FACTORS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN ACCOUNTING AMONG MICRO, SMALL MEDIUM ENTERPRISES (MSMES)

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Abstract. This study investigated the factors that influence the adoption of artificial intelligence (AI) in accounting among Malaysian Micro, Small Medium Enterprises (MSMEs). It focused on three factors based on the Technology, Organization, and Environment (TOE) framework, and the Diffusion of Innovation (DOI) theory. The factors examined include compatibility, complexity, security and privacy, top management support, business strategy support, organizational resources, business market structure, competitive pressure, and government regulations. A quantitative approach was employed to collect data which were then analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) software. The study's findings indicate that compatibility, top management support, business strategy support, organizational resources, business market structure, competitive pressure, and government regulations significantly impact AI adoption in MSMEs. However, the study did not find significant influences of complexity as well as security and privacy on AI adoption of Malaysian MSMEs. In conclusion, this study's findings offer valuable insights on how organizations can effectively navigate these factors to achieve successful AI adoption in their accounting practices.
Keywords: *artificial intelligence, accounting, micro small medium enterprises, Malaysia*

Introduction

In 1956, the term "artificial intelligence" was first introduced by John McCarthy, an American scientist. One notable AI and law project that emerged early on was the development of "Taxman", a knowledge-based system created by McCarthy during his tenure as an assistant professor at Harvard University in 1977 (Karlinsky et al., 1992). As the availability of computers and the internet increased, the use of AI technology witnessed significant growth, allowing more efficient problem-solving capabilities. Today, businesses are increasingly adopting AI-based solutions, leading to a growing number of applications for cognitive technology. This progress in AI has been propelled by building upon both past successes and failures, creating an evolutionary trajectory in the current era (Hasan, 2021), culminating in the rapid expansion of the industry 4.0 sector with the expectation of increased accessibility to AI technologies.

Background

The 21st century has been marked by outstanding technological advancements, with AI being one of the most notable developments. AI includes subsets such as machine learning and deep learning, which enable computers to mimic human behavior. Digital transformation has revolutionized manual processes, and companies with adequate resources have been quick to invest in AI to enhance their profitability. The adoption of digital technologies has become increasingly important in light of the fourth industrial revolution, especially for Micro, Small and Medium Enterprises (MSMEs) in

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accounting services, where the workload can be overwhelming without the help of advanced systems (Gupta et al., 2020). While MSMEs have widely adopted accounting software to alleviate manual data entry, these existing software solutions often lack the decision-making capabilities of AI, which are now being integrated into major accounting firms such as PwC, EY, Deloitte, and KPMG (Ashok and MS, 2019). Consequently, AI adoption has become a significant competitive trend, offering an improved competitive edge and sustainability (Davenport and Ronanki, 2018).

Despite concerns about job displacement, there are conflicting opinions on whether AI will create new opportunities or eliminate jobs. Nevertheless, it is worth noting that AI still requires human supervision and input to ensure quality control and data interpretation. The improved efficiency and productivity resulting from AI can boost the performance of accountants and auditors, allowing them to shift their attention toward more advanced tasks that require human judgment and decision-making skills (Das, 2021). Hence, despite the challenges posed by AI, embracing innovation and adapting to change can enhance productivity, job satisfaction, and overall performance.

Problem statement

AI technology has advanced rapidly, garnering global recognition and yielding significant results, particularly in sectors where it has been employed to boost productivity and competitiveness (Emetaram and Uchime, 2021). The significance of AI lies in its effects on different facets of society, such as the substitution of human work and its gradual assimilation into everyday existence. In the field of accounting, the incorporation of AI and the development of accounting software have brought about a comprehensive transformation in accounting practices, resulting in significant changes such as a substantial decrease in bookkeeping functions. However, it remains to be seen whether these changes will encourage Malaysian MSMEs to adopt AI, and which key factors influence the industry's adoption of AI in accounting practices.

