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RESEARCH ARTICLE

Modeling AI Adoption Intention in the Banking Sector Using the TOE Framework: The Mediating Role of Complexity

Sangita Basak[1*], Rosli Mahmood[2], Noor Maimun Abdul Wahab[3]
Nur Shazwani Rosli[4], Rasel Barua[5]

[1]Department of Management Studies, Comilla University, Cumilla-3506, Bangladesh;
Putra Business School, UPM, 43400 Seri Kembangan, Selangor, Malaysia.
Email: sangitamgt@cou.ac.bd
[2]Putra Business School, UPM, 43400 Seri Kembangan, Selangor, Malaysia.
Email: rosli@putrabs.edu.my
[3]Putra Business School, UPM, 43400 Seri Kembangan, Selangor, Malaysia.
Email: noormaimun@putrabs.edu.my
[4]Sunway Business School, Sunway University, Selangor, Malaysia.
Email: shazwanir@sunway.edu.my
[5]Al-Arafah Islami Bank PLC., Dhaka, Bangladesh.
Email: rbcou2016@gmail.com

CORRESPONDING AUTHOR (*):
Sangita Basak
(sangitamgt@cou.ac.bd)

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ABSTRACT

The introduction of AI is one of the best changes any industry can adopt; the global banking sector is no exception, given that it brings both efficiency and highly personalised service, as well as systematic, data-driven decision-making. Empirical case studies of AI adoption in banking are limited, despite its strategic importance. Based on an extended Technology–Organisation–Environment (TOE) framework, this study investigates the factors influencing Artificial Intelligence adoption intention in Bangladesh's banking sector. In particular, relative advantage, top management support and competitive pressure are conceptualised as significant executives in the technology, organisational and environmental contexts, respectively, whereas complexity is added as a mediating mechanism to extend the TOE framework. The proposed model was tested on a cross-sectional survey database of 360 employees and managers from scheduled commercial banks using the Partial Least Squares Structural Equation Modelling (PLS-SEM). Increases in both competitive pressure and top management support were found to significantly positively influence AI adoption intention. On the contrary, relative advantage has little impact. Similarly, the complexity mediation effect is rejected, indicating that perceived technological difficulty does not serve as a significant mechanism through which TOE factors affect adoption intention in this context. This article adds to the target selection literature by conducting empirical research grounded in a recognized antecedent TOE framework that extends an in-use TOE model in the context of AI adoption in emerging-economy banking. The findings offer theoretical insights into the boundary conditions of complexity as a mediating construct and provide practical implications for banking executives and policymakers aiming to accelerate AI-driven transformation.

Contribution/Originality: This study contributes to the AI adoption literature by introducing complexity as a mediating mechanism within the TOE framework, linking relative advantage, top-management support, and competitive pressure to AI adoption intention. This study, focusing on the banking sector in Bangladesh, extends innovation adoption theory by explaining how organizational and environmental factors shape intentions to implement AI in a developing economy.

1. Introduction

AI encompasses a range of cutting-edge methods, procedures, and technologies that are essential to the current and future development of our society and businesses. (Musaab, 2018). A modern organisation can significantly benefit from using artificial intelligence techniques, which automate repetitive tasks, enhance customer experiences, and analyse data, among other benefits. Rao and Verweij (2017) predicted that the world's GDP would increase by $ 15.7 trillion by 2030. Gartner (2017) reports that 37% of businesses have already utilised AI in some capacity, representing a 270% increase over the last four years. AI is applied in a wide range of industries, including banking services, autonomous vehicle technology, optical character recognition, and disease diagnosis. (Musaab, 2018). Fintech companies, which have long adopted AI, are playing a crucial role in financial intelligence through their innovations, while traditional banks are quickly catching up with computational intelligence technologies, such as Chatbots (Das et al., 2015). Artificial Intelligence (AI) has become a critical driver of innovation in banking, automating routine tasks, enhancing predictive analytics, and improving customer experiences (Davenport & Ronanki, 2018). Banking 1.0, founded on traditional banking, gave way to Banking 4.0, which incorporates cutting-edge technology across various banking areas, including AI (Biswas et al., 2020). The quick development of AI technologies in banks made it possible to lower the cost of data processing, storage, and faster connectivity starting in 2017 (Noreen et al., 2023).

