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Determinants of AI technologies adoption in Bangladeshi accounting firms: A PLS-SEM analysis using the TOE framework

Faieza Chowdhury[1+]
Ahmed Razman Abdul Latiff[2]
Rosli Mahmood[3]

[1,2,3]*Putra Business School, UPM, Malaysia.*
[1]*Southeast University, Bangladesh.*
[1]*Email: faiezac30@gmail.com*
[2]*Email: razman@putrabs.edu.my*
[3]*Email: rosli@putrabs.edu.my*

(+ Corresponding author)

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ABSTRACT

Artificial intelligence (AI) developments have produced cutting-edge technologies that offer significant potential for corporate transformation. This study examines the key factors influencing the adoption of AI-based accounting technologies by Bangladeshi accounting firms. The proposed research model is grounded in the Technology–Organization–Environment (TOE) framework, which provides a comprehensive perspective for analyzing adoption drivers across various contextual dimensions. A quantitative research approach was employed to gather data from 160 accounting professionals through an online survey. The study utilized Partial Least Squares (PLS), a statistical technique based on structural equation modeling (SEM), to achieve its objectives. Empirical results indicate that the adoption of AI accounting technology in Bangladeshi accounting firms is significantly affected by factors such as relative advantage, complexity, employees' capabilities, and customer pressure. Conversely, factors like cost, financial resources, rivalry pressure, management support, and vendor support did not demonstrate a substantial impact within this context. The research highlights the technological, organizational, and environmental factors that influence the integration of AI-based accounting tools. Practical implications suggest that policymakers, vendors, and professionals should focus on reducing barriers and enhancing readiness for adoption. Overall, the study provides both empirical evidence and practical strategies to promote AI adoption in emerging economies.

Contribution/ Originality: The study significantly contributes to the limited body of research on the deployment of AI technology in Bangladeshi accounting firms by addressing a notable gap in the existing literature. The findings of this research provide valuable insights for the successful integration of AI accounting technology by end-users and accounting firms in Bangladesh.

1. INTRODUCTION

Several emerging technologies have been sparked in recent years by the development of new innovations, the accessibility of Big Data, and an exponential rise in computing power (Agrawal, Gans, & Goldfarb, 2018; Brundage et al., 2018; Deloitte, 2019). These new technologies exhibit radical novelty, rapid growth, coherence, significant impact, uncertainty, and ambiguity. In 1956, at the Dartmouth Conference in the United States, the concept of artificial intelligence was first introduced by American computer scientist John McCarthy (Crevier, 1993). Later, AI gradually started to materialize from people's thoughts in research laboratories into the real world. Since 2000, and particularly from 2015 onward, the rapid growth of sophisticated hardware, advancements in algorithms, and the assistance of big data have all contributed to the integration of AI. Currently, numerous AI applications are available. Today, AI can write complex scripts, make predictions about decisions, interact with people in real time, mine trillions of bits of information, and provide solutions. Artificial intelligence technologies such as deep learning, machine learning, and natural language processing have a significant positive impact on how organizations are managed, planned, and operated (Kasemsap, 2017). According to Al-Beladi, Dawood, and Makki (2014), the essence of AI lies in its ability to perform specific tasks that forecast, enhance, and learn non-cognitive work. This capability is made possible by its inherent capacity to consider future scenarios and develop plans based on historical trends. Consequently, most companies today aim to utilize AI to improve their ecosystems, decision-making processes, and customer experiences. With the use of AI, machines adapt new actions to perform tasks similarly to humans. Self-driving cars, which utilize natural language processing, are among the most prevalent applications of artificial intelligence in modern times (SAS, 2020).

Artificial intelligence has opened a wide range of opportunities for the accounting profession, which has successfully expanded since the discovery of bookkeeping with double entry system in 1494 (Bolinger, 2017). There is anecdotal evidence that accountants and auditors are actively trying to embrace AI tools in their daily work. Data analytics, process automation, and artificial intelligence are just a few of the cutting-edge technologies that are changing the role of Chartered Accountants (CAs) in the business world and presenting new opportunities and challenges to the accounting profession (Bizcommunity, 2018). In terms of their capacities, innovation, and future employment, accounting firms are currently reimagining their future. CAs today need to make career investments in the form of AI skills development. 67% of the knowledge and abilities currently needed for accountants are related to digital competency, and a modern accountant cannot survive today without such technical abilities (Zhyvets, 2018). The top four accounting firms have already made big investments in cutting-edge technologies such as AI and providing a lot more training to their staff members so that they may improve their digital skills (Bakarich & O'Brien, 2021). As a result, the accounting firms today need to have a solid grasp of how AI may be used to solve accounting and auditing issues.

