Reliability and Validity of Instruments Measuring Technology Scale in Adoption of Artificial Intelligent

Elly Julieanatasha Juma'at, Amizatulhawa Mat Sani*, Norhidayah Mohamad

Faculty of Technology Management and Technopreneurship / Universiti Teknikal Malaysia Melaka, Malacca, Malaysia

***Corresponding Author**

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ABSTRACT

This study examined the internal consistency of the data by testing the reliability of the adapted questionnaire. Reliability was measured using Cronbach's Alpha, a common indicator of internal consistency. The assessment involved 31 respondents. The questionnaire contained items rated on a 5-point Likert scale, focusing on key factors influencing AI adoption among SMEs, such as Relative Advantage and Compatibility. The Cronbach's Alpha results showed an adequate level of internal consistency, confirming that the instrument effectively measured the targeted aspects. These results proved the reliability of the questionnaire, and the variables studied, demonstrating their effectiveness in analyzing factors affecting AI adoption. Therefore, developing a thorough questionnaire is essential to collect valid and meaningful data that can help SMEs make well-informed decisions about AI implementation.

Keywords: Technology, Relative Advantage, Compatibility, AI Adoption

INTRODUCTION

The Industrial Revolution 4.0 has been rapidly advancing over the past decade. IR4.0 has created significant social and economic opportunities alongside challenges. It will enable companies to innovate in organizing, managing, and controlling value chains, while requiring governments to adapt (Manda and Dhaou, 2019). Malaysia's socio-economic growth will strengthen the digital economy by encouraging SMEs to adopt digital technologies in manufacturing, processes, and business services, especially on the backend (SME Corp, 2021).

However, today's increasingly challenging business environment demands that every industry adopt the latest technologies, including artificial intelligence (AI) (Davenport et al., 2020). According to the latest McKinsey Global Survey (2024) on AI, 65 percent of participants reported that their organizations frequently use AI. AI will play a crucial role in pioneering and driving the exploration of all possibilities in the future (Lu et al., 2022). Additionally, there has been recent debate about SMEs not implementing AI in their business processes early on due to high costs and the need for fewer technical skills (Govori et al., 2023).

Research indicates that many SMEs in emerging economies lack full access to AI application tools (Rawashdeh et al., 2023). SMEs often appear less financially attractive, causing them to fall behind multinational companies in attracting top ICT graduates (European Digital SME Alliance, 2019). Moreover, because of their slower adoption rates, SMEs can greatly benefit from integrating AI into their customer relationship management systems, which can significantly enhance service efficiency (Nwaimo, et al., 2024).

With the rise of this new technology, the global market has become more accessible, especially for Small and Medium Enterprises (SMEs). A study by SME Corporation Malaysia revealed that only 28.8 percent of SMEs use technology in their daily operations (Bernama, 2024). Technology also plays a key role in decision-making regarding the digital transformation of businesses (SME Corp, 2021). Previous research shows evidence that AI is viewed as a relative advantage that can improve customer satisfaction and responsiveness, ultimately strengthening a company's reputation (Gupta et al., 2022; Badghish et al., 2024; Alsheibani et al., 2020).

Additionally, an analysis of multiple studies on AI use and adoption highlights a significant gap in research focusing on compatibility during adoption, along with debates about AI being complex to implement and understand, which may hinder firms from adopting AI (Jadhav, 2021). AI tools are often difficult to transfer from one company to another and require extensive customization, increasing compatibility (Kant and Johannsen, 2022; Lu et al., 2022). Given the challenges of AI adoption in digital environments, SMEs need to rethink and redesign their businesses by ensuring their strategies, processes, and infrastructure are fully aligned and integrated to support digital transformation (SME Corp, 2024). Furthermore, most small business entrepreneurs come from rural backgrounds where they have less exposure to the increasingly sophisticated and modern technologies available today (NST, 2024).

LITERATURE REVIEW

Technology

Digital transformation has fundamentally changed manual processes, with resource-rich companies already investing in AI to enhance their profitability (Wong et al, 2024). Additionally, emerging trends in AI-driven automation indicate a significant shift in the AI landscape. This shift is reflected in businesses' revised strategies, interests, and investments related to AI implementation (S. Verma et al, 2021; S. Dimitrieska et al, 2018; U. Arsenijevic et al, 2019). Automating business processes is expected to improve efficiency and productivity, enhance decision-making, offer personalized services, and lower costs, which are recognized as major benefits (Tikkanen et al., 2022; Bettoni et al., 2021). For example, AI capabilities such as process automation and optimization, analytics, dynamic pricing, and forecasting can be applied in various ways across different business functions to empower organizations (Alsheibani, Cheung, & Messom, 2020; Dwivedi, Hughes, et al., 2021; McKinsey, 2020; Min, 2010; Rauchter, Dallas, 2010; Syam & Sharma, 2018).