The banking industry in Bangladesh is utilising AI in various ways to enhance productivity, reduce costs, and improve customer experiences (Ahmed, 2022). The national AI strategy of Bangladesh has listed several potential applications for AI in the country's financial industry, including AI-based credit management systems for fraud detection and prevention, credit decisions to reduce risk in loan sanction process, AI-based risk management solutions, personalised banking solutions, financial process automation, virtual customer support assistance, and shell banking monitoring (Limited et al., 2021). Several banks in Bangladesh are using AI-powered tools to detect fraud, including credit card fraud and money laundering. For instance, Dutch-Bangla Bank uses an AI-powered fraud detection tool to monitor transactions in real time and identify irregular behavior (Ahmed, 2022). Standard Chartered Bank uses a chatbot named SCB Joy to provide customer assistance (The Daily Star, 2023). RobiLoan, an AI-powered lending platform used by Prime Bank, enables quick, efficient credit processing (Islam, 2020). Mutual Trust Bank monitors and manages financial risks using an AI-powered risk management system. (Aziz & Hossain, 2019). City Bank uses CityLive, an AI-powered marketing and sales platform that offers customers personalised offers and suggestions (The Daily Star, 2023). According to the Bangladesh Institute of Bank Management

(BIBM), 71% of Bangladeshi banks do not employ any AI-based solutions. Many banks, however, plan to launch AI-based solutions shortly (BIBM, 2021).

Banks are strategically implementing AI to enhance customer convenience, with a focus on digitalisation and cybersecurity measures (Öztürk & Kula, 2021). AI's role in enhancing decision-making processes in banking is highlighted, emphasising its ability to remove human bias and improve sustainability and growth (Smith & Nobanee, 2020). AI technologies can help banks make strategic decisions, optimise processes, and enhance customer experiences, potentially leading to significant cost savings and competitive advantages (Fares et al., 2022). Ghani et al. (2022) examine the determinants of artificial intelligence (AI) adoption in Malaysian manufacturing firms. Specifically, the study focuses on the influence of IT capacity, top management support, and government support within the Technology, Organisation, and Environment (TOE) framework. Neumann et al. (2022) utilise the technology-organisation-environment (TOE) framework to analyse AI adoption across eight Swiss public organisations. Gupta et al. (2022) investigate the elements that impact insurance workers' intent to adopt AI using the technology-organisation-environment (TOE) paradigm. In the insurance sector, behavioural intention to adopt AI is strongly predicted by technological characteristics, such as relative advantage and complexity, as well as by environmental factors, including market dynamics, regulatory support, and competitive pressure (Gupta et al., 2022). Top management support and financial readiness also show a significant association with the intention to adopt AI, while technical competencies do not (Gupta et al., 2022). Gangwar et al. (2015) identify key factors influencing cloud computing adoption, including relative advantage, compatibility, complexity, organizational readiness, top management support, and training and education. From the above discussion, it can be found that relative advantages, complexity, top-management support, competitive pressure, etc., are the key factors that influence technology adoption according to the past research (Musaab,2018; Noreen et al., 2023; Ghani et al., 2022; Chen et al., 2020; Neumann et al., 2022; Gangwar et al., 2015; Gupta et al., 2022). There are still some gaps in the existing literature. It recognizes relative advantage, complexity, top management support and competitive pressure as significant factors. However, there is a limited grasp of their subtleties, context-specific variations or real-world strategies for evaluation and quantification. Future research needs to develop in these directions to better understand the dimensions, factors, and strategies, as well as the contextual influences on technology adoption, for more sustainable and successful implementation. Furthermore, past studies have examined technology adoption using the Technology-Organization-Environment (TOE) framework; however, few have focused on Artificial Intelligence (AI) adoption, particularly in the banking sector, creating a significant literature gap.

In technology adoption research, several factors have acted as mediators, such as perceived usefulness, perceived ease of use, attitude and belief, social influences, perceived risk, trust, self-efficacy, subjective norms, etc. (Davis, 1989; Venkatesh et al., 2003; Rogers, 2003; Fishbein & Ajzen, 1975; Ajzen, 1991; Venkatesh et al., 2012). There may be other mediators that have received less attention, like complexity. A growing body of literature recognizes organizational or implementation complexity as a key construct in understanding technology adoption, yet explicit empirical measurement of this variable remains limited (Alamsyah et al., 2021; Uddin et al., 2020). While several studies explore the challenges of implementing complex technologies in organisations, few offer precise, validated measurement scales for organisational complexity in the context of technology assimilation (Liu et al., 2024; Jeilani et al., 2025). Technology adoption processes can vary significantly across contexts, including the type of technology, industry, cultural factors, and organizational settings. Numerous studies generalise their findings across contexts, while there may be specific mediation effects applicable only to a specific context that deserve more attention. The discussion indicates that complexity was not used very much as a mediator in earlier studies. Studies examining complexity as a mediator across different contexts, especially in the banking sector, can advance our understanding of technology adoption. The emended adoption of AI in Bangladesh will serve as a bulwark against growing competition, regulatory pressures, and customer appetite for digital services. However, adoption is not uniform across banks, suggesting a stronger need for empirical research on the determinants of AI adoption intention.