However, the mainstream use of AI in the accounting firms of Bangladesh is still at its infancy. Despite the adoption of some AI initiatives by the top accounting firms in Bangladesh, many AI accounting applications are still in the conceptual stages (Afroze & Aulad, 2020). Applications using AI are therefore up against challenges and the adoption process of AI is slower in Bangladesh compared to other countries in South Asia. Although the adoption of AI has been studied in some prior existing literatures (Oliveira & Martins, 2011) most of them are in the context of developed economies. Techniques and applications are the key topics of some prior studies on AI integration (Qi, Wu, Li, & Shu, 2007; Walczak, 2018). Organizational or management concerns related to AI, particularly the factors influencing AI adoption in emerging economies, are often overlooked. There are few studies in Bangladesh that empirically investigate the underlying technological, organizational, and environmental factors affecting the adoption of AI technologies within Bangladeshi accounting firms. Therefore, to explore the adoption of AI-based accounting technologies by Bangladeshi firms and to address existing gaps in the literature, this research employs the Technology-Organization-Environment (TOE) framework. The TOE framework is pertinent because it offers valuable insights into the factors that motivate and hinder technological adoption by businesses. It encompasses technological, organizational, and environmental perspectives, making it a comprehensive model. The following research questions (RQs) were developed to address the identified literature gaps.

RQ1: Do technological factors such as cost, complexity, and relative advantage significantly influence the adoption of AI-based technologies by Bangladeshi accounting firms?

RQ2: Do organizational factors such as employee capabilities, financial resources, and top management support significantly influence the adoption of AI-based technologies by Bangladeshi accounting firms?

RQ3: Do environmental factors such as vendor support, customer pressure, and competitive pressure significantly influence the adoption of AI-based technologies by Bangladeshi accounting firms?

By answering these questions, this article aims to ascertain the impact of the TOE framework on Bangladeshi firms' adoption of AI-based accounting technologies. This research contributes to the scientific knowledge regarding the adoption of AI within the accounting sector in Bangladesh and other similar emerging economies. It assists in decision-making and resource allocation for accounting firms and professionals. Additionally, it offers insights for the academic community, future adopters, governments, and AI vendors.

The remainder of this article is organized as follows. Section two presents the theoretical foundation, hypotheses, and the study's model. Section three details the study's methodology. Section four presents the results, while section five discusses the findings and conclusions. Finally, section six concludes the article with implications, limitations, and directions for future research.

2. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

2.1. TOE Framework and Research Model

The Technology–Organization–Environment (TOE) framework, developed by Tornatzky and Fleischer (1990) was introduced as a comprehensive model to explain how various contextual factors influence an organization's decision to adopt and implement technological innovations. In their seminal work "The Processes of Technological Innovation", Tornatzky and Fleischer (1990) emphasized that technology adoption is not solely determined by the intrinsic qualities of the innovation itself, but also by the internal attributes of the organization and the external environmental pressures that it faces. The TOE framework consolidates insights from organizational theory, innovation diffusion, and strategic management, offering a holistic lens through which to understand adoption behaviors.

While both the TOE framework and Rogers' (2010) Diffusion of Innovation (DOI) theory consider technological and organizational dimensions, the TOE framework advances beyond DOI by explicitly integrating the environmental context. This addition significantly strengthens its predictive capability in explaining organizational decisions to adopt new technologies, as it accounts for market dynamics, regulatory pressures, and the broader competitive landscape. Researchers have widely applied the TOE model to differentiate between adopters and non-adopters of technological innovations (Nam, Dutt, Chathoth, Daghfous, & Khan, 2021; Sun, Hall, & Cegielski, 2020).

Despite its extensive use, the TOE framework has not yet been applied to examine the determinants of AI-based accounting technology adoption within accounting firms of Bangladesh. Furthermore, prior research has largely focused on large-scale enterprises (Abed, 2020; Hsu, Ray, & Li-Hsieh, 2014; Pillai et al., 2022) and on organizations in more developed economies (Ahmad, Hussain, & Khan, 2019; Clohessy & Acton, 2019; Rahman, Islam, & Uddin, 2020). These limitations highlight the importance of applying the TOE framework to Bangladeshi accounting firms, where the dynamics of an emerging economy and the diverse structures of the firms present unique challenges and opportunities.

The TOE framework comprises three interrelated contexts. First, the technological context refers to the attributes of an innovation such as relative advantages, compatibility, and complexity that influence an organization's propensity to adopt it Abed (2020). Second, the organizational context encompasses internal characteristics such as firm size, managerial structure, employee skill sets, and resource availability that shape adoption readiness. Third, the environmental context captures external influences, including competitive pressures, regulatory requirements, the presence of technology vendors, and industry infrastructure (Awa, Ukoha, & Nwankpa, 2016).

Thus, in this study, the TOE framework was employed to explore all three contexts in relation to the adoption of AI-based accounting technologies in Bangladeshi accounting firms. Specifically, the technological perspective incorporates the constructs of complexity, cost, and relative advantage; the organizational perspective consists of employee capabilities, financial resources, and top management support; and the environmental perspective considers vendor support, customer pressure, and rivalry pressure (See Figure 1).

2.2. Hypotheses Development

After reviewing some prior studies, several constructs have been developed to achieve the purpose of this study. The hypotheses of this research are formulated, and the operational definitions of the research constructs are discussed in the following section.

