Technological Readiness and Perceived Relative Advantage as Drivers of AI Adoption Intention: Evidence from Service Sector SMEs in Gampaha District, Sri Lanka

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ABSTRACT

Although artificial intelligence offers significant advantages, including streamlined service delivery, superior decision-making, faster customer response, and driven innovation, its adoption among small and medium enterprises remains uneven. Many SMEs currently lack the necessary technological systems and internal capabilities to integrate AI tools successfully. Thus, this study examined the impact of technological factors, organizational factors, environmental factors, and perceived relative advantage on the intention to adopt AI in service sector SMEs of Gampaha district in Sri Lanka. The study was designed under the positivist research philosophy, following deductive approach. The study used a quantitative cross-sectional survey to collect data from 126 SME owners and managers. The data were analyzed using Partial Least Squares Structural Equation Modelling. Technological factors played a significant role in determining the intention to use AI, as did the perceived relative advantage. The results highlight that digital readiness and the benefit to the business are key factors in fostering SMEs to adopt AI. At the component level, both IT infrastructure and data availability contributed significantly to technological readiness, with data availability contributing most, whereas employee digital skills and government support were not significant contributors.

Keywords: *Artificial intelligence, AI Adoption Intention, Service-Sector Smes, Technological Readiness, Relative Advantage*

1. INTRODUCTION

Artificial intelligence (AI) is a key contributor to digital transformation, enabling organizations to automate routine tasks, analyze data, improve forecasting, and support decision-making and personalized services. Technologies such as chatbots, recommendation systems, predictive analytics, and intelligent automation create new opportunities for business value. AI also influences service delivery, business models, and management practices, offering benefits in productivity and innovation while creating challenges related to organizational readiness and capabilities (Huang & Rust, 2018; Kaplan & Haenlein, 2019; Dwivedi et al., 2021).

Small and medium-sized enterprises (SMEs) are important contributors to economic development (Deyshappriya & Maduwanthi, 2020). In Sri Lanka, they account for 75% of active enterprises, 45% of employment, and 52% of GDP (National SME Strategy Framework, 2026). However, limited financial, technological, and human resources may restrict their ability to adopt AI, despite its potential to improve efficiency and market responsiveness. Successful AI adoption requires more than access to appropriate software. It also depends on organizational readiness, suitable infrastructure, reliable data, employee skills, management support, financial resources, and a clear business purpose (Nambisan et al., 2019; Chatterjee et al., 2021). In particular, access to high-quality data strengthens an organization's ability to use data-driven technologies effectively (Brynjolfsson & McElheran, 2016).

The Technological – Organizational – Environmental (TOE) framework identifies three contexts that influence innovation adoption (Tornatzky & Fleischer, 1990). The Technological context refers to the attributes of the technology and the firm's IT environment. In addition, prior technology adoption studies show that TOE dimensions should be considered together because technological readiness, organizational resources, and environmental conditions can jointly influence adoption decisions (Oliveira & Martins, 2011; Baker, 2012; Chatterjee et al., 2021). Therefore, the TOE framework is useful for explaining AI adoption intention among SMEs because successful adoption depends on multiple internal and external conditions rather than one factor alone. Further, Rogers (2003) identified several perceived attributes of innovations that influence adoption, including relative advantage, comparability, complexity, trialability, and observability. These attributes refer directly to the degree to which an innovation is perceived as superior to the technology it replaces. Generally, organizations are more willing to adopt innovations quickly when they expect clear benefits such as improved efficiency, quality decision-making, cost reduction, and enhanced customer service or competitive advantage.

Previous studies recognize AI adoption as a multidimensional process influenced by technological, organizational, and environmental factors (Chatterjee et al., 2021). Strategy, resources, knowledge, organizational culture, and data capabilities also contribute to AI readiness (Jöhnk et al., 2021). Perceived value is especially important for SMEs because they must assess the benefits of AI while operating with limited resources. Although SMEs contribute significantly to Sri Lanka's economy, their levels of AI adoption vary considerably. As previous research has mainly focused on developed economies and large organizations, further investigation within the Sri Lankan SME context is required. This study addresses this gap by examining how IT infrastructure, data availability/quality, top management support, employee digital skills, financial readiness, competitive pressure, government support, and relative advantage influence SMEs' intention to adopt AI.