Literature review and hypothesis development

Artificial intelligence in accounting

The adoption of AI has become prevalent in the accounting industry, with its applications evident in various areas including electronic documentation, audits, tax practices, and fraud prevention techniques. The adoption of AI in accounting has received a positive response as it enables accountants to concentrate on more important tasks by automating the tedious processes of data input and management (Ionescu, 2019; Chukwudi et al., 2018). Clearly, utilizing AI in accounting has various advantages, including the enhancement of productivity, efficiency, and accuracy (Damerji and Salimi, 2021; Faccia et al., 2019). Additionally, AI provides real-time data analysis and reporting, allowing businesses to make quick and informed decisions. With AI-powered systems processing large volumes of data in a short period, decision-makers can access up-to-date and accurate information about their financial status (Faccia et al., 2019). Furthermore, AI can identify patterns and trends in financial data that might be overlooked by humans, providing valuable insights into business operations and performance (Ionescu, 2019). By leveraging AI's capabilities, businesses can make better-informed decisions, optimize their financial performance, and improve their client services. While concerns remain around the potential displacement of human workers, the integration of AI technology remains essential for businesses to remain competitive and to ensure sustainable growth by improving productivity and scalability through operational uniformity (Chukwudi et al., 2018).

Technological factors

Compatibility (CPT)

One important element that has been identified as impacting AI adoption is compatibility. Compatibility refers to the extent to which an innovation can satisfy the demands of prospective customers, provide value, and seamlessly integrate with their experiences. The compatibility of a company's technology adoption reflects how well it aligns with its culture and business processes. However, businesses can be more flexible with their rules and processes to create a positive relationship between compatibility and the use of AI. Therefore, this study suggests that organizations are more likely to adopt AI across their various departments if they believe that it is compatible with their existing procedures and standards. Hence, Hypothesis 1 (H1) was developed:

H1: The adoption of AI by Malaysian MSMEs is positively correlated with the level of compatibility.

Complexity (CPX)

The adoption of a new technology may fail if it is viewed as being highly ambitious and difficult to execute. Technical complexity is a measure of the level of difficulty in comprehending and utilizing an innovation. To facilitate the adoption process, the organization's employees must quickly grasp the new technology, as the adoption process can become more unpredictable and challenging with the introduction of more advanced technologies (Gangwar, 2018). In contrast to other variables that influence technological innovation, the acceptance of new technology is negatively correlated with complexity, which increases uncertainty for decision-makers evaluating the adoption of the technology (Asiaei and Ab. Rahim, 2019; Alshamaila et al., 2013; Ghobakhloo et al., 2011). Therefore, organizations are less likely to adopt innovations that require significant effort. Hence, Hypothesis 2 (H2) was constructed:

H2: The adoption of AI in Malaysian MSMEs is negatively influenced by complexity.

Security and Privacy (SP)

Alshamaila et al. (2013) claimed that uncertainty is considered a risk that hinders the adoption and maintenance of innovations within a company's existing structure. Data-related innovations, such as those involving AI, also present security concerns related to the risks of outsourcing (Asiaei and Ab. Rahim, 2019). These risks are associated with the use of third-party resources for developing AI solutions or availing AI services (Asiaei and Ab. Rahim, 2019). For instance, many companies outsource their projects and seek external assistance because they lack in-house expertise in establishing and managing an AI environment within their organization, especially given the emerging nature of AI-related advancements (Hannan and McDowell, 1984). However, outsourcing may lead to companies losing control of their data when shared with

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contractors and external providers, thereby raising concerns about security and privacy. Hence, Hypothesis 3 (H3) was formulated:

H3: The negative association with AI adoption among MSMEs is linked to their perception of a high level of uncertainty and insecurity regarding AI.

Organizational factors

Top Management Support (TMS)

According to El-Haddadeh et al. (2021), a successful adoption of new technological systems heavily relies on the extent to which top management recognizes and accepts their potential. Previous studies related to implementation of innovations like AI (Chong et al., 2009), cloud computing, and big data have also supported the importance of top management support in their adoption. Top managers play a vital role in facilitating the adoption of AI because they are responsible for creating an environment where sufficient resources are allocated for the adoption of technology (El-Haddadeh et al., 2021; Bauer et al., 2020). This is underscored by Elbanna (2013) who emphasized the need for consistent managerial support throughout the implementation of a project to ensure its success. Therefore, top management support accelerates the process of business transformation and AI adoption (Hannan and McDowell, 1984). Hence, Hypothesis 4 (H4) was developed:

H4: The AI adoption of Malaysian MSMEs is positively associated with top management support.