2.2.1. Relative Advantage

Relative advantage refers to the degree to which an organization perceives an innovation as superior to its predecessor (Thong, 1999). The recognized benefits of a new technology often motivate its adoption (Sun et al., 2020). To and Ngai (2006) highlighted that relative advantages may include enhanced social status, competitiveness, and value creation. Some empirical studies have identified relative advantage as a critical determinant of technology adoption, including cloud computing (Khayer, Talukder, Bao, & Hossain, 2020) and social customer relationship management (Ahani, Rahim, & Nilashi, 2017). In the context of AI, relative advantage has consistently emerged as a key factor influencing adoption decisions (Chen, Li, & Chen, 2021; Huang, Chao, De la Mora Velasco, Bilgihan, & Wei, 2021; Pillai & Sivathanu, 2020b). AI adoption provides organizations with a variety of benefits (Mikalef & Gupta, 2021). Thus, this research proposes the following hypothesis.

H_1: Relative advantage has a positive and significant effect on the adoption of AI accounting technologies.

2.2.2. Complexity

The complexity of a system can negatively influence adoption decisions, as the more difficult a technology appears to implement, the lower the likelihood of its adoption (Chang & Chen, 2021; Moriuchi, 2021; Zhou et al., 2020). Research has shown that ease of use is a critical factor for AI-based product acceptance (Sohn & Kwon, 2020) and for customer adoption of robo-advisors (Belanche, Casaló, & Flavián, 2019). Similarly, studies on wearable technology highlight the impact of perceived complexity on adoption behaviour (Talukder, Chiong, Bao, & Hayat Malik, 2019). AI adoption is similarly hindered by complexity (Pan, Froese, Liu, Hu, & Ye, 2021; Von Walter, Kremmel, & Jäger, 2021). Therefore, if AI technologies are perceived as excessively complex, they are less likely to be adopted. The following is proposed.

H_2: Complexity has a significantly negative effect on the adoption of AI accounting technologies.

2.2.3. Cost

High start-up costs, including software acquisition and implementation cost can discourage technology adoption (Kim, Jang, & Yang, 2017; Mikalef, Fjørtoft, & Torvatn, 2019). Start-up costs significantly influence firms' adoption decisions (Wong, Leong, Hew, Tan, & Ooi, 2020). Research demonstrates that cost factors positively correlate with the adoption of advanced technologies such as smart manufacturing (Ghobakhloo & Ching, 2019) and IT systems in SMEs (Kamdjoug, Djuitchou Chengo, & Gueyie, 2021). Similarly, AI adoption may be hindered by high perceived costs (Pillai & Sivathanu, 2020a). Based on prior studies, the following hypothesis has been developed.

H_3: Cost has a significantly negative effect on the adoption of AI accounting technologies.

2.2.4. Top Management Support

Higher management support encompasses the allocation of resources, provision of authority, and strategic direction to facilitate technology adoption (Sun et al., 2020; Wang & Dass, 2017). Decisions to adopt innovative technologies are positively influenced by management motivation and commitment (Alsetoohy, Ayoun, Arous, Megahed, & Nabil, 2019). Prior research confirms the critical role of top management support in technology adoption (Pateli, Mylonas, & Spyrou, 2020; van De Weerd, Mangula, & Brinkkemper, 2016), including cloud-based software (Oliveira, Martins, Sarker, Thomas, & Popovič, 2019) and mobile applications (Swani, 2021). In the context of AI, top management support has been linked to a higher likelihood of adoption in some studies (Chatterjee, Chaudhuri, Vrontis, & Papadopoulos, 2022; Pillai & Sivathanu, 2020b). As a result, the following hypothesis is proposed.

H_4: Top management support has a significant positive effect on AI accounting technologies adoption.

2.2.5. Financial Resource

The availability of financial resources significantly influences the adoption of innovative technologies (Maduku, Mpinganjira, & Duh, 2016). Sufficient funding enables the acquisition, implementation, and ongoing maintenance of new systems (Maduku et al., 2016). Empirical evidence shows that financial resource availability is a key determinant in ICT adoption among Nigerian firms (Okundaye, Fan, & Dwyer, 2019) and Vietnamese firms (Chau, Deng, & Tay, 2020). Accordingly, accounting firms with adequate financial resources are expected to demonstrate higher AI adoption, so the following is hypothesized.

H_5: Financial resources have a significant positive effect on AI accounting technologies adoption.

2.2.6. Employee Capability

Employee capability, including knowledge and technical skills, is essential for facilitating technology adoption (Maduku et al., 2016). A lack of IT skills among employees negatively affected cloud computing adoption (Hsu et al., 2014). Prior research further highlighted the importance of skilled employees in adopting new technologies (Baker, 2012; Eze et al., 2019). Thus, accounting firms with capable employees are better positioned to implement and maintain AI technologies successfully. In this study, the following hypothesis is proposed.

H_6: Employee capability has a positive and significant effect on the adoption of AI accounting technologies.

2.2.7. Rivalry Pressure

Competitive pressure arises when organizations face external pressures from industry competitors (Sun et al., 2020). Early adopters often gain a first-mover advantage, motivating competitors to follow suit (De Mattos & Laurindo, 2017). Firms may imitate leading competitors to maintain market position (Al-Omoush, 2022). Competitive pressure has been shown to positively influence technology adoption in various contexts, including ERP (Xu, Ou, & Fan, 2017) Enterprise 2.0 (Jia, Guo, & Barnes, 2017), and AI adoption (Chen et al., 2021; Dora, Kumar, Mangla, Pant, & Kamal, 2021; Pillai & Sivathanu, 2020b). As a result, the following hypothesis is proposed.

