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Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation

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A B S T R A C T

The study examines the technological factors influencing the adoption of artificial intelligence (AI) technology. In addition, this study examines the mediating role of accounting automation on AI adoption in a small and medium-sized enterprise (SMEs) context. The owners and managers of SMEs were surveyed online using a convenience sampling technique. The proposed model was tested using SEM. The findings confirmed the relationships between the predictive variables and AI adoption. The results showed that accounting automation partially mediated the relationship between predictive variables and the adoption of AI. The results contribute to the TOE model by incorporating accounting automation into the TOE framework as a mediating variable. The study also contributed to the literature by including new variables in the model, such as saving time and efficiency-improving.

1. Introduction

SMEs employ disruptive technologies to grow their enterprises and advance their operational activities in the modern day (Akpan et al., 2022). The fourth industrial revolution's digitalisation race has heightened the demand for SMEs to embrace digital technology (Ghobakhloo & Iranmanesh, 2021; Maroufkhani et al., 2022). Digitalisation provides excellent opportunities and prospects for entrepreneurs who lead and manage SMEs to stand out in the market and grow their businesses (Ghobakhloo & Iranmanesh, 2021; Maroufkhani et al., 2022; Richter et al., 2017). In addition, there is a strong desire to adopt innovative technology to grow quicker and remain competitive in the face of inadequate financial and non-monetary resources (Maroufkhani et al., 2022). Emerging technologies, particularly AI-based accounting automation, are paving the way for SMEs to be more optimized in the age of Industry 4.0 phenomena (Jagatheesaperumal et al., 2021; Surianti, 2020). AI could help SMEs, in particular, move toward automation and embrace new business models. According to Vantage Market Research's (2022) most recent report on the Artificial Intelligence in Accounting Market, the increase in the need to automate the accounting process is hastening the market expansion of AI-based accounting automation. As a result, the global Artificial Intelligence in Accounting market is expected to reach USD 16069.8 million by 2028, primarily because of the COVID-19 epidemic. AI-based accounting automation is a new technology that has the potential to improve operational, strategic, and other business performance. However, it hasn't been widely adopted by businesses yet, especially small and medium-sized businesses (SMEs) (Oke & Arowoiya, 2021). Savlovschi and Robu (2011) have demonstrated that SMEs play a critical role in the growth of national economies and that AI-based accounting automation can play a significant role in this growth

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(Mohammad et al., 2020). Despite this, SMEs have slowly adopted this game-changing technology (Anshari & Almunawar, 2021; Hradecky et al., 2022). A few studies have recently examined AI-based accounting automation adoption in SMEs (Bhalerao et al., 2022; Lee & Tajudeen, 2020). However, there is still a need for a more significant examination of the role of developing technologies (Chatterjee, Chaudhuri, et al., 2021; Kumar & Kalse, 2021) and, notably, the impact of AI-based accounting automation on SMEs. Since it is stated that SMEs are less adopted than big enterprises in implementing AI-based accounting automation, this study specifically focuses on SMEs and their possible directions for adoption. Apart from the necessity for AI-based accounting automation deployment among SMEs, recognizing the various elements that may impact its adoption is a precondition for the value delivery of technology adoption (Maroufkhani et al., 2022). The Technological-Organizational-Environmental (TOE)model has attracted increased attention from experts to understand the antecedents of technology adoption. The TOE model claims that TOE circumstances are crucial in determining firms' decisions to embrace the technology. When studying the adoption of artificial intelligence, previous studies didn't look at the role of accounting automation as a mediating variable. They also didn't look at important predictive factors like saving time and improving efficiency. This study was done to fill this gap in the literature on artificial intelligence in SMEs. In this context, the current study posits that accounting automation mediates technological determinants' impacts on AI adoption. Therefore, the present study intends to investigate the mediating role of accounting automation among compatibility, saving time, efficiency-improving, and readiness for the challenge and artificial intelligence (AI) adoption. The results of this study add to the body of knowledge about the TOE model by assuming that accounting automation plays a mediating role in the time-saving and efficiency-improving effects. Furthermore, the current study examines whether past studies on AI adoption in SMEs have underestimated the influence of technological variables on AI adoption by assessing the mediating role of accounting automation. It is hoped that the findings of this study will help business owners and managers, as well as policymakers and companies offering AI-based accounting automation services, better understand how TOE plays a role in technology adoption.

2. TOE Framework

The TOE framework (Technology-Organization-Environment) is a theoretical framework that describes how organizations acquire technology and how technological, organizational, and environmental contexts all influence the process of adopting and implementing technological innovation. The model was published by Tornatzky et al. (1990). Existing research shows that the TOE model can explain occurrences in various technical, industrial, and national/cultural contexts. The TOE model has been used to describe the adoption of inter-organizational systems. The TOE model has also been proven in European, American, and Asian contexts, as well as in developed and developing countries (Chiu et al., 2017; Clohessy & Acton, 2019). Thorough research, like most models and theories, extends the framework to achieve its goals (Chiu et al., 2017; Cho et al., 2021). On the other hand, some components of this model are eliminated based on the study's aims and limits. For the objectives of this study, the TOE framework gives flexibility and knowledge of technological factors. According to several studies, the three factors of technology, organization, and environmental factors affect how a company determines the need for new technology, searches for it, and uses it. Researchers used somewhat different technological, organizational, and environmental factors in many empirical studies examining the TOE framework. In essence, researchers agreed with Tornatzky et al. (1990) that the three TOE contexts affect adoption, but they assumed that each technology or setting under study has its own set of factors or metrics.