In light of the above discussion and gaps identified, this paper aims to address the following research questions-

RQ1: Do Relative Advantage, Top-Management Support, and Competitive Pressure significantly influence AI Adoption Intention in the banking Sector in Bangladesh?

RQ2: Does Complexity mediate the relationship between Relative Advantage, Top-Management Support, Competitive Pressure, and AI Adoption Intention?

2. Literature Review and Hypothesis Development

2.1. Relative Advantage (RA)

Relative advantage refers to the perceived superiority of adopting AI at the organizational level compared to existing alternatives (Chen et al., 2020). It is the extent to which the innovation is perceived as offering substantial benefits over the current idea it supersedes, encompassing factors such as cost-effectiveness and social status incentives (Rogers, 2003). Perceived relative advantage plays a crucial role in an organisation's intention to adopt innovative technologies (Chen et al., 2020). When an innovation is perceived as having significant advantages over current alternatives, the organization is more likely to adopt it (Almaiah et al., 2021). In the case of AI, the perceived benefits may include improved efficiency, reduced costs, increased productivity, enhanced decision-making, competitive advantage, and improved customer experiences (Chen et al., 2020; Chong et al., 2019; Martins & Oliveira, 2016; Almaiah et al., 2021). These perceived advantages can influence an organization's decision to adopt AI and the speed at which it integrates AI into its operations (Almaiah et al., 2021). It is logical to assume that individuals will adopt a new idea, product, or service only if they perceive it as superior to what is currently in practice (Almaiah et al., 2022; Chen et al., 2020). Consequently, the greater the perceived advantage of the innovation, the faster it diffuses within a social system (Roger, 1995, 2003; Chen et al., 2020; Almaiah et al., 2022; Wani & Ali, 2015).

H1: *Relative advantage is significantly related to AI adoption in the banking sector in Bangladesh.*

2.2. Top-Management Support (TMS)

Top management support (TMS) is a crucial factor in influencing technology adoption and the successful implementation of technological transformation in organizations (Garrison et al., 2015; Alsheibani et al., 2020). According to Venkatesh et al. (2003), Top-management support refers to the visible, vocal, and sustained backing provided by senior executives or leaders within an organization for initiatives, projects, or changes. It involves allocating resources, providing guidance, removing barriers, and reinforcing the initiative's importance to ensure its success and alignment with organizational goals (Venkatesh et al., 2003). The role of management support entails the active involvement and backing of senior leaders and decision-makers to integrate AI technologies within the organization's operations and strategy (Cruz-Jesus et al., 2019). Such provision of appropriate resources entails financial and human resources to support AI adoption and to ensure that cultural readiness within the organisation prevails (Garrison et al., 2015). It includes fostering a culture of experimentation and learning that enables the organisation to adapt and improve its AI use over time (Cruz-Jesus et al., 2019). Top management creates a positive atmosphere and supportive culture, moreover backing technological initiatives (Chatterjee et al., 2021; Hradecky et al., 2022), leading to the embracement of new technologies within existing systems. Management support is the most commonly mentioned factor in the TOE literature (Alshiebani et al., 2020). Managerial support is important for AI applications to align with a business's strategic goals, as managers exercise considerable influence over IT adoption (Chen et al., 2021). Prior research has found that management support is likely one of the primary reasons for a successful technological transformation (Duan et al., 2012; Hsu et al., 2019; Ifinedo, 2008; Low et al., 2011; Maroufkhani et al., 2022; Oyewobi et al., 2022).

H2: *Top Management support is significantly related to AI Adoption in the banking sector in Bangladesh.*

2.3. Competitive Pressure (CP)

Competitive pressure drives technological innovation (Gupta et al., 2022). In the face of market competition, firms often find it strategically necessary to adopt innovation (Gupta et al., 2022). When competitors adopt new technologies, organizations often experience pressure to keep up and typically implement similar technologies to meet competitive standards (Dutt, 2020; Neumann et al., 2022). This pressure stems from the threat of losing competitive advantage, motivating organizations to adopt innovations (Aboelmaged, 2018). Organizations have realized that incorporating modern digital technologies into their capabilities and operations can enhance their competitive advantage and improve innovation performance and processes (Spanjol et al., 2018). One such digital technology is Artificial Intelligence (AI), which plays a crucial role in shaping how businesses innovate (Verganti et al., 2020; Wamba et al., 2020) and respond to evolving customer needs (Mustak et al., 2021). AI enables organizations to gain a competitive edge, reduce costs (Press, 2016), explore opportunities in new markets (Ransbotham et al., 2017), boost top-line profits, improve efficiency, and augment human intelligence (Gupta et al., 2022; Curran & Purcel, 2017; Wamba et al., 2020). According to a study by Malak (2016), there is a relationship between competitive pressure and cloud computing adoption. The majority of wealthy nations employing advanced ICTs experience competitive pressure (Sayginer & Ercan, 2020). Organizations are increasingly adopting AI technology to adapt to or disrupt their ecosystems while optimizing their strategic and competitive advantages (Udell et al., 2019). Companies that want to compete in the market frequently need to adopt new technology (Chen et al., 2021). Businesses face pressure when rivals adopt new technologies. To stay competitive, they often implement these technologies immediately (Oliveira & Martins, 2008). Businesses that effectively implement novel artificial intelligence technology to enhance their offerings will secure a competitive edge over their rivals (Chen et al., 2021).