H_7: Rivalry pressure has a significantly positive effect on the adoption of AI accounting technologies.

2.2.8. Customer Pressure

Customer expectations and pressures play a crucial role in shaping technology adoption decisions (Abed, 2020). Firms adopt technologies to enhance interactions and meet customer needs (Marikyan, Papagiannidis, & Alamanos, 2020). Empirical evidence demonstrates that businesses adopt innovations in response to perceived customer demands (Nam et al., 2021; Savastano, Bellini, D'Ascenzo, & De Marco, 2019; Sharma, Singh, & Sharma, 2020). Customer attitudes have been shown to influence the adoption of technologies (Lorente-Martínez, Navío-Marco, & Rodrigo-Moya, 2020). Based on prior studies, the following hypothesis is developed.

H_8: Customer pressure has a positive and significant effect on the adoption of AI accounting technologies.

2.2.9. Vendor Support

Vendor support, including training and assistance, has a positive impact on technology adoption (Alshamaila, Papagiannidis, & Li, 2013; Maduku et al., 2016). Vendor assistance reduces perceived risk and facilitates innovation (Weigelt & Sarkar, 2009). Studies highlight the role of vendor support in ICT adoption, hospital information systems (Ahmadi, Nilashi, Shahmoradi, & Ibrahim, 2017), and cloud computing (Sharma & Sehrawat, 2020). In AI adoption, vendor support positively influences adoption decisions throughout the pre-adoption, adoption, and post-adoption phases (Pillai & Sivathanu, 2020a). As a result, the following hypothesis is proposed.

H_9: Vendor support has a significant positive effect on AI accounting technologies adoption.

Based on these nine hypotheses, which are grounded in the TOE framework, this study's model was developed to illustrate the relationships discussed earlier (See Figure 1).

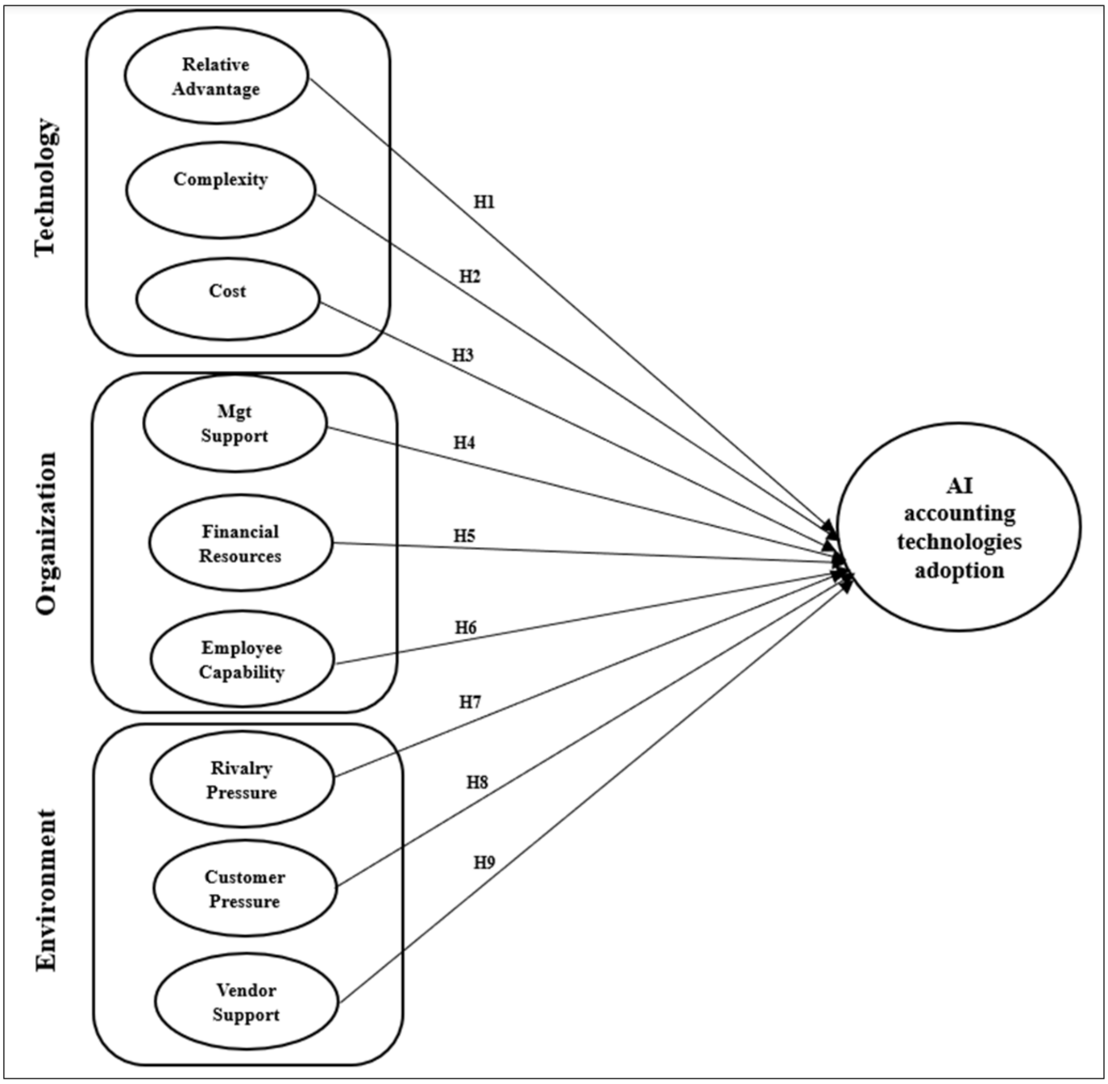

Figure 1. Research model.

