligible to small effect, although it remains theoretically important due to its statistical significance. These findings reinforce that no single factor strongly drives adoption, supporting the AI adoption paradox.

Table 10: Hypothesis Testing Summary

Hypothesis	**Relationship**	**Path Coefficient (β)**	**P-value**	**Result**
H1	AI Awareness → AI Adoption	0.286	0.000	Supported
H2	Technological Infrastructure → AI Adoption	0.303	0.000	Supported
H3	Digital Skills Readiness → AI Adoption	-0.722	0.024	Supported (Inverse Relationship)
H4	Top Management Support → AI Adoption	0.273	0.000	Supported

H5	Organisational Culture × Digital Skills Readiness → AI Adoption	0.247	0.009	Supported

Source: Data Analysis Results, 2026

The hypothesis testing results indicate that H1, H2, and H4 are supported, confirming that AI awareness, technological infrastructure, and top management support positively influence AI adoption. H3 is also supported; however, digital skills readiness demonstrates a significant inverse relationship, reinforcing the AI adoption paradox where readiness alone does not guarantee implementation success. H5 is supported, showing that organisational culture significantly moderates the relationship between digital skills readiness and AI adoption, highlighting the importance of contextual alignment in strengthening adoption outcomes.

Discussion

This study examined the determinants of AI adoption in organisational contexts and tested the proposed AI adoption paradox. The findings reveal that AI awareness, technological infrastructure, and top management support have significant positive effects on AI adoption, while digital skills readiness demonstrates a significant negative relationship. In addition, organisational culture significantly moderates the relationship between digital skills readiness and AI adoption. These findings provide important theoretical and practical insights into how AI adoption occurs within developing economy contexts.

The significant positive effects of AI awareness, technological infrastructure, and top management support are consistent with prior literature and established technology adoption theories. AI awareness reduces uncertainty and improves managerial understanding of the strategic and economic value of AI adoption, thereby supporting implementation decisions (Lachaiah & Hajdu Barat, 2026; Wang et al., 2025). Similarly, technological infrastructure provides the operational foundation necessary for AI deployment, including data integration, system compatibility, and process automation, which directly improve productivity and innovation efficiency (Faiz et al., 2024; Chen et al., 2023). Top management support also remains a critical driver, as leadership commitment facilitates strategic resource allocation, legitimises digital transformation initiatives, and strengthens organisational competitiveness (Kraus et al., 2022; Venugopal et al., 2024).

However, the most theoretically significant finding is the negative effect of digital skills readiness on AI adoption. This contradicts prior studies that assume skilled employees naturally accelerate AI implementation (Kumar & Mittal, 2024; Deepa et al., 2024). The result supports the AI adoption paradox, where readiness alone does not guarantee adoption success. In practice, employees with stronger digital skills may become more critical of poorly designed AI systems, more aware of implementation risks, and more resistant to technologies that threaten autonomy, expertise, or professional identity. Rather than promoting adoption automatically, digital competence may increase

evaluative resistance when organisational systems are not aligned with employee expectations. This can lead to underutilised digital capital, inefficient AI investment, and weaker firm-level performance despite apparent readiness.

The significant moderating role of organisational culture further strengthens this paradox perspective. Organisational culture positively moderates the relationship between digital skills readiness and AI adoption, indicating that employee capability requires a supportive environment to translate into actual implementation. This finding is consistent with studies showing that cultures promoting learning, collaboration, and innovation enhance the practical value of workforce skills (Ali et al., 2022; Kwong et al., 2021; Zhang et al., 2023). In innovation-oriented cultures, employees are more likely to apply their digital competencies toward experimentation and AI integration. Thus, culture activates skills, whereas without cultural support, those same skills may produce scepticism rather than adoption.

The study deliberately examined moderation only between organisational culture and digital skills readiness because digital skills represent a capability-based construct that depends heavily on behavioural activation. In contrast, technological infrastructure and top management support operate at structural and strategic levels where culture functions less distinctly as a moderator. This selective moderation approach improves theoretical coherence and avoids unnecessary model complexity.