Accordingly, the study seeks to achieve four objectives: first, examine the influence of technological factors; second, investigate the influence of organizational factors; third, assess the influence of environmental factors; and fourth, determine the impact of perceived relative advantage on service sector SMEs' intention to adopt AI.

2. METHODOLOGY

This section explains the research design of the study. This study lies within the positivist research paradigm based on ontological and epistemological assumptions. Hence, the quantitative research method under the deductive approach was utilized. The anticipated relationships among the study variables are depicted in Figure 01. Accordingly, the independent variables were the technological factors, organizational factors, environmental factors, and Relative advantage of innovations. The intention to adopt AI was the dependent variable.

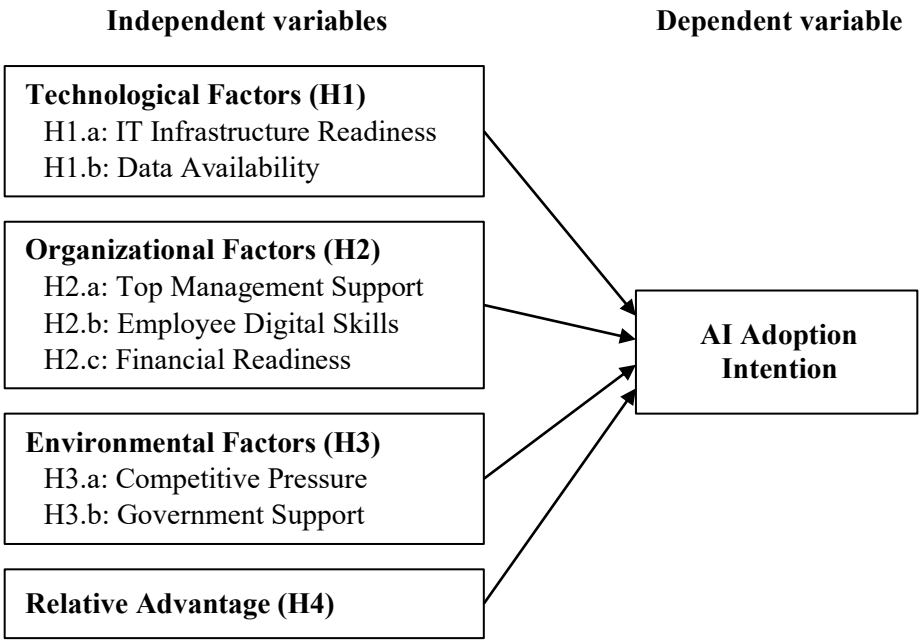

Figure 1. Conceptual Framework

Source: Authors constructed, 2026

Eight hypotheses were formulated and evaluated based on the conceptual framework depicted in Figure 1. Additionally, the corresponding research model was established and tested.

Equations: 1

$$AII = \beta_0 + \beta_1(TI) + \beta_2(DA) + \beta_3(TMS) + \beta_4(EDS) + \beta_5(FR) + \beta_6(CP) + \beta_7(GS) + \beta_8(RA) + \varepsilon \quad (1)$$

Where;

AII = AI Adoption Intention
β0 = Constant (Intercept)
β1=T Infrastructure Readiness
β2=Data Availability
β3 =Top Management Support
β4 =Employee Digital Skills
β5=Financial Readiness
β6= Competitive Pressure
β7=Government Support
β2=Relative Advantage
ε= Error Term

The study's target population consisted of both registered and unregistered SMEs in the services sector in Gampaha District in Sri Lanka. A non-probability convenience sampling method was used since there was no complete list of SMEs that met the inclusion criteria in the sampling frame.

Respondents were the owner's decision makers who had knowledge on their firms' capacity to adopt AI technology. The number of valid responses collected was 126. Prior to full-scale deployment, the instrument was pilot tested with 35 respondents, confirming construct reliability through acceptable Cronbach's alpha values.