3. METHODOLOGY

3.1. Research Design and Measurement

This study adopted a quantitative research approach, employing a survey as the primary research technique. A structured questionnaire was used to collect data, focusing on participants' intentions to use AI-based accounting technologies. The target population for this study comprises accounting professionals from Bangladeshi accounting firms who are potential users of AI-based tools. Due to time and resource constraints, this study was conducted in a single city in Bangladesh, namely Dhaka. For data analysis, SmartPLS software was utilized.

The survey instrument adapted pre-validated items from prior studies, with detailed items and their respective sources (See Table 1). All items were measured using a Seven-point Likert scale, selected for its proven reliability in capturing nuanced responses (Chen, Wang, Herath, & Rao, 2011).

Table 1. Instrumentation and operationalization of constructs.

Constructs	Items	Sources
Relative advantage (RA)	RA1- The AI-based accounting tools would enable firms to provide better services to the clients. RA2- AI-based accounting tools would enable firms to communicate with clients more effectively. RA3- AI-based accounting tools would enable firms to deliver services in a timelier manner.	Lian, Yen, and Wang (2014) and Ghobakhloo, Arias, and Benitez-Amado (2011)
Complexity (CM)	CM1- The use of AI-based accounting tools would require much mental effort. CM2- The skills to use AI-based accounting tools would be too complex for the employees. CM3- The use of AI-based accounting tools would be too frustrating.	Lian et al. (2014) and Ghobakhloo et al. (2011)
Cost (CO)	CO1- The cost involved in adoption of AI-based accounting tools would be far greater than the benefits. CO2- The cost of maintaining AI-based accounting tools would be very high. CO3- The training cost for using AI-based accounting tools would be very high.	Maduku et al. (2016) and Lian et al. (2014)
Top management support (TS)	TS1- Top management would provide the necessary financial resources for adoption of AI-based tools. TS2- Top management would provide the necessary IT support for adoption of AI-based tools. TS3- Top management would provide the necessary training for adoption of AI-based tools.	Borgman, van der Meijden, and van Dijk (2013) and Lian et al. (2014)
Financial resource (FR)	FR1 - Firms possess the necessary financial resources to adopt AI-based tools. FR2 - The firm's budget will allocate funds for the adoption of AI-based tools. FR3- It will be easy to obtain financial support from external parties for adoption of AI based tools.	Lian et al. (2014) and Ifinedo (2011)
Employee capability (EC)	EC1- Employees would be capable of learning AI based tools easily. EC2- Employees will be capable of using AI-based tools for solving problems. EC3- Employees would be capable of using AI-based tools to interact with clients.	Lin and Ho (2011) and Maduku et al. (2016)
Rivalry pressure (RP)	RP1 - The decision to adopt AI-based tools will be strongly influenced by the actions of competitors within the industry. RP2- Firm is under a lot of pressure from rival firms to use AI based accounting tools. RP3 - Firms need to adopt AI-based accounting tools to gain a competitive advantage over their competitors.	Ghobakhloo et al. (2011) and Ifinedo (2011)
Customer pressure (CP)	CP1- many clients expect that firm will adopt AI based accounting tools. CP2 - The relationship with clients could suffer if firms do not adopt AI-based accounting tools. CP3 - Customers will perceive the firm as forward-thinking if it adopts AI-based accounting tools.	Wu and Lee (2005) and Wu, Mahajan, and Balasubramanian (2003)
Vendor support (VS)	VS1- There will be adequate technical support for AI-based accounting tools from vendors. VS2- Training for AI-based accounting tools would be adequately provided by the vendors. VS3- Vendors are actively marketing AI-based accounting tools.	Ghobakhloo et al. (2011) and Al-Qirim (2007)
AI accounting tools adoption intention (AI)	AI1- Our firm intends to use AI-based accounting tools. AI2-Our firm intends to use AI-based accounting tools regularly in the future. AI3- Our firm intends to utilize AI-based accounting tools to provide comprehensive services to our clients.	Maduku et al. (2016)

3.2. Participant Characteristics

As reflected in Table 2, a total of 160 accounting professionals from selected accounting firms in Bangladesh participated in the survey. All participants held professional certifications. In terms of gender, the majority were male (76.3%), while females constituted 23.7% of the sample.

Regarding age distribution, nearly half of the participants were between 45 and 60 years old (48.1%), followed closely by those aged 31 to 44 years (46.9%). A small proportion of participants were under 31 years of age (5%). Work experience varied across the sample, with the majority having between 5 and 10 years of experience (51.9%). Participants with 11 to 20 years of experience represented 38.7%, those with more than 20 years accounted for 6.3%, and a small group had less than 5 years of experience (3.1%).