The technology context refers to internal and external technologies relevant to the company. Characteristics associated with technology include reliability, security, quality, relative advantage, compatibility, and cost (Al-Qirim, 2007; Khemthong & Roberts, 2006). Recently, Badghish et al. (2024) provided substantial evidence that these technological characteristics significantly influence a firm's likelihood of adopting new technology. Based on these findings, the author identified factors such as relative advantage and compatibility as crucial in the decision-making process for AI adoption (Badghish et al., 2024).

The characteristics that are included with technology include reliability, security, quality, relative advantage, compatibility, and cost (Al-Qirim, 2007; Khemthong & Roberts, 2006). Recently, Badghish et al. (2024) have provided considerable evidence that these technological characteristics significantly influence the likelihood of a firm adopting technology. Based on these findings, the author set the factors such as relative advantage and compatibility as playing an essential role in the decision-making process in AI adoption (Badghish et al., 2024).

Relative Advantage

Relative advantage refers to how much a new technology or innovation is seen as better than its predecessor (Rogers, 2003). When combined with Rogers and Williams (1983), this idea highlights how much innovation is viewed as an improvement over the previous idea. Some analysts have stated that relative advantages are crucial for adoption processes, and the decision to switch to a new technology can be heavily influenced by the relative advantage to company performance (Baker, 2012; Nimfa et al, 2020; Shahzad et al, 2023).

Compatibility

Compatibility refers to how well an innovation matches the current values, experiences, and needs of its potential users (Rogers, 2003). It shows how closely innovation aligns with the company's values, culture, and business processes (Ahmi et al., 2014; Chatterjee et al., 2021; Siew et al., 2020). SMEs are more likely to adopt AI when they see it as compatible with their existing practices and values (Chatterjee et al., 2021; Azmi et al., 2016).

When AI is used heavily in SMEs, it can meet innovation needs and fit with work requirements, leading to higher adoption rates (Tajudeen et al., 2020). Technologies with high compatibility integrate smoothly into operations, lower resistance, and encourage quicker adoption (Bruno et al., 2017; Rogers, 1995), making it easier for companies to increase operational availability, adapt business models, and stay aligned with the innovation (Alsetoohy et al., 2021).

AI Adoption

AI is rapidly becoming a common technology adopted by business owners and entrepreneurs (Harvard Business Review, 2023). As a result, organizations are emphasizing AI due to its significant potential to enhance performance (Mikalef et al, 2021). Many studies indicate that SMEs plan to invest in AI technologies to monitor user behavior, offer recommendations, improve customer purchasing decisions, optimize search results and media interactions, increase sales, enhance organizational performance, and reduce costs (Hansen & Bøgh, 2021; Ulrich et al., 2021; Basri, 2021; Ulas, 2017 & Polkowski). Consequently, SMEs can adopt affordable AI tools and start their journey toward AI integration. Organizations typically aim for growth and expansion, and AI can play a key role in helping them achieve these goals (Govori et al, 2023; Baabdullah et al., 2021).

Conceptual Framework

This study highlights Malaysia as an example of rapid technology adoption and innovation among SMEs. The country has demonstrated a strong commitment to becoming a developed nation by integrating AI into business operations. Significant investments have been made to modernize services, leading Malaysia to achieve a high ranking in AI adoption. This progress reflects not only technological advancements but also a competitive market environment supported by increasing digital literacy. This study proposed a conceptual framework that focuses on two technological factors: relative advantage and compatibility.

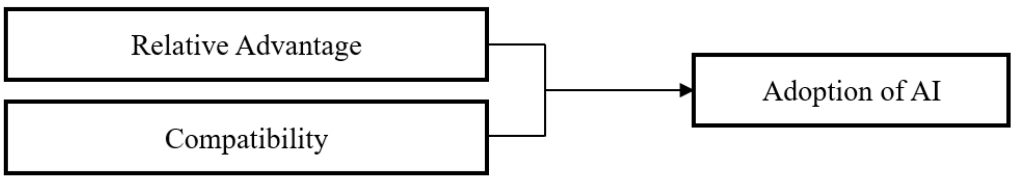

Fig. 1. Conceptual framework

RESEARCH METHODOLOGY

Sample and Data Collection

This study used a survey method and was carried out from January to July 2025. The sample included 31 respondents, consisting of entrepreneurs, business owners, and individuals from marketing departments of Small and Medium Enterprises (SMEs) in Malaysia. All respondents were employed in the retail sector. Before starting, permission was obtained from the owners. The survey was distributed online through email, social media, and face-to-face to ensure accessibility and convenience. The researcher introduced himself and explained the study's purpose before giving out the permission letter and questionnaire. Each respondent was asked to review the instructions before answering and to submit their responses individually based on their views. They had about 10 to 15 minutes to complete the questionnaire. Finally, the questionnaires were collected for data analysis.