H3: *Competitive pressure is significantly related to AI adoption in the banking sector in Bangladesh.*

2.4. The Mediating Role of Complexity in Technology Adoption

Complexity refers to the degree to which an innovation can be easily understood, perceived, and used (Rogers, 2003). It encompasses perceptions regarding the difficulty of comprehending and utilizing the innovation (Chen et al., 2020). When an innovation incorporates new technologies and features, it is considered highly advanced and advantageous if it has a lower level of complexity and can be described as simple (Almaiah et al., 2022). Complexity is the most important factor governing technology adoption, serving as both a barrier and a mediator between antecedent factors and adoption outcomes. This section summarises research on its role as a mediator across different industries. In ERP adoption, Uddin et al. (2020) found that organization and technical complexity mediated both of the relationships between ERP features and firm performance, as well as implementation trajectories. Patterns in manufacturing are similarly highlighted by Rossetti et al. Supply-chain complexity weakened the positive effects of Lean practices on plant performance (2023). Similarly, the mediating role of complexity centrality has also been found to be significant in consumer-oriented research. Liu et al. It has been proposed by (2024) that perceived complexity indirectly influences attitudes toward self-service parcel systems and, therefore, the connection between technological design and adoption intentions. In healthcare, Novak et al. Task difficulty was identified as a mediator between health IT use and clinical efficiency (2012). Jeilani et al. (2023) examined public services, noting that technological readiness decreases perceived complexity, thereby increasing e-government. On the other hand, managers with digital literacy also indirectly paved the way for adoption by reducing perceived complexity (Author, 2025). In all these contexts, complexity works in the same way, transforming technical and organisational factors into adoption outcomes. This makes its inclusion in frameworks like the Technology–Organization–Environment (T-O-E) model theoretically and empirically justified.

H4a: *Complexity mediates the relationship between relative advantage and AI adoption intention.*

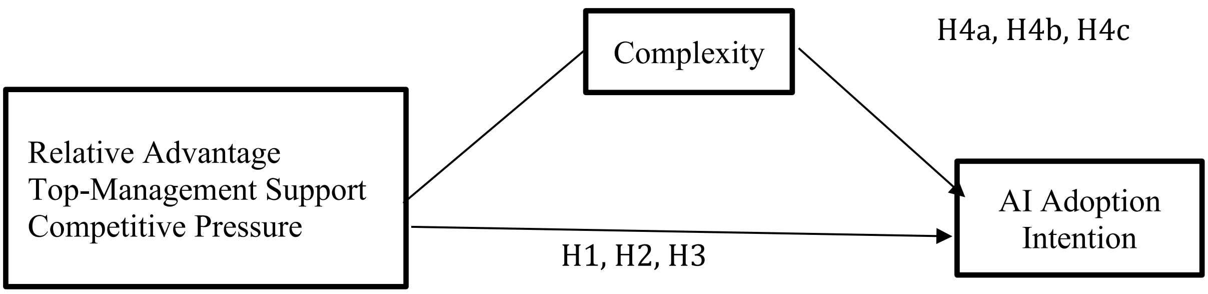
H4b: *Complexity mediates the relationship between top-management support and AI adoption intention.*

H4c: *Complexity mediates the relationship between Competitive pressure and AI adoption intention.*

2.5. Theoretical background and Research framework

The Technology-Organization-Environment (TOE) framework, developed by Louis G. Tornatzky and Mitchell Fleischer (1990), provides insights into the factors that influence the adoption of technological innovations by firms (Saint & Gutierrez, 2017; Low et al., 2019; Kurse et al., 2019). The technological context focuses on the characteristics of the technology itself, including its functionality, complexity, compatibility with existing systems, and ease of use s (Baker, 2011; Martín et al., 2012; Wang et al., 2016; Eze et al., 2019; Chau et al., 2020). The organizational context considers the characteristics of the firm and its resources, including the quality of the employees' technology usage expertise, managerial structure, amount of resource slack, degree of centralization, level of formalization, human resources and employee linkages (Lippert & Govindarajulu, 2006; Baker, 2011; Matikiti et al., 2018; Eze et al., 2019), and firm's size (Baker, 2011; Lu et al., 2015; Wang et al., 2016). The environmental context of the TOE framework encompasses the external characteristics of the business environment that influence the adoption of innovation (Tornatzky & Fleischer, 1990; Baker, 2011; Wang et al., 2016; Eze et al., 2019; Chau et al., 2020). This framework was originally developed based on the interplay of technological, organizational and environmental contexts for shaping the adoption processes (Saint & Gutierrez, 2017; Low et al., 2019; Kurse et al., 2019). TOE is perceived as an alternative and more holistic approach for understanding organizational adoption of IT innovations (Yang et al., 2013). It is not also restricted by industry and company (Wen & Chen, 2010). TOE has been effectively used as a major contextual factor explaining the organizational-level new IT adoption (Baker, 2012; Oliveira & Martins, 2011). The Technology–Organization–Environment (T-O-E) Framework (Tornatzky & Fleischer, 1990) is an all-encompassing model for analyzing the adoption of technology. This study investigates three predictors (relative advantage of AI, top-management support, and competitive pressure) and the mediation effect of complexity on AI adoption intention.