Table 2. Demographic details of the respondents (n = 160).

Participant characteristics	Frequency	Percentage
Gender		
Male	122	76.3
Female	38	23.7
Age		
Under 31	8	5
31 to 44	75	46.9
45 to 60	77	48.1
Work experience		
Less than 5 yrs	5	3.1
5–10 years	83	51.9
11–20 years	62	38.7
More than 20 years	10	6.3
Education		
Undergraduate	-	-
Postgraduate (Professional certifications)	160	100.0
Total	160	100.0

3.3. Sampling Procedure

In the context of quantitative research, Hair, Black, Babin, Anderson, and Tatham (1998) posit that the minimum sample size should be no less than five times the total number of indicators employed in the measurement model, thereby ensuring a minimum of five observations per parameter.

This study satisfies this criterion, as supported by prior methodological guidance (Bentler & Chou, 1987; Bollen, 1989). Specifically, the measurement model comprised 30 items, which were evaluated using a sample of 160 accounting professionals. While Sideridis, Simos, Papanicolaou, and Fletcher (2014) suggested that structural relationships within SEM can be reliably estimated with as few as 70–80 participants, Wolf, Harrington, Clark, and Miller (2013) emphasized that no universal standard exists for determining sample size. Furthermore, Barclay, Thompson, and Higgins (1995) introduced the "10-times rule," subsequently applied in PLS-SEM literature, which stipulates that the minimum sample size should equal ten times either the largest number of structural paths directed toward a single latent construct or the largest number of formative indicators used to measure a construct (Hair, Hult, Ringle, & Sarstedt, 2017).

Collectively, these considerations substantiate the adequacy of the 160 participants selected as sample for this study, thereby reinforcing the robustness of the research findings.

Table 3. Validation of the measurement model.

Constructs	Indicators	Loadings	Composite reliability	Average variance extracted
Relative advantage	RA1	0.932	0.961	0.892
	RA2	0.948		
	RA3	0.953		
Complexity	CM1	0.937	0.946	0.854
	CM2	0.938		
	CM3	0.896		
Cost	CO1	0.900	0.909	0.77
	CO2	0.793		
	CO3	0.933		
Top management support	TS1	0.909	0.941	0.843
	TS2	0.936		
	TS3	0.908		
Financial resource	FR1	0.960	0.971	0.918
	FR2	0.962		
	FR3	0.953		
Employee capability	EC1	0.967	0.977	0.935
	EC2	0.972		
	EC3	0.962		
Rivalry pressure	RP1	0.924	0.958	0.883
	RP2	0.961		
	RP3	0.933		
Customer pressure	CP1	0.587	0.837	0.639
	CP2	0.901		
	CP3	0.872		
Vendor support	VS1	0.772	0.881	0.712
	VS2	0.88		
	VS3	0.876		
Intention to Adopt AI Accounting Tools	AI1	0.898	0.929	0.813
	AI2	0.909		
	AI3	0.898		

4. RESULTS

4.1. Measurement Model

Before evaluating the structural model, it is essential to conduct the measurement model analysis. This involves examining the indicator loadings, composite reliability (CR) and average variance extracted (AVE) (Hair et al., 2017). As reflected in Table 3, all indicator loadings exceed the recommended threshold of 0.7 for CR, and AVE values meet the established criteria. Furthermore, the results of the discriminant validity assessment, based on cross-loadings and the Fornell–Larcker criterion, also confirm that the constructs are empirically distinct from one another. Consequently, the measurement model in this study demonstrates adequate reliability and validity.

4.2. Structural Model

The first step in structural model analysis is to verify the absence of multicollinearity. According to Hair et al. (2017), inner VIF (Variance Inflation Factor) values should be below 5. In the present study, all inner VIF values were less than the recommended threshold, indicating no multicollinearity issues. Following this confirmation, the proposed hypotheses were examined using coefficients, *t*-statistics, and *p*-values, as suggested by Hair et al. (2017). The empirical results provided support for hypotheses H1, H2, H6, and H8 (See Table 4).

The structural model analysis revealed mixed support for the proposed hypotheses. Relative advantage (H1) had a positive and significant influence on AI accounting tools adoption intention ($\beta = 0.186$, $t = 1.981$, $p = 0.024$), supporting the hypothesis. Complexity (H2) showed a significant negative effect on adoption intention ($\beta = -0.586$, $t = 6.144$, $p < 0.000$), indicating that higher complexity reduces the likelihood of adoption. Employee capability (H6) was also positively and significantly related to adoption intention ($\beta = 0.330$, $t = 3.272$, $p = 0.001$), as was customer pressure (H8) (β = 0.167, t = 2.204, p = 0.014). In contrast, cost (H3), top management support (H4), financial resources (H5), rivalry pressure (H7), and vendor support (H9) were not significantly associated with adoption intention, as their p-values exceeded the 0.05 threshold. These results suggest that relative advantage, reduced complexity, strong employee capability, and customer pressure are key drivers of AI adoption intentions, while cost, managerial support, financial resources, competitive pressure, and vendor support appear less influential in this particular context. The graphical representation of the structural model is illustrated in Figure 2.