2.1 Technological Component

2.1.1. Compatibility

According to Rogers (2003), "compatibility" relates to the degree to which an innovation is judged to conform to the values, needs, and experiences of potential adopters, and it has been found to influence technology adoption (Ahmi et al., 2014; Azzeh et al., 2022; Siew et al., 2020). Compatibility with a company's work practices, needs, and culture are instances where AI adoption has been proven to be influenced (Chatterjee, Rana, et al., 2021). As a result, if SMEs believe AI technology satisfies and aligns with all of their work requirements and meets innovation needs, they will be more open to employing it. This suggests.

H_1: *Compatibility has a positive influence on AI technology adoption.*

2.1.2. Readiness for Challenge

According to challenge and response theory (Niehans, 1982), when confronted with a challenge, an individual may respond adversely by being unprepared and excluding the concept, or positively by accepting the challenge, recognising it, and preparing for and then seeking to overcome it. According to theory, challenges are undefined difficulties for which there is no apparent solution but can be ready to overcome. Financial resources (Adejuwon et al., 2016), technology readiness (Mankins, 2009), and training (Prause, 2019) are examples of how SMEs can prepare for the adoption of artificial intelligence (AI), and they have been found to influence technology adoption. Readiness for challenge favourably predisposes SMEs by permitting them to respond positively to difficulty. This suggests

H_2: *The* readiness for the challenge *positively influences AI technology adoption.*

2.1.3. Saving Time

Because time is widely recognized as a limited and scarce resource, "saving time" refers to reallocating time from one activity to another to boost efficiency (Hanwananont, 2005). This means that intelligent technology can improve users' views of how much time they can save. It has been demonstrated that more free time, more tasks (Bergschöld, 2018), and less effort impact technology adoption (Gazori et al., 2020). The use of AI technologies is also expected to be driven by time savings. For example, if the time-saving benefits of AI-based accounting automation outweigh the possible negatives of manual operations, SMEs will adopt new technology. This suggests

H$_3$: *Saving time has a direct positive influence on AI technology adoption.*

When SMEs believe that accounting automation based on artificial intelligence does not lead to saving time, they will not adopt artificial intelligence because of the tremendous effort and modification required to implement accounting automation. Looking at the results of previous studies on the relationship between time-saving and automation (Olson & Levy, 2018), this study suggested accounting automation as an explanation of the effect of time-saving on adopting artificial intelligence. Hence, this study develops the following hypothesis:

H$_4$: *Accounting automation mediates the association between saving time and AI adoption.*

2.1.4. Efficiency-improving

According to Shekhar (2019), employees can be efficient at a job or grow to be so after some time, but no matter how efficient people are, they will still make mistakes. But an Automation solution is way more foolproof and will not indulge in many errors. With time it will also be able to learn from the outputs and improve its efficiency (Shekhar, 2019). Efficiency-improving results in the capacity to perform jobs more rapidly, reducing the number of overtime hours employees must work (Karna et al., 2019). Companies that invest in AI technology get benefits from automation. Automating repetitive processes decreases human error, automation improves credit management, automation provides real-time reporting, automation boosts client and employee satisfaction, and automation boosts productivity and profits are examples of how SMEs can improve efficiency (Aloe et al., 2019; Yashiro et al., 2022), and they have been shown to influence technology adoption (Wei & Ismail, 2009). Advantageously predisposes SMEs by allowing them to predict a high level of efficiency improvement. This suggests

H$_5$: *Efficiency-improving has a direct positive influence on AI technology adoption.*

The company's perception of the significance of accounting automation based on artificial intelligence as a means of enhancing efficiency favors its motivation to embrace artificial intelligence. Korhonen et al. (2020) noted that increasing efficiency-improving results in accounting automation and explains the adoption of artificial intelligence (Chukwuani & Egiyi, 2020). The study hypothesizes that a hypothesis estimation mediates the relationship between enhancing efficiency and adopting artificial intelligence and that improving efficiency indirectly influences adopting intelligence via accounting automation. Consequently, the following theory was put forward:

H$_6$: *Accounting automation mediates the association between efficiency-improving and AI adoption.*