Variables used in this research were operationalized through multi-item scales derived from existing literature. Technological variables were operationalized using IT Infrastructure Readiness Scale (Tornatzky & Fleischer, 1990; Bharadwaj et al., 2013) with 4 items and the Data Availability Scale (Brynjolfsson & McElheran, 2016; Gupta et al., 2022). Organizational variables included Top Management Support (Jeyaraj et al., 2006; Hwang & Kim, 2022), Employee Digital Skills (Venkatesh et al., 2012; OECD, 2019), and Financial Readiness (Oliveira et al., 2014; Hsu et al., 2006), all operationalized through 4-item scales. Environmental variables included Competitive Pressure (Porter, 1980; Tornatzky & Fleischer, 1990) and Government Support (Gupta et al., 2022; World Bank, 2025), while Relative Advantage was measured separately (Rogers, 2003; Moore & Benbasat, 1991; Jöhnk et al., 2021). Finally, AI Adoption Intention was operationalized through 5 items. Items used for measuring all these constructs were on 5-point Likert scale where 1 means Strongly Disagree and 5 means Strongly Agree.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). To accommodate both first-order reflective and higher-order formative constructs within the model, a two-stage hierarchical component approach was implemented. Because this framework precludes a single-step evaluation, a multi-step procedure was followed to separately evaluate the lower-order measurement properties and the higher-order component relationships (Sarstedt et al., 2019). In the first stage, the reflective measurement model was evaluated through indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity. The second stage involved assessing formative collinearity and component weights, followed by testing the structural paths. Hypotheses were evaluated using non-parametric bootstrapping with 10,000 subsamples. Finally, model explanatory power was evaluated using R^2 and effect sizes (f^2), while out-of-sample predictive capability was assessed using PLSpredict, as recommended by Shmueli et al. (2019).

3. FINDINGS AND DISCUSSION

The data contained with no missing values and all the items had valid responses. Numeric checks confirmed all values fell within the 1–5 Likert range and each CaseID was unique. Thus, no imputation or deletion was

necessary. Therefore, all 126 valid responses were retained for the lower-order measurement-model assessment and subsequent higher-order structural analysis. The demographic analysis revealed a few specific features of the selected sample. 78.6% of the sample consisted of micro-enterprises (1-10 employees), and 66.7% of respondents were the owner or manager of these enterprises. Thus, the data primarily reflect high-level managerial and owner perspectives. Further, most of the enterprises have already made use of digital systems. The assessment of normality of the data distribution indicated non-normal behavior, and PLS-SEM was employed for the data analysis. PLS-SEM does not require multivariate normality in the same manner as covariance-based SEM, and statistical significance is commonly assessed using non-parametric bootstrapping, making the method suitable for data that depart from normal-distribution assumptions (Hair et al., 2022; Ringle et al., 2024).

Table 1. Construct Reliability and Validity

Construct	Cronbach's α	Composite Reliability	AVE	Max VIF
AI Adoption Intention	0.895	0.923	0.706	3.631
Competitive Pressure	0.746	0.831	0.552	1.850
Data Availability	0.726	0.830	0.549	1.996
Employee Digital Skills	0.740	0.818	0.547	2.252
Financial Readiness	0.812	0.874	0.635	1.989
Government Support	0.835	0.880	0.648	2.250
IT Infrastructure	0.705	0.820	0.536	1.736
Relative Advantage	0.824	0.884	0.660	3.482
Top Management Support	0.828	0.877	0.644	1.923

Source: Authors constructed, 2026

The results of descriptive statistics reveal that the respondents' attitude towards AI was generally positive: the highest score in favor of AI was revealed for Perceived Relative Advantage (M = 4.442, SD = 0.551), the next was obtained for AI Adoption Intention (M = 4.354, SD = 0.625), followed by Technological Factors (M = 4.140, SD = 0.507). The table 1 shows the construct reliability and convergent validity. For reflective constructs, Cronbach's α, and composite reliability ≥0.70 indicate acceptable internal consistency, and AVE ≥0.50 indicates adequate convergent validity. All nine first-order constructs exceed these thresholds. The weakest reliability is for IT Infrastructure (α = 0.705, CR = 0.820) and Data Availability (α = 0.726, CR = 0.830), which are just above 0.70. The highest reliability is for AI Adoption Intention (α = 0.895, CR = 0.923) and Government Support (α = 0.835, CR = 0.880). All AVEs

exceed 0.536, and no composite reliability or alpha exceeds 0.95, so there is no evidence of indicator redundancy. Thus, all first-order constructs demonstrate acceptable internal consistency and convergent validity (Hair et al., 2022; Fornell & Larcker, 1981).