Moreover, as reflected in Table 5, the model demonstrated high predictive accuracy, as the R^2 value for AI accounting tools adoption intention calculated at 0.838, indicates that approximately 83.8% of the variance in AI adoption intention is explained by the model's independent variables. According to Hair et al. (2017), this represents a substantial level of explanatory power.

Table 4. β, standard error, t-values, *and* p-values.

Hypotheses	Relationship	β	Std. error	t-value	p-value	Assessment
H1	RA -> AI	0.186	0.094	1.981	0.024	Supported
H2	CM -> AI	-0.586	0.095	6.144	0.000	Supported
H3	CO-> AI	-0.007	0.076	0.091	0.464	Not supported
H4	TS -> AI	0.053	0.084	0.631	0.264	Not supported
H5	FR -> AI	0.132	0.095	1.382	0.083	Not supported
H6	EC-> AI	0.33	0.101	3.272	0.001	Supported
H7	RP -> AI	0.11	0.11	1.005	0.157	Not supported
H8	CP -> AI	0.167	0.076	2.204	0.014	Supported
H9	VS-> AI	0.066	0.066	0.991	0.159	Not supported

Table 5. Predictive accuracy of the model.

	R^2 value	Interpretation
AI accounting tools adoption	0.838	High

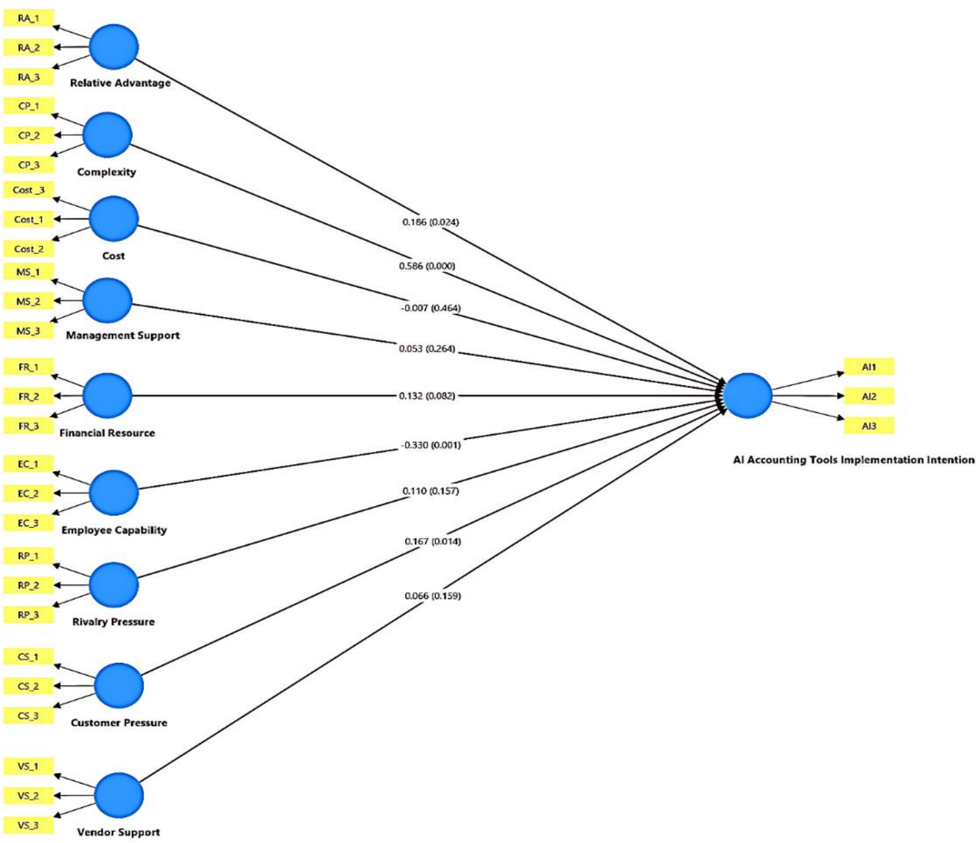

Figure 2. Structural model for AI accounting tools adoption intention.

5. DISCUSSION AND CONCLUSION

5.1. Discussion of Key Findings

This study investigated the adoption of AI-based accounting technologies by Bangladeshi accounting firms, with nine hypotheses formulated based on the theoretical framework of the TOE model. Statistical analysis of the study supported four hypotheses (H1, H2, H6, and H8).

H1 tested the positive relationship between relative advantage and the adoption of AI-based accounting tools, which was supported. This finding aligns with earlier studies that highlight the perceived benefits of new technologies as a key driver of adoption (Alsetoohy et al., 2019; Ezzaouia & Bulchand-Gidumal, 2020; Wong et al., 2020). This indicates that accounting firms which recognize the advantages of AI tools are more inclined to implement them. The section that examined the negative relationship between complexity and the intention to adopt AI-based accounting systems also received support. This result is consistent with Belanche et al. (2019) and Zhou et al. (2020); Moriuchi (2021); Chang and Chen (2021), who found that ease of use encourages technology adoption. For accounting firms, AI systems that are straightforward to install and operate are more likely to be embraced. H3 investigated the negative relationship between cost and AI adoption, although the relation was found to be negative but not statistically significant. This aligns with findings from Wong et al. (2020), Ghobakhloo and Ching (2019), and Kamdjoug et al. (2021), who observed that high implementation and maintenance costs such as updates, troubleshooting, and external consultancy, can discourage adoption.