2.2. Accounting automation

The study hypothesizes that accounting automation mediates the association between time savings and efficiency-improving. Automation of accounting processes is primarily motivated by the company's desire to save time and increase productivity. In addition, accounting automation is one of the elements requiring the organization to embrace artificial intelligence services that facilitate accounting automation. According to Hayes (2020), accounting automation is a form of accounting solution that employs artificial intelligence to automate repetitive operations like data input and document analysis. Effective technology adoption necessitates the presence of automation (Acemoglu & Restrepo, 2018; Kar & Kushwaha, 2021). Automation is, therefore, a significant role in adopting AI in the accounting industry. Accounting automation is vital in developing an atmosphere receptive to embracing artificial intelligence, where a corporation may automate various accounting activities (Ahmad & Mustafa, 2022; Qasaimeh et al., 2022). The adoption of artificial intelligence and accelerating organizational transformation can be achieved through accounting automation (Acemoglu & Restrepo, 2018; Kar & Kushwaha, 2021). Because of these findings and others like them, the researchers believe that accounting automation is a mediating factor in the relationship between time savings and improved productivity. To what degree does one intend to make an effort necessary to carry out a behavior? (Ajzen, 1991). The Theory of Planned Action claims that behavioral intention is the most significant predictor of conduct; individuals behave according to their intentions. Sheppard et al. (1988) identified a link between intentions and actions. Consequently, based on the TPB, accounting automation and AI adoption intention are expected to have a favorable association.

H$_7$: *Accounting automation has a positive influence on AI technology adoption.*

3 Research methodology and Analysis

3.1. Sample

No sampling frame holding respondent information is suitable for the study's objectives. However, technological advancement enabled target responders who fit the study's objectives (Stokes et al., 2019). Facebook has the most significant users, the most considerable global reach, the fewest subscription panels, and verifies the identity of respondents. Previous research collected survey responses through Facebook (Stokes et al., 2019). Several researchers (Brickman Bhutta, 2012; Facebook, 2022; Schneider & Harknett, 2022; Stokes et al., 2019; Zagheni et al., 2017) have created samples of the general population using Facebook. Recently, demographers showed that Facebook's advertising platform could be used as a "digital statistic" and used it to estimate immigrant numbers by country, such as US states (Zagheni et al., 2017). Convenience sampling was used to recruit artificial intelligence-knowing owners and managers because they sufficiently understand the company's strategic direction (Rawashdeh et al., 2022). Through sponsored ads on Facebook, the target population consisted of SME owners and managers with AI expertise residing throughout the United States. The a-priori Sample Size Calculator for Structural Equation Models (SEM) from Daniel Soper's website has been used to determine the suggested minimum sample size (Soper, 2017). There were six latent and twenty-four observable variables, with a probability of 0.05 and an expected effect size of 0.30. The suggested minimum sample size is 236 respondents, yet 4,500 respondents clicked the link on the first page to access the questionnaire. Where the questionnaire instructions describe the study's goal and the intended population, 410 respondents (9.1 %) completed the questionnaire, and 353 valid questionnaires were analysed (86%). This figure exceeds the Soper-recommended sample size, suggesting that the sample size is adequate for statistical analysis.

3.2. Questionnaire Design

The questionnaire contains 29 items, five of which are demographic questions in nature and 16 of which are technological, four of which are related to AI adoption and four of which are related to accounting automation. The questionnaire is based on the hypotheses drawn in Fig. 1, developed following a thorough review of the literature on technology adoption and accounting automation. The questionnaire was introduced to a small group of respondents and some academics in related disciplines to test the validity of the designed questions. The participants were asked to provide comments defining whether the questions were grammatically correct and understandable and to indicate further improvements. The participants proposed some valuable modifications. This questionnaire was pilot tested with 40 owners and managers who completed it and provided constructive input. Cronbach's was used to test the reliability of the measurement scales. The analysis results revealed a Cronbach's value greater than 0.70 for the multi-item barrier scale, indicating satisfactory internal reliability. According to the pilot research participants' feedback, relevant changes were made to the questionnaire to increase readability, ensuring its appropriateness and accuracy. The descriptive statistics of the respondents' demographic characteristics in the pilot study were analyzed. 90% of all Owners and managers are male, while 10% are female. The average age of respondents is 44 years old. The most common degree for owners and managers is a bachelor's degree, at 75%.

3.3. Demographic Profile

Table 1 summarizes the demographics of the survey respondents. From the 353 responses, 60.1% were in the over-40 age group, which formed the most significant response category, while the 31–40 age groups were the largest at 26.9%. Regarding gender, more males (85%) than females (15%) participated in the survey. All respondents possessed high educational qualifications: 72% had bachelor's degrees, 11.9% had associates, and 11% had master's degrees. The responses come from three different sectors of SMEs: 100–249 employees 10.0%, 50–100 employees 20%, and less than 50 employees 70%. 73% of the participants are Owners and managers and work for SMEs, and 27% are owners. 65% have previous experience with accounting automation in their business. There were 505 questionnaires distributed, and 353 were returned, for a response rate of 70%.