Business Strategy Support (BSS)

Organizations that have centralized their business strategy can effectively adapt to emerging AI technologies. Business strategy involves prioritizing analytics as a key component of strategic planning and employing AI to provide business value within the context of an AI conceptual framework. The level of heterogeneity in a company’s business environment can impact how quickly it adopts new technologies. In addition to strategy, external normative factors also impact an organization’s plans for using AI. The current wave of AI technology can provide a competitive advantage to a company when used in conjunction with a clear digital business strategy that takes into account the organization’s needs, rules, and automation. Therefore, this study argued that organizations with a clear business strategy have a significant influence on AI adoption. AI-capable systems can improve the efficiency of accounting practices, providing a competitive edge. Hence, Hypothesis 5 (H5) was formulated:

H5: The adoption of AI in Malaysian MSMEs is positively associated with a business strategy support.

Organizational Resources (OR)

Organizational resources refer to both human and technological aspects of a business. Adoption of new technology is influenced by financial resources, IT infrastructure, analytical skills, and human capital. Adequate access to these resources can promote the adoption of AI and improve internal processes. Management support is

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also crucial in creating a data culture and encouraging data-driven policies. While AI is not a commodity that can be purchased, it requires long-term strategy, investment in resources, and cultural changes. Without adequate resources and expertise, any investment in AI is rendered useless, as pointed out by Al-Dmour et al. (2022). Hence, Hypothesis 6 (H6) was developed:

H6: The availability of organizational resources is positively associated with the AI adoption of Malaysian MSMEs.

Environmental factors

Business Market Structure (BMS)

Hao et al. (2018) stated that uncertain market factors such as product demand, market competition, and customer loyalty can significantly impact organizational performance. Despite the infancy of AI technology and the shortage of skilled professionals and technical experts, AI has demonstrated remarkable resilience and provided companies with increased opportunities to compete. Intense competition is a reliable driver of the adoption of new technologies, especially in rapidly expanding industries. Companies operating in such industries need to consider the industry life cycle, while those in industries experiencing a decline in economic activity may find innovation processes and procedures ambiguous. However, AI can automate many of the routine tasks that accountants and auditors perform, such as data entry, reconciliation, and transaction classification. Hence, Hypothesis 7 (H7) was formulated:

H7: The business market structure is significantly and positively associated with the AI adoption of Malaysian MSMEs.

Competitive Pressure (CP)

Environmental factors refer to the external conditions that organizations face while conducting business beyond their local boundaries. Competitive pressure is one such factor identified by the TOE framework that may influence an organization’s adoption of AI. Chen et al. (2015) defined competitive pressure as external environmental forces that drive businesses to adopt AI, such as pressure from customers, suppliers, and competitors. Asiaei and Ab. Rahim (2019) study in the SME context found that organizations that feel more pressure to compete are more likely to adopt newer technologies effectively. Moreover, several researchers proposed that the growing utilization of AI among rivals can encourage managers and executives to systematically collect and evaluate business information to uphold their market standing. Hence, Hypothesis 8 (H8) was developed:

H8: Competitive pressure is positively associated with the AI adoption of Malaysian MSMEs.

Government Regulations (GR)

Previous studies have shown that government regulations have a positive effect on AI adoption. Government regulation which included incentives and restraints, can greatly influence a company’s decision to adopt new technologies. Expanding on this notion, government policies that offer incentives, establish technical standards, and provide legal frameworks can encourage organizations to adopt AI technology. The Malaysian government could support the increase of AI adoption among Malaysian companies, as suggested by introducing industrial policy blueprint. Through the implementation of policies and procedures, governments can create a favorable environment for the propagation and management of AI (Ghani et al., 2022). Previous studies have shown that companies that face more regulations and government intervention are more likely to adopt AI technology (Ghani et al., 2022). Hence, Hypothesis 9 (H9) was developed:

H9: Government regulations are positively associated with the AI adoption of Malaysian MSMEs.