Discriminant validity was assessed primarily using the Heterotrait–Monotrait ratio (HTMT). HTMT values below 0.90 indicate adequate discriminant validity, with a more stringent threshold of 0.85 when constructs are conceptually very distinct (Henseler et al., 2015; Hair et al., 2022). Table 2 shows the HTMT matrix for the nine reflective constructs. Only one HTMT value exceeds 0.90: HTMT (IT, DA) = 1.046, reflecting a high correlation between IT Infrastructure and Data Availability. This indicates that there could possibly be some conceptual overlap between these two constructs. This is because of the close association between the IT infrastructure of the organizations and the capacity of these organizations to capture, retrieve, and utilize the data. Therefore, discriminant validity for these two constructs was not entirely supported.

Table 2. HTMT Discriminant Validity Matrix

Construct	IT	DA	TMS	EDS	FR	CP	GS	RA	AII
IT	1.000								
DA	1.046	1.000							
TMS	0.451	0.226	1.000						
EDS	0.519	0.182	0.770	1.000					
FR	0.514	0.285	0.632	0.540	1.000				
CP	0.454	0.340	0.507	0.422	0.498	1.000			
GS	0.411	0.297	0.527	0.455	0.555	0.745	1.000		
RA	0.553	0.312	0.505	0.573	0.669	0.646	0.570	1.000	
AII	0.585	0.378	0.514	0.596	0.678	0.586	0.586	0.814	1.000

Source: Authors constructed, 2026

The higher-order constructs Technological Factors (TF), Organizational Factors (OF), and Environmental Factors (EF) were modeled formatively from their component scores. For formative constructs, internal consistency measures (α, CR, AVE) are not interpreted in the same way. Instead, the study focusses on collinearity and the significance of the indicator weights (Becker et al., 2012; Hair et al., 2022). Table 3 shows the variance inflation factors (VIFs) for the components. All VIFs are well below 3.00, indicating no serious multicollinearity among the components of TF, OF, or EF. the outer weight

and significance for each formative component. In Technological Factors, both IT and DA components contribute positively (weights 0.307 and 0.693, $p<0.05$), indicating each is a relevant source of TF. In Organizational Factors, Top Management Support (weight 0.603, $p<0.001$) and Financial Readiness (0.405, $p=0.041$) are significant, while Employee Digital Skills is not (weight –0.118, $p=0.559$). In Environmental Factors, Competitive Pressure has a very strong weight (0.873, $p<0.001$), whereas Government Support's weight (–0.199) is not significant ($p=0.133$). All components align with theoretical expectations.

Table 3. Formative Measurement Model Assessment: Collinearity and Component Weights

Higher-Order Construct	Component	VIF	Weight (β)	t-value	p-value
Technological Factors (TF)	IT Score	1.460	0.307	2.153	0.032
	DA Score	1.460	0.693	3.746	0.000
Organizational Factors (OF)	TMS Score	2.208	0.603	4.201	0.000
	EDS Score	2.208	–0.118	0.585	0.559
	FR Score	1.809	0.405	2.048	0.041
Environmental Factors (EF)	CP Score	1.270	0.873	11.234	0.000
	GS Score	1.270	–0.199	1.505	0.133

Source: Authors constructed, 2026

Where;
VIF = Variance Inflation Factor
IT = IT Infrastructure
DA = Data Availability
TMS = Top Management Support
EDS = Employee Digital Skills
FR = Financial Readiness
CP = Competitive Pressure
GS = Government Support
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The significant weights ($p<0.05$) suggest that IT and DA jointly form TF, TMS and FR jointly form OF, and CP chiefly forms EF. The insignificance of EDS and GS suggests those components contribute little explanatory variance to their respective HOCs in this sample. However, their removal would change the content of the constructs, so they are retained for completeness. All VIFs in Table 3 were <3.0, confirming that collinearity among components is not problematic (Hair et al., 2022). The structural model's explanatory power for AI Adoption Intention is $R^2 = 0.511$ (adjusted $R^2 = 0.495$), indicating moderate explanatory power for behavioral intention. By conventional PLS guidelines,

R^2 values ~0.50 can be considered moderate to substantial (Hair et al., 2022). A nonparametric bootstrap was used to assess the significance of path coefficients.