Table 1
Demographic Information

Profile of the companies		**Freq.**	**Percent**	**Profile of the companies**		**Freq.**	**Percent**
	20-30 Years	46	13.00%		< 50	247	70%
Respondent Age	31-40 Years	95	26.90%	Number of Employees	50 - 100	71	20%
	40+ years	212	60.10%		100 - 249	35	10%
Total		**353**	**100%**	**Total**		**353**	**100%**
	Bachelors	254	72.00%	Gender	Male	300	56%
	Associate	42	11.90%		Female	53	44%
Highest Education	Masters	39	11.00%	**Total**		**353**	**100%**
	High School	7	2.00%				
	Other Degrees	11	3.10%				
Total		**353**	**100%**	**Total**		**353**	**100%**

3.4. Common Method Bias (CMB)

Table 2 explains the CMB. CMB was empirically examined using Harman's single factor technique. First, whether a single factor had a preponderant explanatory power was determined. CMB has used a single-factor analysis developed by Harman. It is determined by conducting an unrotated factor analysis with data to determine if one component loads more than 50% of the variance owing to CMB (Aguirre-Urreta & Hu, 2019). However, the results indicate that the first factor accounted for just 26.15% of the overall variance, which is less than 50%, indicating that the existence of CMB does not threaten the data. It is now time to move on to causal modelling (Fig. 1).

Table 2
Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	4.18	26.15	26.15	4.18	26.15	26.15
2	3.72	23.27	49.42			
3	3.42	21.37	70.79			

3.5. Model Fit Measures

Table 3 presents the model fit measures, HTMT analysis and validity analysis. To examine the convergence of the constructs, the factor loadings, composite reliability (CR), and average variance extracted (AVE) were assessed. The factor loadings, CR, and AVE values must exceed 0.7, 0.5, and 0.7, respectively (Hair et al., 2019). This study's constructs satisfied the minimum requirements and demonstrated satisfactory convergent validity (Table 3). The discriminant validity using the Heterotrait–Monotrait (HTMT) criteria was determined by evaluating the HTMT criteria (Henseler et al., 2015). All HTMT values were less than 0.85, showing adequate discriminant validity (Table 4) (Kline, 2015).

Table 3
Model Fit Measures

Measure	Estimate	Threshold	Measure	Estimate	Threshold
Absolute Fit Measures			**Incremental Fit Measures**		
CMIN	303.093	--	TLI	0.99	Close to 1
DF	241.000	--	GFI	0.93	Close to 1
CMIN/DF	1.258	Between 1 and 3	AGFI	0.92	≥ 0.90
CFI	0.993	P<=0.05	NFI	0.97	≥ 0.90
SRMR	0.038	>0.95	**Parsimonious Fit Measures**		
RMSEA	0.027	<0.08	PNFI	0.85	Close to 1
PClose	1.000	<0.06	PGFI	0.76	Close to 1

Table 4
The results of HTMT

	HTMT Analysis						Validity Analysis	
	COMP	**SATI**	**IMEF**	**PRCH**	**ACAU**	**AIAD**	**AVE**	**MSV**
Compatibility							0.98	0.92
Saving Time	0.009						0.95	0.84
Efficiency-improving	0.052	0.097					0.83	0.63
Readiness for the Challenge	0.036	0.101	0.028				0.98	0.91
Accounting Automation	0.363	0.41	0.248	0.371			0.88	0.64
AI Adoption	0.423	0.57	0.2	0.583	0.667		0.78	0.56

The goodness-of-fit (GoF) of the measurement models was estimated using various GoF criteria. AMOS's output demonstrates this goodness-of-fit criterion, which includes absolute fit measures, incremental fit measures, and parsimonious fit measures. To show good model fit in the final fit measurement criteria, the likelihood ratios of Chi-Square (2)/CMIN; probability; CMIN/DF (Degree of Freedom); GFI (Goodness-of-Fit Index); and RMSEA (Root Mean Square Error of Approximation) values are used. In the incremental fit measurement criteria, the AGFI (Adjusted Goodness-of-Fit Index), TLI (Tucker-Lewis Index), and NFI (Normalized Fit Index) values are used to demonstrate satisfactory model fit. The PNFI (Blunch, 2012; Collier, 2020) and PGFI (Parsimonious Goodness-of-Fit Index) values are used to illustrate acceptable model fit when using the parsimonious fit measurement criteria (Blunch, 2012; Collier, 2020). In terms of absolute fit, the observed values of 323, 0.99, and 0.03 for CMIN, CFI, and RMSEA, respectively, indicate a model fit within the recommended value. A practical value of 0.93; 0.99; 0.97 for AGFI, TLI, and NFI indicates a good model fit. A parsimonious fit value of 0.87; 0. 77 for PNFI; and 0. 773 for PGFI demonstrates that the model fits well within the suggested range. Table 3 shows the results of a structural testing model based on goodness-of-fit criteria (Gaskin & Lim, 2016; Hu & Bentler, 1999).