Materials and Methods

A questionnaire survey was conducted to collect data for this study. The questionnaires were distributed to a range of professionals from Malaysian MSMEs, including owners, directors, CEOs, accountants, auditors, and staff members. The main objective of the questionnaire was to collect data on independent variables such as compatibility, complexity, security and privacy, top management support, business strategy support, organizational resources, business market structure, competitive pressure, and government regulations. In addition to the independent variables, the questionnaire also incorporated the dependent variable which was the intention to adopt AI in accounting. Responses collected through the questionnaire were subsequently analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationships between the independent and dependent variables.

Results and Discussion

This study employed PLS-SEM to analyze the sample data gathered from 196 respondents. PLS-SEM is a second-generation multivariate analysis technique, which was advanced by Chin et al. (2003), that allows precise analyses of multivariate data. The data collected through the questionnaire were analyzed using PLS-SEM, which involved conducting descriptive, measurement, and structural analyses. During the analysis, the construct reliability, collinearity, discriminant validity, coefficient of determination, and goodness of fit were evaluated. The results of the analyses, based on the data obtained for this study, are presented and discussed in the subsequent paragraphs. *Table 1* shows the descriptive statistics of the dependent variables. As shown in *Table 1*, the statement reflecting the respondents' belief that the adoption of AI would be effective in accounting practice received the highest mean score, at 4.25. This belief was closely followed by the expectation that many organizations intend to start using AI regularly in the future, evidenced by a mean score of 4.18. Meanwhile, the statement suggesting that organizations intend to adopt AI in accounting practice obtained the lowest mean score, at 4.08. Overall, the respondents generally agreed that the adoption of AI technology in their organization would be a positive development.

***Table 1**. Descriptive statistics for artificial intelligence adoption.*

Items	Mean	Std. Deviation

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Our organization intends to adopt AI in accounting practice.	4.08	0.76
Our organization intends to start using AI on a regular basis in the future.	4.18	0.83
Our organization expects that adoption of AI will be effective in accounting practice.	4.25	0.70
Our organization would strongly recommend other industries adopt AI.	4.14	0.82

Convergent validity is crucial for measuring the degree of association between a new scale and other variables or measures related to the same construct. In this study, internal consistency and convergent validity were evaluated using outer loadings, composite reliability (CR), and average variance extracted (AVE). As shown in *Table 2*, the outer loadings of all items were above the recommended value of 0.7 (Hair et al., 2010), except for CPX2 and SP3. Nevertheless, these items were retained as the AVE result was achieved. The CR of the latent constructs ranged from 0.78 to 0.90, indicating strong internal consistency, exceeding the recommended threshold of 0.7 (Hair et al., 2017). The AVE values were also found to exceed the threshold of 0.5, indicating that, for each construct, its items accounted for over 50% of its variance (Hair et al., 2017). Thus, the convergent validity requirements for the reflective measures of this study were achieved. Additionally, collinearity statistics were determined to verify that there was no presence of lateral collinearity that might impact the internal model of the research. The Variance Inflation Factor (VIF) is a method utilized in PLS-SEM to assess the degree of collinearity (Hair et al., 2014). Two commonly accepted thresholds were used to identify potential collinearity issues: a VIF of 5 or higher, or a VIF of 3.3 or higher (Hair et al., 2015; Diamantopoulos and Siguaw, 2006). The values presented in *Table 3* consistently fall below both thresholds, with values ranging between 1.15 and 2.07 and an average value of approximately 1.5. Thus, it can be inferred that all formative variables are sufficiently independent, thereby validating the reliability of the inner model.

***Table 2**. Results of internal consistency and convergent validity.*

First order constructs	Items	Loadings	Composite reliability	Average variance extracted
Compatibility	CPT1	0.82	0.85	0.59
	CPT2	0.73		
	CPT3	0.77		
	CPT4	0.75		
Complexity	CPX1	0.74	0.78	0.54
	CPX2	0.68		
	CPX3	0.78		
Security and privacy	SP1	0.73	0.77	0.53
	SP2	0.63		
	SP3	0.75		
Top management support	TMS1	0.80	0.88	0.64
	TMS2	0.81		
	TMS3	0.81		
	TMS4	0.80		
Business strategy support	BSS1	0.79	0.87	0.63
	BSS2	0.77		
	BSS3	0.75		
	BSS4	0.87		
Organizational resources	OR1	0.72	0.84	0.58
	OR2	0.76		
	OR3	0.78		
	OR4	0.78		
Business market structure	BMS1	0.85	0.89	0.73
	BMS2	0.87		
	BMS3	0.84		
Competitive pressure	CP1	0.78	0.83	0.63
	CP2	0.78		
	CP3	0.81		
Government regulations	GR1	0.86	0.90	0.74
	GR2	0.88		
	GR3	0.84		