Instruments

Instruments are the measurement tools used in research for data collection, and the overall quality of the study heavily depends on the research instruments employed (Creswell, 2013). Operational definitions clarify abstract ideas or concepts by specifying the procedures needed to make them measurable (Babbie, 2020). To encourage cooperation and engagement during the questionnaire, straightforward language that is easily understandable is used for all respondents. This research questionnaire starts with a cover letter, informing respondents about the purpose of the research and ensuring the confidentiality of their responses. It consists of three sections related to the use of AI: Section A and Section B. Section A gathers demographic information from respondents, while Section B focuses on the study's constructs. In Section A, nine questions collect background data, including gender, age, education level, job title, length of work experience, state, current employee count, annual sales revenue, and types of AI tools used. Section B includes two factors and 14 items, covering two constructs related to independent variables and one construct related to the dependent variable concerning the adoption of AI by SMEs.

Table I Construct of Technology Scale in Adoption of Ai

No	Domain	Number of items	Adapted
1	Relative Advantage	5 items	Badghish et al, (2024); Shahzad et al (2023)
2	Compatibility	4 items	Badghish et al, (2024); Shahzad et al (2023)
3	Adoption of AI	5 items	Ghobakhlooetal. (2011); Raguseo and Vitari (2018); Badghish et al (2024)

Choosing effective Likert-type items is essential for collecting accurate and meaningful data in survey research. Selecting well-crafted Likert items provides a clear and balanced range of response options that truly reflect respondents' attitudes or opinions. Additionally, providing brief instructions or preambles at the beginning of Likert-type scales is important to help respondents accurately interpret and use the scale (Koo, 2025). A balanced scale ensures that respondents have equal chances to express positive, negative, or neutral feelings when appropriate. This balance minimizes response bias and boosts the reliability of the data gathered (Lazano, 2008).

As a result, a scale with odd numbers was used to evaluate the views of respondents in this study. Participants received a five-point Likert scale that included responses such as Strongly Disagree (1), Disagree (2), Neutral (3), Agree (4), and Strongly Agree (5) (Koo, 2025). Each response choice is linked to corresponding values from one to five.

The study involved 31 respondents, including entrepreneurs, business owners, and marketing staff from small and medium enterprises (SMEs) across various states in Malaysia. The gender split was almost even, with 48.4% male and 51.6% female participants. Most respondents were aged between 23 and 28 years (45.2%) and 29 to 34 years (32.3%), showing a young workforce. Regarding education, the majority held either a diploma (29.0%) or a bachelor's degree (29.0%), followed by those with a master's degree (22.6%). A small percentage had completed SPM (12.9%) or held a PhD (6.5%). In terms of job roles, 41.9% of respondents were executives, followed by supervisors (22.6%), managers (16.1%), directors (9.7%), and administrative staff (9.7%).

Most participants had substantial work experience, with 32.3% having worked for 11–20 years and 29.0% for over 30 years. The respondents came from various states, with the highest numbers from Pahang, Terengganu, and Perlis (each 12.9%), and smaller groups from Selangor, Johor, Sabah, and Sarawak. Regarding firm size, 29.0% of respondents were from SMEs with 31–40 employees, while 25.8% were from firms with 21–30 employees. Most businesses (80.6%) reported average annual sales between RM300,000 and under RM3 million, with the remaining 19.4% reporting annual sales of RM3 million to RM20 million. This demographic profile highlights a diverse and experienced group of SME representatives actively involved in marketing and business operations in Malaysia.

RESULT

Reliability Analysis for Pilot Test

A pilot study was conducted after refining the questionnaire based on feedback from an expert. The goal of the pilot study was to test the internal reliability of the questionnaires. The questionnaire for the pilot study was

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prepared using Google Forms. The link to the Google Form was shared online on social media platforms where the researcher is a member. The researchers also specified that respondents must have experience using AI marketing tools in their company.

For pilot studies, a common recommendation is to have at least 30 participants (Browne, 1995). This is because a sample size of 30 or more is often used as a rule of thumb in statistical procedures to approximate a normal distribution. In this research, 31 responses (more than 30) were collected for the pilot study. The sample was obtained within two days of distributing the questionnaire. The collected data were analyzed using SPSS software. Cronbach's Alpha reliability coefficients (Hair et al., 2014) were used to assess the internal consistency of the data from the pilot study.