The findings challenge the linear assumptions of the Technology–Organisation–Environment (TOE) framework (Awa et al., 2017) by demonstrating that readiness factors do not automatically produce adoption outcomes. The model explains 51.3% of variance in AI adoption, supporting the practical relevance of the paradox perspective. AI adoption is not solely a function of resources, but also of behavioural alignment and organisational context. Managers should therefore move beyond readiness indicators and focus on building cultures that convert organisational capability into sustainable AI adoption and long-term economic value.

Conclusion and Recommendations

This study contributes to the growing literature on artificial intelligence adoption by demonstrating that organisational readiness alone does not guarantee successful implementation. While AI awareness, technological infrastructure, and top management support show significant positive effects on AI adoption, digital skills readiness presents a significant negative relationship, revealing a critical theoretical contradiction. This finding challenges the conventional assumption within the Technology–Organisation–Environment (TOE) framework that stronger readiness factors automatically produce higher adoption outcomes (Awa et al., 2017). Instead, the results support the existence of an AI adoption paradox, where organisations may possess readiness determinants yet still experience weak or inconsistent adoption outcomes. The significant moderating role of organisational culture further confirms that employee capability must be supported by a conducive socio-organisational environment to translate into practical adoption.

From a policy perspective, these findings suggest that AI adoption strategies in developing economies should move beyond infrastructure investment and technical

training alone. Policymakers should focus on strengthening organisational ecosystems that support innovation, experimentation, and continuous learning. Leadership development programmes, organisational change frameworks, and institutional incentives for digital transformation should be prioritised to improve strategic competitiveness and sustainable economic value creation. At the firm level, managers should avoid assuming that workforce digital skills automatically lead to implementation success. Instead, organisations must align capability-building efforts with trust-building, collaborative cultures, and practical opportunities for employees to apply digital knowledge.

For research translation, the study highlights the importance of reconceptualising AI adoption models by integrating behavioural and contextual dimensions alongside structural determinants. AI investment should be understood not only as a technological decision but also as a strategic organisational process involving labour transformation, cultural alignment, and long-term productivity outcomes. Sustainable AI integration therefore depends on the interaction between readiness and organisational context rather than readiness alone. Ultimately, successful AI adoption depends not on readiness alone, but on the organisation's ability to transform readiness into behavioural acceptance, strategic action, and sustainable economic value.

Implementation and Future Research

Effective implementation of AI requires organisations to move beyond technical preparedness and actively embed digital transformation within organisational culture. Practical implementation strategies should include structured change management programmes, leadership-led innovation agendas, and continuous employee upskilling linked to real operational application. Rather than treating digital skills as isolated competencies, organisations should create environments where employees are encouraged to experiment, collaborate, and apply AI solutions without fear of resistance or professional displacement. Internal innovation ecosystems, such as pilot projects, cross-functional teams, and departmental AI experimentation platforms, can support this process and improve the productive use of digital capabilities.

From a policy perspective, stronger collaboration between industry, academia, and government is essential to accelerate context-sensitive AI adoption. National digital transformation strategies should include sector-specific implementation support, institutional learning networks, and incentives for firms that successfully integrate AI into productivity improvement and sustainable business performance. This would strengthen firm-level competitiveness while supporting broader economic development.

Future research should extend this study by examining additional moderating and mediating mechanisms such as leadership styles, organisational learning, institutional pressures, and employee trust in AI systems. Longitudinal studies are recommended to capture how AI adoption evolves over time rather than relying solely on cross-sectional evidence. Comparative studies across industries and countries would also provide deeper insights into contextual differences, improving the generalisability of findings and advancing theoretical understanding of the AI adoption paradox in diverse organisational settings.

Declaration of AI Use

During the preparation of this manuscript, the authors used artificial intelligence (AI)-assisted language tools including; e.g., ChatGPT / Grammarly / DeepL Write solely for the purposes of improving language fluency, grammar, spelling, and sentence clarity. No AI tools were used to generate research ideas, analyse data, interpret findings, or produce the core intellectual content of this study. All AI-generated language suggestions were reviewed, edited, and approved by the authors, who take full responsibility for the final content of this manuscript.

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