Table 4. Hypothesis Testing Summary

Hypothesis	Sub-factor / Variable	Component Weight (β)	t-value	p-value	Decision
H1a	IT Infrastructure	0.307	2.153	0.032	Supported
H1b	Data Availability	0.693	3.746	0.000	Supported
H2a	Top Management Support	0.603	4.201	0.000	Supported
H2b	Employee Digital Skills	-0.118	0.585	0.559	Not supported
H2c	Financial Readiness	0.405	2.048	0.041	Supported
H3a	Competitive Pressure	0.873	11.234	0.000	Supported
H3b	Government Support	-0.199	1.505	0.133	Not supported
H4	Perceived Relative Advantage	0.431	2.769	0.006	Supported

Source: Authors constructed, 2026

Competitive Pressure ($\beta = 0.873$) and Data Availability ($\beta = 0.693$) are by far the most powerful determinants driving AI adoption intent among service sector SMEs. Top Management Support ($\beta = 0.603$), Perceived Relative Advantage ($\beta = 0.431$), Financial Readiness ($\beta = 0.405$), and IT Infrastructure ($\beta = 0.307$) play significant positive roles. Employee Digital Skills and Government Support do not significantly influence the intention to adopt AI in this context ($p > 0.05$). Using the out-of-sample predictive ability, $Q^2 = 0.470$ was generated using PLSpredict. In general, the major direct predictors for the overall level were technological readiness and relative advantage. The level of AI adoption intention was thus largely contingent on whether companies had a credible digital foundation and whether AI would create meaningful value for the company.

4. CONCLUSION

The results reveal that technological readiness and relative advantage are the key determinants of AI adoption intention of service sector SMEs in Gampaha District. Service sector SMEs need a basic level of technical maturity before considering AI integration, though it is not the strongest overall driver. Access to structured, usable data is a primary determinant of AI adoption intention. Since AI relies entirely on

data to train algorithms and extract insights, service SMEs that collect and manage quality data feel significantly more ready and willing to adopt AI tools. Leadership commitment, vision, and resource allocation strongly drive adoption intention. In SMEs, decision-making is highly centralized. If leaders understand AI, the organization is more likely to move forward with adoption. Current employee digital skill levels have no statistically significant impact on the intention to adopt AI. Service SMEs likely view AI tools as user-friendly or expect vendor support/training, indicating existing skill gaps do not act as an immediate barrier to intention. Available budget and financial stability positively influence AI adoption intent. Investing in AI involves upfront software, integration, and maintenance costs. Therefore, SMEs with dedicated financial resources show higher willingness to adopt.

External pressure from market rivals adopting AI is the single strongest driver in the entire model. Service sector SMEs are heavily reactive to market dynamics. Fear of falling behind competitors who leverage AI for efficiency or customer service acts as the primary catalyst for adoption. Government policies, subsidies, or institutional initiatives do not significantly influence adoption intention. Service SMEs rely far more on market forces and internal capabilities than state incentives when considering cutting-edge tech adoption. Recognizing that AI offers clear benefits over existing methods significantly boosts adoption intention. When SME decision-makers perceive tangible value (ex: faster response times, higher productivity, reduced operating costs), they are much more inclined to adopt AI.

There are several limitations in the interpretation of the findings This information should be understood considering the sample of service sector SMEs that were used in the study conducted in Gampaha District. Because the study used non-probability convenience sampling and was limited to one specific region and industry, the findings may not be generalizable to SMEs across Sri Lanka. In addition, because of the cross-sectional nature of the survey and self-reports of intentions and not actual behavior, the information is temporal. Therefore, future research is needed using wider probability-based sampling, comparing sectors and regions, using longitudinal research to follow up the applications of new technology and adopting actual adoption behaviors as a measure, as well as examining mediation or moderation variables. Despite such constraints, the study offers empirical findings indicating that service-sector SMEs are most likely to transition to AI when they have technological readiness, and the belief that AI offers them improved business value is clear.

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