3.6. Analysis Model

The test statistic CR (Critical Value) is used to determine the statistical significance of parameter estimations generated by SEM. It is defined as the parameter estimate divided by the parameter estimate's standard error (SE). The CR value must be greater than or equal to 1.96 at a 0.05 level of significance (Blunch, 2012; Collier, 2020). If the value of this parameter is less than this, it can be considered insignificant to the model's performance. Based on the findings in Table 4, the following study model hypotheses (Fig. 1) are all accepted and have a statistically significant positive effect on AI adoption: As shown in Table 5 and Fig. 1, the findings indicate that the following standardized regression weights were estimated:

Table 5
Regression Weights for Digital transformation vision

			Estimate	S.E.	C.R.	P	β
Accounting Automation	←	Saving Time	0.177	0.021	8.54	***	0.414
Accounting Automation	←	Efficiency-improving	0.24	0.044	5.513	***	0.284
Accounting Automation	←	Compatibility	0.165	0.021	7.857	***	0.372
Accounting Automation	←	Readiness Challenge	0.159	0.021	7.543	***	0.357
AI Adoption	←	Saving Time	0.093	0.023	3.973	***	0.235
AI Adoption	←	Efficiency-improving	0.116	0.046	2.523	0.012	0.148
AI Adoption	←	Accounting Automation	0.168	0.072	2.345	0.019	0.181
AI Adoption	←	Compatibility	0.115	0.024	4.875	***	0.279
AI Adoption	←	Readiness Challenge	0.059	0.023	2.555	0.011	0.143

The study's conceptual model's predictive accuracy was evaluated using the variance proportion (R^2) (Hair et al., 2019). The R^2 values of AI adoption and accounting automation were 0.49 and 0.81, respectively (Fig. 1). The structural model was analyzed using non-parametric bootstrapping with 5,000 replications (Hair et al., 2019). The results showed that saving time and efficiency-improving, directly and indirectly, affect accounting automation on AI adoption (Table 4). The results also showed that compatibility and readiness for the challenges directly affect AI adoption (Table 4). Figure 1 indicates the significant role the desire for accounting automation played as a mediator between predictive variables and the adoption of artificial intelligence, which explained 45% of the variance.