Artificial intelligence adoption	AIA1	0.82	0.86	0.61
	AIA2	0.78		
	AIA3	0.77		
	AIA4	0.76		

Table 3. *Results of collinearity statistics.*

Items	Variable inflation factor
AIA1	1.79
AIA2	1.62
AIA3	1.55
AIA4	1.46
BMS1	1.84
BMS2	1.78
BMS3	1.76
BSS1	1.61
BSS2	1.60
BSS3	1.65
BSS4	2.07
CPT1	1.58
CPT2	1.46
CPT3	1.52
CPT4	1.40
CPX1	1.19
CPX2	1.15
CPX3	1.17
CP1	1.34
CP2	1.36
CP3	1.40
GR1	1.96
GR2	1.93
GR3	1.75
OR1	1.35
OR2	1.41
OR3	1.58
OR4	1.53
SP1	1.23
SP3	1.13
SP4	1.15
TMS1	1.66
TMS2	1.68
TMS3	1.79
TMS4	1.73

In this study, coefficient of determination (R2) was included to confirm the extent to which the variance in the dependent variable can be explained by the independent variables in the model. The acceptable R2 values were taken as 0.75, 0.50 and 0.25, representing substantial, moderate, and poor levels of predictive accuracy, respectively, as recommended by Hair et al. (2017). *Table 4* shows that an R^2 value of 0.73 was obtained for the construct of artificial intelligence adoption (AIA), suggesting that 73% of the variance in the AIA variable can be explained by the predictor variables in the model. The adjusted R^2 for the AIA construct was 0.71, which provides a value that accounts for the number of predictors in the model, offering a more accurate R^2 value

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by modifying it accordingly. Standardized Root Mean Square Residual (SRMR) was also computed in this study to measure the average difference between the observed correlations and the predicted correlations. A lower value indicates a better fit (Henseler et al., 2014). Generally, values below 0.10 or 0.08 indicate a good fit (Hu and Bentler, 1998). Based on the results in *Table 5*, both models obtained the same SRMR value of 0.076. The d_ULS (the squared Euclidean distance) and d_G (the geodesic distance) represent the difference between the number of observed variables and the number of estimated parameters (Dijkstra and Henseler, 2015). For both models, these values were identical at 3.64 and 4.17, respectively. The chi-square statistic assesses the goodness-of-fit of the model to the data. In this case, both models had the same chi-square value of 2958.81. However, both models obtained a low NFI value of 0.50, indicating a poor fit compared to a null model with no relationships between the variables. Overall, the models had a good fit based on SRMR, d_ULS, d_G, but a poor fit based on NFI.

***Table 4**. Results of coefficient of determination.*

	R^2	R^2 adjusted
AIA	0.73	0.71

***Table 5**. Results of model fit.*

Criterion	Saturated model	Estimated model
SRMR	0.08	0.08
d_ULS	3.64	3.64
d_G	4.17	4.17
Chi-square	2958.81	2958.81
NFI	0.50	0.50

Lastly, the researcher employed non-parametric sampling with 5,000 replications, as recommended by Hair et al. (2019), to evaluate the structural model. The standard significance criterion for social science research is a p-value of 0.05. This means that a researcher can be 95% confident that there is a true and significant correlation between two variables if the p-value is 0.05, and only 5% certain that there is none. *Table 6* presents the PLS output results and provides a concise explanation of the significant and non-significant variables.