Figure 1: Research Framework



As illustrated in Figure 1, the proposed research framework depicts the hypothesized relationships among the study variables. The framework serves as the foundation for this study and guides the development of the research hypotheses. Specifically, H1, H2, and H3 represent the direct relationships between the independent variables and the dependent variable. In addition, H4a, H4b, and H4c represent the proposed mediating relationships. The framework provides a conceptual basis for examining the relationships among the constructs and testing the proposed hypotheses.

3. Research Methodology

In this study, we adopt a positivist research philosophy. This philosophical positioning is appropriate, as the aim of the research is to test relationships derived from predefined theoretical constructs using statistical methods. This involves a descriptive-explanatory research design, which combines a systematic description of factors that influence AI adoption with evaluation of hypothesised cause–and–effect relationships within the T-O-E framework. Within that realm, the investigation design aims to expound on how technological (relative advantage), organisational (top-management support), and environmental (competitive pressure) factors predict AI adoption intention directly, and indirectly through a mediating role of perceived complexity.

The study employs a cross-sectional time horizon, meaning that all information is collected at a single point in time, as the current AI adoption state of Bangladeshi banks can be assessed. Such a time frame is understandable as AI solutions for finance move relatively quickly, and by the time you study behaviour in organisations over years, the situation may already have changed. The organisation has been determined to be the unit of Analysis; this study will include scheduled banks in Bangladesh, which are increasingly exposed to technology-based innovations that are strategically important to the national economy.

Using probability sampling, a systematic random-sampling method was implemented to ensure the sample collected is representative and to prevent sampling bias. The bank managers were selected as the study sample using a pre-sampling interval after determining the total number of scheduled banks in Bangladesh, 360 bank managers were randomly chosen. A structured questionnaire was formed electronically through Google Forms to collect our primary data. The survey instrument consisted of validated measurement items from the literature, each answered on a scale of 1-7, ranging from "Strongly Disagree" to "Strongly Agree". To guarantee that the data gathered is reliable, pertinent, and current survey participants included managers and decision-makers directly dealing with technology and AI-related initiatives within the banks.

Collected data were first cleaned and preprocessed in SPSS by performing checks for missing values, descriptive statistics as well as tests of internal consistency and reliability with Cronbach's alpha. After that, the measurement model then tests the hypothesized relationships in that structural model using PLS-SEM at SmartPLS 4.1. This method was specially selected as appropriate given the complex models being evaluated, the small to moderate sample sizes and the distribution of non-normally distributed data. Direct and indirect effects were examined, with a specific focus on complexity as a mediator in the relationship between constructs of the T-O-E model and AI adoption intention.

4. Results

4.1. Demographic profile of the respondents

The sample consisted of 360 respondents, with males representing a significant majority (82.2%) over females (17.8%). About two-thirds of the respondents were in the age groups of 45 – 49 years (35.3%), 40 -44 years (28.6%) and less than 40 years, while one-fifth were aged above 50 (18.1%). This analysis reflects a sample somewhat further along in their careers. The sample is well educated: 89.2% hold a master's degree or higher, 9.2% hold Honours/bachelor's degrees, and 1.7% hold only low-level degrees as their highest qualification. For organisational affiliation, a range of banks were represented: 40.6 per cent conventional private commercial banks, Islamic Shariah–based private commercial bank (20.0%), state-owned commercial bank (18.9%), foreign commercial banks (11.4%) and specialised banks (9.2%). In general, the demographic characteristics indicate that participants were mostly male, highly educated and of middle age, drawn from various groups within the bank sector.