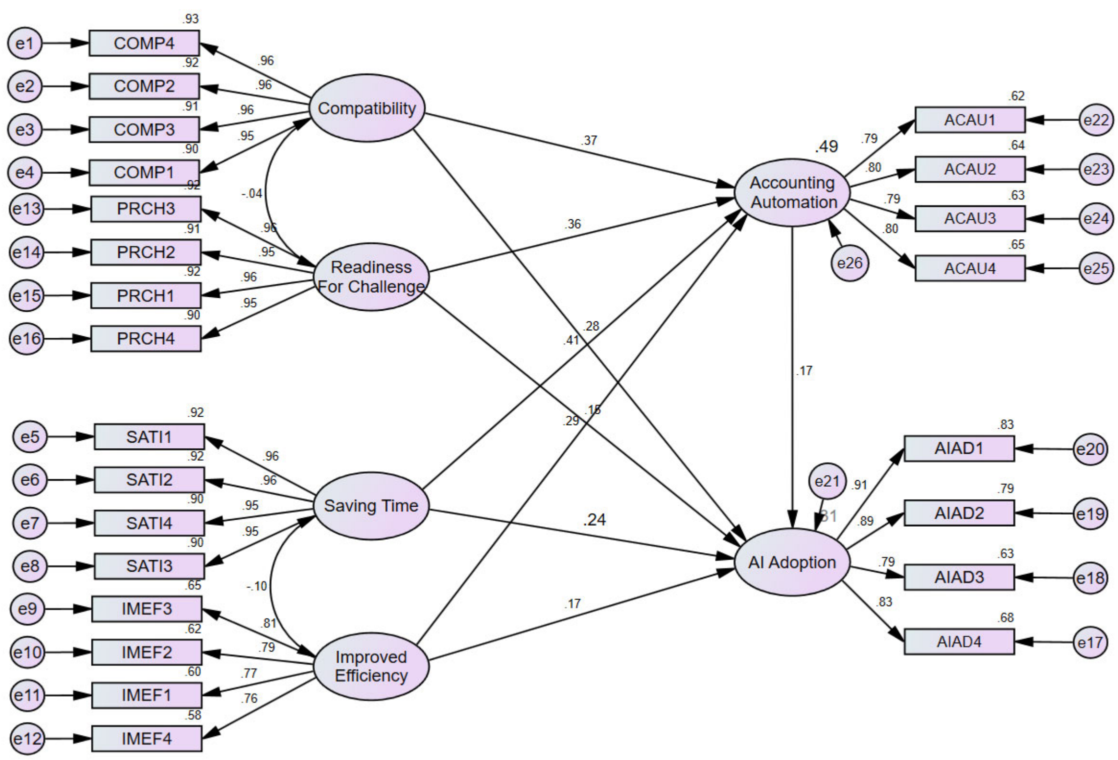

Fig. 1. Study Model

4. Discussion

The four technological factors, compatibility, readiness for the challenge, Efficiency-improving and saving time, have both direct and indirect effects on artificial intelligence adoption through accounting automation (Figure 1). Setiyadi et al. (2019) and Devkota et al. (2022) confirmed the impact of compatibility and readiness for the challenge on artificial intelligence adoption. Lee and Tajudeen (2020) confirmed the effect of Efficiency-improving and saving time on automation. Kokina and Davenport (2017) referred to the relationship between accounting automation and AI adoption. The findings indicate that SMEs' decision to adopt artificial intelligence can be explained by automating the accounting tasks and its consistency with the current firm's business practices, culture, and readiness for the challenge. However, the significant direct effects of Efficiency-improving and saving time on artificial intelligence adoption reveal that accounting automation is not the only reason these two factors are essential in the extent of artificial intelligence adoption. Data in the present study came from American SMEs. The study highlighted the critical role of the desire to automate accounting tasks in increasing the extent of artificial intelligence adoption. This salient role of willingness to automate accounting involved directly enabling artificial intelligence adoption by making it a prerequisite for automation and mediating the associations between other adoption determinants and artificial intelligence adoption. To the best of our knowledge, this is one of the early studies in this field to include accounting automation as a rationale for AI adoption. By investigating AI adoption in this context, the current study contributes to the theory. Although accounting in SMEs is one of the primary users of technological improvements related to data processing, there is an evident lack of research in this field. This study is a unique addition to the area of accounting automation and technology adoption. Moreover, the use of targeting audience methodology utilizing social media, i.e., Facebook, is an essential strength of this work that not only helps to achieve the primary objective of understanding the adoption of AI in SMEs but also goes one step further through the use of modern methods to collect data from respondents.

6. Conclusion

Technology is crucial to improving SME performance (Rehman et al., 2020). Modern technologies, like AI-based accounting automation, provide a way to automate repetitive operations through the rapid and accurate automation of accounting functions with fewer employees. However, many technologies implemented by SMEs failed, not necessarily due to the technology itself, but rather due to underestimating the impact of other linked elements. Examining how various factors impact the adoption of artificial intelligence by SMEs in the United States is a step toward identifying the relative significance of associated variables. Based on the findings, e.g., a positive correlation between accounting automation and AI adoption, the relevant stakeholders can initially focus on how artificial intelligence can help the automation process through a clear vision and strategy for a greater rate of technology adoption. Therefore, the consequences of this research are significant to SMEs, accounting automation, and AI adoption; for the effective adoption of AI technology in this context, a particular method, including automation, is required.

The study found that time-saving significantly and positively influenced accounting automation and AI adoption. This finding offers technology vendors an understanding of how businesses decide to adopt a technology. SMEs often view time consumption as a cost, so clarifying to the SMEs by the AI service provider how much time accounting automation saves and its cost implications will encourage sound decision-making in the adoption process. Most accounting processes are characterized by repetition and time pressure; therefore, technology vendors must, from the beginning, solve all the problems that may lead to consuming more time and mention them. Historically, accounting processing was done manually and then moved to systems with limited automation capabilities. However, applying artificial intelligence to support the automation process requires technology, resources, and specialists to integrate routine operations with artificial intelligence. Automated data entry, processing, and connection to a company database (e.g., an ERP system) are essential, which requires a significant number of resources and expertise. Therefore, being prepared for industry-wide challenges is vital to the expanded use of AI technology. SMEs regard increased efficiency as the capacity to accomplish tasks more rapidly, with fewer human errors, and consequently at a lower cost. Therefore, when promoting AI services, including automation, it is recommended that AI service providers demonstrate how AI technology may enhance job performance and eliminate human error.
The findings showed that AI compatibility with the current practices and culture of the SMEs is instrumental to SMEs' decision of whether to adopt AI. Accordingly, AI service providers should communicate with the SMEs, emphasize the compatibility of the AI tools, and assure them that they support SMEs in AI adoption. Although the study's objectives have been attained, this study, like any other, has limitations. Initially, the restructured TOE model was evaluated in the context of AI adoption, and the study sample was restricted to SMEs. Future research is required to assess the mediating effect of accounting automation in extensive studies. The literature on the TOE model can then be expanded by assessing the mediating influence of accounting automation in the context of organizational and environmental constructs.

This study aimed to uncover the factors linked to AI adoption in American SMEs and explore their direct and indirect effects on AI adoption. This study recommended that such studies explaining technology adoption in SMEs are necessary. The literature evaluation resulted in developing a research model that includes four factors in the technological context of the TOE framework and accounting automation as a mediating variable to explain AI adoption. The quantitative findings demonstrated that the anticipated antecedents have distinct effects on accounting automation and AI adoption. All factors had a beneficial impact that varied depending on the context.

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References

Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda* (pp. 197-236): University of Chicago Press.

Adejuwon, O. O., Ilori, M. O., & Taiwo, K. A. (2016). Technology adoption and the challenges of inclusive participation in economic activities: Evidence from small scale oil palm fruit processors in southwestern Nigeria. *Technology in Society, 47*, 111-120.

Aguirre-Urreta, M. I., & Hu, J. (2019). Detecting common method bias: Performance of the Harman's single-factor test. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 50*(2), 45-70.

Ahmad, H., & Mustafa, H. (2022). The impact of artificial intelligence, big data analytics and business intelligence on transforming capability and digital transformation in Jordanian telecommunication firms. *International Journal of Data and Network Science, 6*(3), 727-732.

Ahmi, A., Saidin, S. Z., & Abdullah, A. (2014). IT adoption by internal auditors in public sector: A conceptual study. *Procedia-Social and Behavioral Sciences, 164*, 591-599.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Akpan, I. J., Udoh, E. A. P., & Adebisi, B. (2022). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship, 34*(2), 123-140.