While 0.70 is generally recognized as the minimum acceptable value for Cronbach's alpha, a value of 0.60 may also be considered acceptable for internal consistency (Ransford et al., 2009). Joseph et al. (2017) define the lower bound of acceptability as values between 0.60 and 0.70. Lower Cronbach's alpha values, such as 0.60, are endorsed by Joseph et al. (2006) for research with small sample sizes. According to Flynn et al. (1994), a minimum Cronbach's alpha of 0.60 can be used to determine a scale’s reliability. Conversely, Moss et al. (1998) stated that Cronbach's alpha should be greater than 0.60. Items with Cronbach's alpha above 0.9 are considered to have excellent internal reliability (Kline et al., 2015).

TABLE II Summary of reliability analysis on of independent and dependent variables

Variables	Cronbach Alpha	Status
Relative advantage	0.871	Good
Compatibility	0.925	Excellent
Adoption of AI	0.932	Excellent

Validity Analysis for Pilot Test

Exploratory Factor Analysis

The Exploratory Factor Analysis (EFA) was started by assessing the sampling adequacy and the factorability of the dataset using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett’s Test of Sphericity. The KMO score was 0.661, which surpasses the minimum acceptable threshold of 0.60, showing that the sample size was adequate for factor analysis (Tabachnick & Fidell, 2007; Pallant, 2007). Furthermore, Bartlett’s Test of Sphericity produced a chi-square value of 282.843 with 78 degrees of freedom and a significance level of $p < .001$, confirming that the correlations among the 14 items were strong enough for factor analysis (Huck, 2012). These results demonstrate that the dataset met the essential assumptions for performing EFA.

TABLE III KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.661
Bartlett's Test of Sphericity	Approx. Chi-Square	282.843
	df	78
	Sig.	<.001

Exploratory Factor Analysis (EFA) was conducted on 14 items using Principal Component Analysis (PCA) with Varimax rotation. A factor loading threshold of 0.40 was used for item retention. This analysis identified three components that together explained the total variance, as shown in Table 6. The first component accounted for 32.83% of the variance, while the second and third components contributed 26.85% and 17.47%, respectively. All three components had eigenvalues greater than 1.0, confirming their retention based on the Kaiser criterion. The Extraction Sums of Squared Loadings matched the Initial Eigenvalues, indicating no variance was lost during extraction. The combined variance of 77.16% suggests the three extracted components strongly represent the data, supporting a stable factor structure within the instrument.

TABLE IV Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.268	32.829	32.829	4.268	32.829	32.829
2	3.491	26.852	59.681	3.491	26.852	59.681
3	2.272	17.474	77.155	2.272	17.474	77.155
4	.634	4.874	82.030			
5	.595	4.580	86.610			
6	.457	3.513	90.123			
7	.347	2.666	92.789			
8	.279	2.146	94.935			
9	.261	2.007	96.942			
10	.145	1.119	98.061			
11	.117	.897	98.958			
12	.075	.578	99.536			
13	.060	.464	100.000			
Extraction Method: Principal Component Analysis.						

The Rotated Component Matrix, derived from Principal Component Analysis with Varimax rotation, identified a clear three-factor structure. Each item had strong loadings on its respective component, all exceeding the recommended 0.40 threshold (Hair et al., 2010) and showed no problematic cross-loadings. Items RA1 to RA5 loaded prominently on Component 1, representing the construct of Relative Advantage. Items AI1 to AI4 loaded strongly on Component 2, associated with AI Adoption. Items COMP1 to COMP4 loaded exclusively and strongly on Component 3, indicating the construct of Compatibility. The absence of significant cross-loadings and the distinct grouping of items across components confirm the scale's discriminant validity. These findings support the multidimensional structure of the instrument and empirically validate its construct validity.

TABLE V Factor Loadings based on a principal component analysis extraction with Varimax rotation

	Component		
	1	2	3
RA1	.843		
RA2	.764		
RA3	.863		
RA4	.738		
RA5	.843		
COMP1			.905
COMP2			.893
COMP3			.931
COMP4			.844
AI1		.937	
AI2		.879	
AI3		.903	
AI4		.900	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 5 iterations.			

Expert Review

The results of the expert validity of the instrument were deemed suitable for use in this study after making some improvements. The researcher revised the items based on the experts' comments, such as transforming items into positive statements, adjusting the items to match different levels of difficulty for appropriate respondents, and using simpler words in sentences for better understanding.