4.2. Construct Validity and Reliability

Table 1 presents the reflective measurement model assessment results, indicating all constructs have good reliability and convergent validity. Based on the results shown (Table 1), all outer loadings exceed the recommended threshold of 0.70, indicating good indicator reliability (Sarstedt et al., 2023). The values of Cronbach's alpha and Composite Reliability for all constructs range from 0.843–0.950 and 0.884–0.960, respectively, supporting their internal consistency (Sarstedt et al., 2023). Moreover, the AVEs for all constructs exceed 0.50, indicating satisfactory convergent validity. In general, these findings suggest the measurement model is reliable, allowing further structural analysis (Sarstedt et al., 2023).

Table 1: Construct Validity and Reliability

Construct/item	Outer loadings	CA	CR	AVE
AI Adoption Intention		0.94	0.952	0.742
AIA1	0.905			
AIA2	0.929			
AIA3	0.92			
AIA4	0.876			
AIA5	0.896			
AIA6	0.774			
AIA7	0.706			
Complexity		0.843	0.884	0.560
CLX1	0.774			
CLX2	0.723			
CLX3	0.706			
CLX4	0.766			
CLX5	0.724			
CLX6	0.792			
Competitive Pressure		0.891	0.917	0.648
CP1	0.783			
CP2	0.775			
CP3	0.787			
CP4	0.802			
CP5	0.869			
CP6	0.811			
Relative Advantage		0.904	0.924	0.636
RA1	0.760			
RA2	0.776			
RA3	0.851			
RA4	0.797			
RA5	0.797			
RA6	0.801			
RA7	0.797			
Top-Management Support		0.950	0.960	0.800
TMS1	0.879			
TMS2	0.894			
TMS3	0.901			
TMS4	0.915			
TMS5	0.920			
TMS6	0.853			

4.3. Discriminant validity, Inner VIF, R-square, and F-square

The HTMT values (Table 2) for all construct pairs are below the conservative threshold of 0.85, demonstrating satisfactory discriminant validity. This indicates that each construct is empirically distinct and measures a unique conceptual domain within the model (Sarstedt et al., 2023). Table 2 also presents the inner VIF values, which range from 1.512 to 2.571, well below the recommended cut-off of 3.3. These results confirm that multicollinearity is not a concern in the structural model, and the predictor variables do not exhibit problematic overlap. Thus, the estimated path coefficients can be interpreted without concern for inflated standard error (Sarstedt et al., 2023). The R^2 values presented in Table 2 indicate that the model explains 45.6% of the variance in AI Adoption Intention (Y1) and 59.6% of the variance in Complexity (Y3). According to standard benchmarks, the R^2 for AI Adoption Intention is moderate (Table 2), while the R^2 for Complexity is substantial. These values suggest that the included predictors collectively provide a meaningful level of prediction for both endogenous constructs (Sarstedt et al., 2023). Regarding effect sizes, the f^2 results (Table 2) indicate that Top-Management Support has the most significant impact on AI Adoption Intention ($f^2 = 0.195$), suggesting a moderate effect. Competitive Pressure shows a small effect ($f^2 = 0.029$), while Relative Advantage and Complexity contribute only negligible effects on AI Adoption Intention ($f^2 < 0.02$). For Complexity (Y3), Relative Advantage demonstrates a large effect size ($f^2 = 0.564$), highlighting its strong influence, whereas Competitive Pressure and Top-Management Support display minimal contributions ($f^2 = 0.039$ and 0.010, respectively) (Sarstedt et al., 2023).

Table 2: Discriminant validity, Inner VIF, R-square, and f-square

Construct	HTMT criterion					Inner VIF		R-square	f-Square	
	Y1	Y2	Y3	Y4	Y5	Y1	Y3		Y1	Y3
AI Adoption Intention (Y1)								0.456		
Competitive Pressure (Y2)	0.640					2.571	2.474		0.029	0.039
Complexity (Y3)	0.475	0.689				2.478		0.596	0.002	
Relative Advantage (Y4)	0.427	0.646	0.841			2.364	1.512		0.001	0.564
Top-Management Support (Y5)	0.684	0.768	0.530	0.460		2.026	2.006		0.195	0.010

4.4. Path coefficient (direct effect and mediating effect)

The hypothesis testing results are presented in Table 3, indicating that Competitive Pressure (B = 0.203, t = 2.083, p = 0.037) has a significant positive impact on AI Adoption Intention, and the corresponding confidence interval (0.013, 0.394) does not include zero, further confirming the statistical significance of this result. On the other hand, Relative Advantage has no significant direct effect on AI Adoption Intention (B = 0.031, t = 0.359, p = 0.720), and the confidence interval (−0.137, 0.196) includes 0, indicating no significant influence. Likewise, the effect of Top-Management Support remains positive (B = 0.464, t = 5.412, p < 0.001), stronger and highly significant, with a confidence interval of (0.285, 0.618), indicating high accuracy in predicting AI Adoption Intention as well. With regard to indirect effects (Table 3) through Complexity, there exist no statistically significant mediation pathways. Hypothesis 5 was rejected as the mediating effect of Complexity on the Relative Advantage and AI Adoption Intention relationship is not significant (B = 0.034, t = 0.818, p = 0.413). Likewise, the indirect effects of Complexity on the relationship between Top-Management Support and AI Adoption Intention (B = 0.005, t = 0.611, p = 0.542); and Competitive Pressure and AI Adoption Intention (B = 0.011, t = 0.785, p = 0.432) are nonsignificant Indeed, all of these confidence intervals for their indirect effects included zero, supporting the conclusion that Complexity does not act as a mediator in any of these relationships.