Aloe, R., Lippi, G., Di Pietro, M., Bonfanti, L., Dipalo, M., Comelli, I., . . . Cervellin, G. (2019). Improved efficiency and cost reduction in the emergency department by replacing contemporary sensitive with high-sensitivity cardiac troponin immunoassay. *Acta Bio Medica: Atenei Parmensis, 90*(4), 614.

Anshari, M., & Almunawar, M. N. (2021). Adopting open innovation for SMEs and industrial revolution 4.0. *Journal of Science and Technology Policy Management*, *13*(2), 405-427.

Azzeh, M., Altamimi, A. M., Albashayreh, M., & AL-Oudat, M. A. (2022). Adopting the Cybersecurity Concepts into Curriculum: The Potential Effects on Students Cybersecurity Knowledge. *Indonesian Journal of Electrical Engineering and Computer Science, 25*(3).

Bhalerao, K., Kumar, A., Kumar, A., & Pujari, P. (2022). A Study of Barriers and Benefits of Artificial Intelligence Adoption in Small and Medium Enterprise. *Academy of Marketing Studies Journal, 26*, 1-6.

Blunch, N. (2012). *Introduction to structural equation modeling using IBM SPSS statistics and AMOS*: Sage.

Brickman Bhutta, C. (2012). Not by the book: Facebook as a sampling frame. *Sociological Methods & Research, 41*(1), 57-88.

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Basile, G. (2021). Digital transformation and entrepreneurship process in SMEs of India: a moderating role of adoption of AI-CRM capability and strategic planning. *Journal of Strategy and Management*.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, 120880.

Chiu, C.-Y., Chen, S., & Chen, C.-L. (2017). An integrated perspective of TOE framework and innovation diffusion in broadband mobile applications adoption by enterprises. *International Journal of Management, Economics and Social Sciences (IJMESS), 6*(1), 14-39.

Cho, J., Cheon, Y., Jun, J. W., & Lee, S. (2021). Digital advertising policy acceptance by out-of-home advertising firms: a combination of TAM and TOE framework. *International Journal of Advertising*, 1-19.

Chukwuani, V. N., & Egiyi, M. A. (2020). Automation of Accounting Processes: Impact of Artificial Intelligence. *International Journal of Research and Innovation in Social Science (IJRISS), 4*(8), 444-449.

Clohessy, T., & Acton, T. (2019). Investigating the influence of organizational factors on blockchain adoption: An innovation theory perspective. *Industrial Management & Data Systems*, *119*(7), 1457-1491.

Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*: Routledge.

Devkota, N., Paudel, R., Parajuli, S., Paudel, U. R., & Bhandari, U. (2022). Artificial Intelligence Adoption Among Nepalese Industries: Industrial Readiness, Challenges, and Way Forward. In *Handbook of Research on Artificial Intelligence in Government Practices and Processes* (pp. 210-225): IGI Global.

Facebook. (2022). Help your ads find the people who will love your business. Retrieved from https://www.facebook.com/business/ads/ad-targeting?_rdc=2&_rdr

Gaskin, J., & Lim, J. (2016). Model fit measures. *Gaskination's StatWiki*, 1-55.

Gazori, P., Rahbari, D., & Nickray, M. (2020). Saving time and cost on the scheduling of fog-based IoT applications using deep reinforcement learning approach. *Future Generation Computer Systems, 110*, 1098-1115.

Ghobakhloo, M., & Iranmanesh, M. (2021). Digital transformation success under Industry 4.0: A strategic guideline for manufacturing SMEs. *Journal of Manufacturing Technology Management, 32*(8), 1533-1556.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review, 31*(1), 2-24.

Hanwananont, S. (2005). A study of selected factors related to consumers' intentions to redeem mobile coupons in Bangkok.

Hayes, D., & Kyobe, M. (2020). *The Adoption of Automation in Cyber Forensics.* Paper presented at the 2020 Conference on Information Communications Technology and Society (ICTAS).

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135.

Hradecky, D., Kennell, J., Cai, W., & Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *International journal of information management, 65*, 102497.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal, 6*(1), 1-55.

Jagatheesaperumal, S. K., Rahouti, M., Ahmad, K., Al-Fuqaha, A., & Guizani, M. (2021). The Duo of Artificial Intelligence and Big Data for Industry 4.0: Applications, Techniques, Challenges, and Future Research Directions. *IEEE Internet of Things Journal, 9*(15).

Kar, A. K., & Kushwaha, A. K. (2021). Facilitators and barriers of artificial intelligence adoption in business–insights from opinions using big data analytics. *Information Systems Frontiers*, 1-24.

Karna, N., Fatihah, N., & Kim, D.-S. (2019). Evaluation of DLX Microprocessor Instructions Efficiency for Image Compression. *Paper presented at the 2019 International Conference on Information and Communication Technology Convergence (ICTC).*

Kline, R. B. (2015). *Principles and practice of structural equation modeling*: Guilford publications.

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of emerging technologies in accounting, 14*(1), 115-122.

Korhonen, T., Selos, E., Laine, T., & Suomala, P. (2020). Exploring the programmability of management accounting work for increasing automation: an interventionist case study. *Accounting, Auditing & Accountability Journal*, *34*(2), 253-280.