H4 explored the positive relationship between top management support and AI adoption, which was also insignificant. Prior research, including Swani (2021), van De Weerd et al. (2016), and Oliveira et al. (2019), identified managerial backing as a critical driver of technology adoption. While the current result was not significant, the implication remains that management support in allocating time and resources can positively influence adoption decisions. H5 assessed the association between financial resources and AI adoption, finding a positive but insignificant relationship. Similar patterns have been reported by Okundaye et al. (2019), Chau et al. (2020), and Mittal, Khan, Romero, and Wuest (2018), suggesting that the availability of adequate financial resources can facilitate the adoption of new technologies. H6 evaluated the relationship between employee capabilities and AI adoption intention, which was positive and significant. This result is in line with Eze et al. (2019), who identified employee competence as a key factor in adopting mobile and other digital technologies. This result implies that successful AI adoption in Bangladeshi accounting firms depends on having skilled and knowledgeable staff capable of setting up and managing AI systems. H7 examined the positive association between rivalry pressure and AI adoption, but this was not supported. This contradicts prior studies of Sun et al. (2020) and Obal (2017), who found rival firms' pressure to be a driver of technology adoption. H8 tested the positive relationship between customer pressure and AI adoption, which was supported. This finding is consistent with Nam et al. (2021), Lorente-Martínez et al. (2020), and Abed (2020), who reported that customer demands often drive firms to adopt innovative technologies. Finally, H9 investigated the relationship between vendor support and AI adoption intention, which was not supported. This finding contradicts earlier research such as Sharma and Sehrawat (2020), Maduku (2021), and Ahmadi et al. (2017), that highlighted vendor assistance as critical in technology adoption. A plausible explanation is that, while vendor support is important, it alone may not be sufficient for accounting firms to commit to adopting AI-based accounting systems.

5.2. Conclusion

This study examined the adoption of AI-based accounting technologies by Bangladeshi accounting firms through the TOE framework by testing nine hypotheses. Four factors namely relative advantage, complexity, employee capability, and customer pressure emerged as significant drivers of AI adoption. These findings highlight that accounting firms are more likely to embrace AI when they perceive clear benefits, face minimal implementation complexity, possess skilled personnel, and respond to client demands. Conversely, cost, top management support, financial resources, rivalry pressure, and vendor support were not found to have a critical influence in this context.

The lack of significance of these factors may be due to the early stage of AI adoption among Bangladeshi accounting firms, where competitive pressures are low and external support alone is insufficient to prompt adoption.

Overall, the results suggest that successful AI implementation in the Bangladeshi accounting sector requires a focus on demonstrating tangible benefits, simplifying technology use, building employee expertise, and aligning adoption decisions with customer expectations, rather than relying solely on competitive forces or external assistance.

6. IMPLICATIONS AND LIMITATIONS

6.1. Practical and Theoretical Implications

While AI adoption has been explored in some prior studies Oliveira and Martins (2011), most of these studies primarily focused on developed nations. Organizational and managerial considerations regarding AI, particularly the factors influencing its adoption in emerging economies, have remained largely underexplored. Empirical studies examining the technological, organizational, and environmental determinants of AI adoption in Bangladeshi accounting firms are scarce. This study addresses this gap in the literature by incorporating multiple variables relevant to the integration of AI-based accounting technologies, grounded in the Technology-Organization-Environment (TOE) framework, thereby contributing valuable empirical evidence.

The findings offer valuable insights for potential users, vendors, and policymakers to enhance the implementation of AI accounting technologies in Bangladeshi accounting firms. For senior accounting professionals, the results provide guidance for strategic decision-making to facilitate AI deployment within organizational workflows. Specifically, the study highlights the critical factors that need to be addressed and the potential barriers that must be mitigated to ensure the successful integration of AI-based accounting tools in the context of Bangladesh.

6.2. Limitations and Future Research Directions

Despite adhering to rigorous research protocols, this study has certain limitations that warrant acknowledgment. First, data were collected from accounting professionals residing in Dhaka, Bangladesh, which may limit the generalizability of the findings. Future research should consider compiling a comprehensive list of accounting professionals nationwide and employing random sampling to enhance representativeness. Second, this study focused exclusively on a single country. Cross-national research could provide a broader understanding of AI accounting tool adoption and allow examination of country-specific influences, such as economic conditions, legal frameworks, technological infrastructure, and cultural factors. Third, the study assessed accounting professionals' behavioral intention to adopt AI-based accounting tools; however, intention does not always translate into actual usage. Subsequent studies can incorporate actual AI system use as a dependent variable to generate more actionable insights. Finally, future research can benefit from a larger sample size to deepen the understanding of AI adoption behavior and provide more robust evidence regarding factors influencing AI-based accounting systems implementation.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
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