Table 3: Path coefficient (direct effect and mediating effect)

Hypothesis	B	T statistics	P values	Confidence Interval 2.50%	97.50%
Competitive Pressure -> AI Adoption Intention	0.203	2.083	0.037	0.013	0.394
Relative Advantage -> AI Adoption Intention	0.031	0.359	0.720	-0.137	0.196
Top-Management Support -> AI Adoption Intention	0.464	5.412	0.000	0.285	0.618
Relative Advantage -> Complexity -> AI Adoption Intention	0.034	0.818	0.413	-0.043	0.121
Top-Management Support -> Complexity -> AI Adoption Intention	0.005	0.611	0.542	-0.008	0.027
Competitive Pressure -> Complexity -> AI Adoption Intention	0.011	0.785	0.432	-0.016	0.042

5. Discussions

The present study examined the determinants of AI Adoption Intention (AIA) and the mediating influence of complexity within an organizational context. The results provide several noteworthy theoretical and practical insights that contribute to the broader literature on technology adoption.

5.1. Direct Effect

The results show that competitive pressure (CP) and top-management support (TMS) have significant effects on AI adoption intention. The positive influence of competitive pressure also aligns with other TOE-based studies that identified external environmental context as a significant precursor to the adoption of digital innovations, such as big data analytics and cloud computing (Oliveira & Martins, 2011; Wamba et al., 2017). The present study corroborates the findings, indicating that organisations view AI adoption as a necessity to remain competitive amid market changes and the interactive automation of services. This supports the idea that environmental pressure is an important driver of disruptive technology adoption; falling behind competitors carries major strategic risks. The most powerful influence on AI adoption intention is top-management support, further supporting the long-held view that upper-management commitment is essential to the successful adoption of innovative technologies (Premkumar & Roberts, 1999; Ifinedo, 2011). Previous studies have demonstrated that managerial support mitigates uncertainty, supports resource allocation, and further enhances worker engagement during technology transitions (Venkatesh et al., 2003). These findings are consistent with the latter report, which postulates that adopting AI is an even more complex, data-driven, and resource-intensive innovation than previous IT upgrades, similarly demanding a greater degree of executive sponsorship.

Surprisingly, Relative Advantage (RA) has no effect on AI adoption intention. Previous diffusion studies have consistently identified RA as one of the most salient predictors of technology acceptance (Rogers, 2003; Moore & Benbasat, 1991). Nevertheless, some recent AI literature has reported controversial results, showing that organisations found it hard to determine the direct or indirect value of AI in the early stages of adoption (Jöhnk et al., 2021). Thus, the results of this study confirm the latest findings, which highlight that organisations may not yet be fully experienced with AI to correctly evaluate its advantages. Such a difference from classical diffusion theory highlights the unique and dynamic nature of AI as opposed to previous information systems.

5.2. Mediating Effect

The results show that complexity does not mediate any of the relationships among CP, TMS, RA and AIA. Traditionally, complexity is treated as a deterrent that weakens the impact of perceived benefits or organizational support on technology adoption (Rogers, 2003). Nonetheless, among the numerous contemporary AI & advanced analytics papers, one thing is clear that organisations view these technologies as complex (Dwivedi et al., 2021). This could help explain the lack of mediation. AI is a complex beast that requires infrastructure, human capital and algorithmic understanding, creating a pervasive perception of high complexity across firms. In addition, many companies nowadays depend on outsourcing certain aspects of their business to third-party vendors, pre-built AI solutions, or cloud-based AI services, further reducing internal tech burdens. Although perceived complexity is theoretically considered an important mediating variable, this externalisation may mitigate its role, for example, in recent empirical work on AI-as-a-service adoption. (Maroufkhani et al., 2022). The current findings also underscore the need to rethink how conventional constructs like complexity operate in newly created AI ecosystems.

5.3. Theoretical Insights

The results yield several key contributions to theory. The nonsignificant effect of Relative Advantage is in line with the traditional understanding of the Diffusion of Innovations (DOI), which indicates that emerging technologies do not follow the same logic as conventional deriving systems. AI has an ambiguous, often long-term nature, so its benefits may be overly diffuse to provide RA predictive power early on in the adoption.