DISCUSSION

Reliability analysis for Relative Advantage showed a Cronbach's Alpha within a reasonable range, indicating good internal consistency. The findings from the Exploratory Factor Analysis (EFA) strongly support the importance of Relative Advantage and Compatibility in influencing the adoption of AI among SMEs. The construct of Relative Advantage showed high factor loadings across all five related items, ranging from 0.738 to 0.863, indicating that SME respondents consistently saw AI tools as providing significant benefits. These benefits include increased marketing efficiency, better customer engagement, and more informed decision-making. These results align with previous studies, which highlight that the relative advantage of technology plays a key role in driving adoption behavior (Rogers, 2003; Tornatzky & Klein, 1982). The distinct grouping of items in the factor structure further affirms the validity of Relative Advantage as a reliable predictor of AI adoption among small businesses.

Similarly, the construct of Compatibility emerged as an important factor, with strong and consistent loadings between 0.844 and 0.931 across all four items. These findings suggest that SMEs are more likely to adopt AI tools that match their current operational practices, values, and technological infrastructure. These findings are particularly relevant for Malaysian SMEs, many of which face resource and capacity constraints. The results are in line with the Technology–Organization–Environment (TOE) framework, which emphasizes the significance of internal organizational fit in adopting innovation (Tornatzky & Fleischer, 1990). In this pilot phase, the focus is limited to the technological context, specifically Relative Advantage and Compatibility, both of which are consistently identified in prior literature as strong predictors of innovation adoption (Rogers, 2003; Badghish et al., 2024).

Additionally, the reliable scores from internal consistency analysis confirm that respondents saw AI technologies as compatible with their existing business environments. These results agree with previous research (Chatterjee et al., 2021; Aziz & Wahid, 2020; Li et al., 2017; Azmi et al., 2016), reinforcing that Compatibility is a key factor in the technology adoption process, especially for SMEs with limited flexibility to change existing systems.

To sum up, the combination of EFA findings and reliability analysis shows that both Relative Advantage and Compatibility, are crucial drivers of AI marketing tool adoption among SMEs. These factors not only reflect the expectations and limitations of small business environments but also provide practical insights for AI solution developers and policymakers seeking to advance digital transformation in the SME sector.

CONCLUSIONS

This study aimed to assess the reliability and validity of measurement tools used to evaluate key technological factors influencing the adoption of Artificial Intelligence (AI) among Small and Medium Enterprises (SMEs) in Malaysia. The pilot test results showed that both Relative Advantage and Compatibility demonstrated strong internal consistency and satisfactory factor loadings, confirming their suitability for further empirical testing. These findings align with existing literature, reaffirming that SMEs are more inclined to adopt AI when technology offers clear operational and integrates smoothly with current business practices and values. As a result, these two constructs are validated as crucial predictors for future research examining AI adoption within the framework use of the Technology-Organisation-Environment (TOE) that focuses on organisational decision-making concerning strategic technology adoption. Therefore, the TOE framework provides a more appropriate theoretical perspective, capturing the complex and multi-layered considerations faced by SMEs when evaluating new technological innovations, such as AI.

However, several limitations must be recognised. This study was conducted as a pilot with a relatively small sample of 31 respondents from the SME sector. While the limited sample size was adequate for validating the instrument, it may restrict the generalisability of the findings to broader SME populations across different industries or regions. Additionally, the study focused solely on technological factors within the TOE framework, thereby excluding other important organisational and environmental elements such as Top Management Support, Organisational Readiness, Government Support, and Competitive Pressure. Furthermore, the cross-sectional nature of the study constrains the ability to track changes in AI adoption over time. Future research should consider larger, more diverse samples and utilise longitudinal or mixed-method approaches to better understand the dynamic evolution of AI integration.

The findings also offer several practical implications for policymakers and business leaders. From a policy perspective, institutions such as SME Corp Malaysia, MDEC, and MITI should consider developing tailored support programmes that focus on increasing SME awareness of AI compatibility and usefulness. Initiatives such as AI training workshops, financial incentives, tax relief, and sector-specific toolkits could lower adoption barriers, especially for SMEs in rural or underserved regions. From a managerial standpoint, SME decision-makers are encouraged to assess their digital readiness and align AI adoption strategies with their firm's operational capabilities and workforce skills. Investing in training, change management, and internal capacity-building can not only reduce resistance to new technologies but also improve the effectiveness of AI implementation. By bridging policy support and internal strategic alignment, SMEs can better position themselves to harness AI technologies as enablers of innovation, efficiency, and long-term competitiveness.

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