Kumar, A., & Kalse, A. (2021). Usage and adoption of artificial intelligence in SMEs. *Materials Today: Proceedings*.

Lee, C. S., & Tajudeen, F. P. (2020). Impact of artificial intelligence on accounting: evidence from Malaysian organizations. *Asian Journal of Business and Accounting, 13*(1).

M Bergschöld, J. (2018). When saving time becomes labor: Time, work and technology in homecare.

Mankins, J. C. (2009). Technology readiness assessments: A retrospective. *Acta Astronautica, 65*(9-10), 1216-1223.

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*.

Mohammad, S. J., Hamad, A. K., Borgi, H., Thu, P. A., Sial, M. S., & Alhadidi, A. A. (2020). How Artificial Intelligence Changes the Future of Accounting Industry. *International Journal of Economics and Business Administration, 8*(3), 478-488.

Niehans, J. (1982). Innovation in monetary policy: Challenge and response. *Journal of Banking & Finance, 6*(1), 9-28.

Oke, A. E., & Arowoiya, V. A. (2021). Critical barriers to augmented reality technology adoption in developing countries: a case study of Nigeria. *Journal of Engineering, Design and Technology*.

Olson, C., & Levy, J. (2018). Transforming marketing with artificial intelligence. *Applied Marketing Analytics, 3*(4), 291-297.

Prause, M. (2019). Challenges of industry 4.0 technology adoption for SMEs: the case of Japan. *Sustainability, 11*(20), 5807.

Qasaimeh, G., Yousef, R., Al-Gasaymeh, A., & Alnaimi, A. (2022). *The Effect of Artificial Intelligence Using Neural Network in Estimating on An Efficient Accounting Information System: Evidence from Jordanian Commercial Banks.* Paper presented at the 2022 International Conference on Business Analytics for Technology and Security (ICBATS).

Rawashdeh, A., Shehadeh, E., Rababah, A., & Al-Okdeh, S. K. (2022). Adoption Of Robotic Process Automation (RPA) And Its Effect On Business Value: An Internal Auditors Perspective. *Journal of Positive School Psychology*, 9832-9847 .

Rehman, N., Razaq, S., Farooq, A., Zohaib, N. M., & Nazri, M. (2020). Information technology and firm performance: mediation role of absorptive capacity and corporate entrepreneurship in manufacturing SMEs. *Technology Analysis & Strategic Management, 32*(9), 1049-1065.

Richter, C., Kraus, S., Brem, A., Durst, S., & Giselbrecht, C. (2017). Digital entrepreneurship: Innovative business models for the sharing economy. *Creativity and innovation management, 26*(3), 300-310.

Rogers, E. M. (2003). Diffusion of innovations. Free Press. *New York, 551*.

Savlovschi, L. I., & Robu, N. R. (2011). The role of SMEs in modern economy. *Economia, Seria Management, 14*(1), 277-281.

Schneider, D., & Harknett, K. (2022). What's to like? Facebook as a tool for survey data collection. *Sociological Methods & Research, 51*(1), 108-140.

Setiyadi, M., Mangiwa, B., & Nugraheni, D. (2019). *Analysis of e-commerce using technology acceptance model and its interaction with risk, enjoyment, compatibility variables.* Paper presented at the 2019 3rd International Conference on Informatics and Computational Sciences (ICICoS).

Shekhar, S. S. (2019). Artificial intelligence in automation. *Artificial Intelligence, 3085*(06), 14-17.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of consumer research, 15*(3), 325-343.

Siew, E.-G., Rosli, K., & Yeow, P. H. (2020). Organizational and environmental influences in the adoption of computer-assisted audit tools and techniques (CAATTs) by audit firms in Malaysia. *International Journal of Accounting Information Systems, 36*, 100445.

Soper, D. (2017). Free statistics calculators. *A-Priori Sample Size Calculator for Multiple Regression [Software]-2018. Available from URL: http://Www. Danielsoper. Com/Statcalc (accessed December 2019)*.

Stokes, Y., Vandyk, A., Squires, J., Jacob, J.-D., & Gifford, W. (2019). Using Facebook and LinkedIn to recruit nurses for an online survey. *Western journal of nursing research, 41*(1), 96-110.

Surianti, M. (2020). Development of Accounting curriculum model based on industrial revolution approach. *Development, 11*(2).

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*: Lexington books.

Vantage Market Research. (2022). *Artificial Intelligence In Accounting Market*. Retrieved from https://www.vantagemarket-research.com/industry-report/artificial-intelligence-in-accounting-market-1472

Wei, O. J., & Ismail, H. B. (2009). Adoption of technology among businesses: The strategic adoption. *Journal of Innovation and Business Best Practices, 1*(1), 1-8.

Yashiro, N., Carey, D., & Purwin, A. (2022). Boosting productivity in New Zealand by unleashing digitalisation.

Zagheni, E., Weber, I., & Gummadi, K. (2017). Leveraging Facebook's advertising platform to monitor stocks of migrants. *Population and Development Review*, 721-734.