***Table 6**. Summary of hypothesis results.*

Hypothesis	Factors	Statistical significance	Supporting evidence
H1	CPT	Positive	Significant (p-value=0.02)
H2	CPX	Negative	Not supported (p-value>0.05)
H3	SP	Negative	Not supported (p-value>0.05)
H4	TMS	Positive	Significant (p-value=0.00)
H5	BSS	Positive	Significant (p-value=0.00)
H6	OR	Positive	Significant (p-value=0.01)
H7	BMS	Positive	Significant (p-value=0.02)
H8	CP	Positive	Significant (p-value=0.00)
H9	GR	Positive	Significant (p-value=0.00)

Hypothesis 1 predicted that technical compatibility positively influences the adoption of AI in accounting. The results in *Table 6* present supporting evidence for H1, as technical compatibility with a p-value of 0.02 is shown to significantly contribute to the factors that affect AI adoption. These results align with previous studies conducted by

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Alsheibani et al. (2020), where the authors suggested that organizations are more inclined to adopt AI in various departments if they believe that it is compatible with their current practices and standards. It was proposed in Hypothesis 2 that the adoption of AI in accounting is negatively affected by technical complexity. However, the estimates of technical complexity, as shown in *Table 6*, were not statistically significant, with a p-value more than 0.05. Therefore, it can be concluded that H2 was not supported. Hypothesis 3 postulated that security and privacy issues are obstacles to the adoption of AI in accounting. However, the result of the statistical analysis, as shown in *Table 6*, indicates that the p-value was not significant. Despite the growing trend of firms outsourcing AI, concerns about losing control of confidential data and exposing sensitive information to competitors may still impede the adoption of AI (Asiaei and Ab. Rahim, 2019). Therefore, it can be concluded that H3 was not supported.

The findings validate Hypothesis 4 where it was posited that top management support affects the adoption of AI in accounting. The evidence provided in *Table 6* supports H4, with a positive and statistically significant p-value of 0.00 for AI adoption with top management support. These results are consistent with the findings from El-Haddadeh et al. (2021) and Elbanna (2013), where the authors emphasized the significance of top management support as a driving force in the business transformation process and the adoption of AI. In Hypothesis 5, it was predicted that technical support for business strategy has a positive influence on the adoption of AI in accounting. The result presented in *Table 6* provides supporting evidence for H5; it shows that business strategy support with a p-value of 0.00 significantly contributed to the factors affecting AI adoption. The organizations should have a clear digital business strategy that considers their specific needs, regulations, and automation requirements. It was proposed in Hypothesis 6 that organizational resources are positively associated with the adoption of AI in accounting. The evidence provided in *Table 6* supports H6, where a positive and statistically significant p-value of 0.01 was obtained for AI adoption in relation to organizational resources. This finding aligns with Al-Dmour et al. (2022) who suggested that having adequate resources, including financial, human capital, and IT infrastructure, can accelerate the adoption process.

Hypothesis 7 suggested that the adoption of AI in accounting is influenced by the structure of the business market. The results from the analysis supported H7. As shown in *Table 6*, a statistically significant p-value of 0.02 was obtained, indicating a positive relationship between AI adoption and business market structure. This is consistent with earlier research such as Mansfield's study in 1968, where it was found that intense competition can drive the implementation of new technologies, particularly in fast-growing industries. Hypothesis 8 proposed that competitive pressure affects the adoption of AI in accounting. The results from the analysis, as presented in *Table 6*, supported this hypothesis. A statistically significant positive correlation between AI adoption and competitive structure was found, with a p-value of 0.01. These findings are consistent with Asiaei and Ab. Rahim (2019) study which found that organizations are more likely to adopt advanced technologies in response to competitive pressures. It was posited in Hypothesis 9 that government regulations play a role in the adoption of AI in accounting, and this was validated by the study's findings. Specifically, the result presented in *Table 6* demonstrates a statistically significant and positive correlation between AI adoption and government support, with a p-value of 0.00. These results are in line with the findings, which they argued that government policies such as incentive

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programs, technical standards, and legal frameworks can encourage organizations to adopt AI technology.

Conclusion

In conclusion, the study found that Malaysian MSMEs have a positive perception of AI adoption in accounting and identified several key factors that influence the adoption process, including technical compatibility, top management support, business strategy support, organizational resources, business market structure, competitive pressure, and government regulations. The study highlights the importance of considering technological, organizational, and environmental factors in AI adoption. It also provides insights into the current state of AI adoption and offers a framework for future research and decision-making by MSMEs. However, it should be noted that the study has limitations, and further research is required to improve its validity and reliability. Overall, this study offers a valuable contribution to the understanding of AI adoption in accounting by Malaysian MSMEs, enriching the existing body of knowledge in the field.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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