Secondly, the significant role of top-management support underscores that organisation-centric variables are important for AI adoption, aligning with the TOE framework, which highlights internal readiness and strategic alignment as critical contexts. This is consistent with recent recommendations to incorporate leadership theory and digital transformation literature into AI adoption models (Ly, 2023).

Third, the absence of mediation by complexity offers fresh perspectives on how this construct manifests itself in advanced technology contexts. In contrast to traditional IS models, where complexity is a barrier, the findings suggest complexity may represent a common background feature of AI, as acknowledged but not distinguishing between intended adoption. This suggests that future models would be better served by using other mediating variables, including data governance capability, digital maturity, and organisational readiness, which might better mediate how organisational or environmental variables affect AI adoption.

6. Implications of the study

6.1. Theoretical Implication

This paper expands on the growing literature on AI adoption by applying the TOE framework to a relevant and challenging modern technology area. Our main finding that Relative Advantage is an insignificant predictor disputes the established innovation adoption models like Diffusion of Innovations (Rogers, 2003) and indicates new patterns for early-stage AI adoption separate from research in information systems done decades prior. However, our finding that complexity does not mediate AI adoption highlights the potential influence of other mediators, such as organisational readiness, digital maturity and trust in AI, in sketching a fuller picture of the dynamics surrounding AI adoption. Such insights can help to sharpen theoretical lenses for analyzing advanced emerging technologies in the coming decade.

6.2. Managerial Implication

The findings suggest several key recommendations for managers and organisational leaders, those involved in policy formulation in the banks. The strongest driver of AI adoption intention is still top-management support, which means that company leaders need to be engaged in resource allocating and prescribe the cultural shift needed for digital transformation and an innovation-driven culture. Organisations should recognise that the pressure to adopt artificial intelligence is increasingly determined by who they compete with, where their industry is headed and how digitally mature, they are — while preparing a strategy for making AI an ally against competition. As relative advantage was not found to play a great role here, organizations should invest the upfront resources needed to convey concrete value with pilot projects; having publications of successful case studies and being able to provide hard performance metrics. As complexity did not mediate adoption, organisations must act more aggressively on the technology and operational factors by improving their data governance policies, training employees in new systems implemented as a result of these agreements and building alliances with advanced service providers. Such implications will feed organizations to define the level of readiness for AI.

7. Limitations and Future Research Directions

Although this study provides additional information, there were limitations that leave room for future scientists to build on our research. Because the present study employed a cross-sectional design, this precludes cause and effect inference. Future studies may adopt longitudinal or mixed-method designs to capture perceptions on AI not just during the implementation phase, but starting from the intention of organisational advances from intention to implementation. Second, as this is based on self-reported survey data, it is more susceptible to biases such as standard-method variance. They will augment prediction by allowing qualitative interviews, objective performance indicators, or multi-staged datasets. Third, results are often context-specific based on industry, region or digital maturity levels. Generalizability would then be more beneficial since comparative studies can be performed across sectors or countries, while making us aware of contextual differences. A fourth limitation was the consideration of complexity as the only mediator. An extension can be made by including mediators such as perceived usefulness, data quality, organizational readiness, information climate or trust in AI to clarify the mechanisms of AI adoption. Finally, with the acceleration of AI evolution that continues today, future research should also explore the implications of emerging tools e.g. generative AI, autonomous decision systems and responsible AI frameworks on how organisations may respond to such phenomena in terms of their perceptions and adoption behaviours.

8. Conclusion

This paper examined the factors influencing AI Adoption Intention (AIA) using the Technology–Organisation–Environment (TOE) framework, specifically considering the mediating role of complexity. The findings show that Competitive Pressure and Top-Management Support are more drivers of AI Adoption Intention. This indicates that both external momentum and organisational commitment to AI are among the main success factors for driving AI initiatives. In particular, Relative Advantage was not a significant predictor of adoption intention, suggesting that organisations may still struggle with accurately evaluating or expressing the concrete benefits of (or comparison against) AI visions. The mediating analysis showed that complexity does not mediate the relationship between the predictors and AI adoption intention. It implies that organisations might consider applying AI using a technology-independent or organisation-agile approach, irrespective of specific technological factors or organisational problems, or to mitigate complexity by outsourcing implementations and leveraging external expertise. Collectively, these findings suggest that we need to revisit how conventional innovation constructs work in the context of novel, sophisticated technologies—like A.I. Despite the advancement of AI, it is essential to examine strategic, organizational, and environmental variables that affect acceptance.

Ethical Approval and consent from participants

The researchers followed the research ethics guidelines of the PUTRA Business School, UPM, Malaysia. Informed consent was obtained from all respondents, who were informed of their anonymity, and their responses were kept strictly confidential. They were also informed that the study was low risk and that they could withdraw at any time without repercussions.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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