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Critical Factors Affecting the Adoption of Artificial Intelligence: An Empirical Study in Vietnam*

Thanh Luan NGUYEN[1], Van Phuoc NGUYEN[2], Thi Viet Duc DANG[3]

Abstract

The term "artificial intelligence" is considered a component of sophisticated technological developments, and several intelligent tools have been developed to assist organizations and entrepreneurs in making business decisions. Artificial intelligence (AI) is defined as the concept of transforming inanimate objects into intelligent beings that can reason in the same way that humans do. Computer systems can imitate a variety of human intelligence activities, including learning, reasoning, problem-solving, speech recognition, and planning. This study's objective is to provide responses to the questions: Which factors should be taken into account while deciding whether or not to use AI applications? What role do these elements have in AI application adoption? However, this study proposes a framework to explore the significance and relation of success factors to AI adoption based on the technology-organization-environment model. Ten critical factors related to AI adoption are identified. The framework is empirically tested with data collected by mail surveying organizations in Vietnam. Structural Equation Modeling is applied to analyze the data. The results indicate that Technical compatibility, Relative advantage, Technical complexity, Technical capability, Managerial capability, Organizational readiness, Government involvement, Market uncertainty, and Vendor partnership are significantly related to AI applications adoption.

Keywords: Artificial Intelligence Adoption, Technology Organization Environment Model, Structural Equation Model

JEL Classification Code: C02, C44, D81, E44, L91

1. Introduction

Advances in artificial intelligence have prompted software and system engineers to design unique techniques for boosting revenue, cutting costs, and increasing

[1]First Author. Lecturer, Faculty of International Business Administration, Ho Chi Minh University of Foreign Language and Information, Ho Chi Minh City, Vietnam [Postal Address: 320 Cao Thang Street, Ward 12, District 10, Ho Chi Minh City, Vietnam] Email: luannguyen@huflit.edu.vn
[2]Corresponding Author. Faculty of Business Administration, Posts and Telecommunications Institute of Technology, Hanoi, Vietnam [Postal Address: 94 Tran Phu Street, Ha Dong, Hanoi, Vietnam] Email: nguyenvanphuoc@ptithcm.edu.vn
[3]Dean, Faculty of Finance and Accounting, Posts and Telecommunications Institute of Technology, Hanoi, Vietnam. Email: ducdtv@ptit.edu.vn

organizational efficiency. Today, artificial intelligence (AI) is a significant competitive trend in the industry (Davenport & Ronanki, 2018). AI is defined as "a collection of tools and technology capable of augmenting and enhancing organizational performance" (Alsheibani et al., 2018). This is accomplished by creating "artificial" systems capable of resolving complex environmental difficulties, with "intelligence" referring to the emulation of human intelligence. This intelligence is essential for strategic planning and has been effectively employed by businesses to gain a competitive advantage over their competitors (Varian, 2018).

It is widely expected that artificial intelligence (AI) will deliver benefits such as human augmentation, which should be considered while discussing economic growth (Ransbotham et al., 2017). AI has been used and applied at the federal, industrial, and personal levels. Furthermore, the Government of the Socialist Republic of Vietnam set a clear policy for adopting artificial intelligence in the public sector by 2030, which is gradually gaining traction in the ASEAN region, notably the Vietnam government. Examining the significance of government bodies taking the initiative and

beginning artificial intelligence projects in their surroundings that fulfill their business needs. AI is the simulation of various human intelligence processes by computers, notably computer-related systems (Agrawal et al., 2019).

Google, Amazon, IBM, and Apple have all employed AI to improve consumer experiences (Brynjolfsson & Mcafee, 2017) and productivity (Varian, 2018) through easier collaboration (Hunter, 2018). The global adoption of AI presents a big opportunity for Vietnamese businesses (Nguyen & Tran, 2019). Furthermore, the survey predicts that AI and automation will help the Vietnamese economy to the tune of 1.2 trillion USD by 2030 (Chua et al., 2021). Despite this excellent demonstration of AI, (Chua et al., 2021) study of business leaders indicated that only 6% of Vietnamese enterprises are consistently investing in AI and automation, compared to more than 25% in the US. Vietnamese businesses are increasingly lagging behind their worldwide competitors in the use of AI applications (Infosys, 2016). Many companies appear to be figuring out how to create a business case for AI deployment, as well as the organizational competencies needed to assess, build, and implement AI solutions, and are confused about the business applications of AI (Ransbotham et al., 2017). As a result, in the Vietnamese context, a full understanding of AI adoption and associated drivers have yet to be produced. As a result, the purpose of this research is to acquire a complete understanding of how AI is being implemented by organizations in Vietnam.

The purpose of this study was to investigate the impact of technological context, organizational context, and environmental context on the adoption of AI applications. Data obtained from middle-level AI specialists, Information technology (IT) managers, IT executives (CIO, CEO), and IT professionals in Vietnam are used to test the study model and hypothesized linkages. Furthermore, the findings of this study contribute to empirical research on contextual factors that influence AI application adoption decisions using a large data set as opposed to a few isolated cases. Given the importance of AI application adoption in modern organizations and the future, the findings of this study are also intended to assist AI application project managers and practitioners in formulating policies and targeting appropriate contextual factors to support effective AI application adoption.

2. Theoretical Background

2.1. Technology Adoption Perspective

Adopting new technologies is a proven strategy for corporate success (Alsheibani et al., 2018). Previous research has primarily focused on innovative information technology (IT) or new system adoption at the personal and organizational levels (Oliveira et al., 2019). For individuals' technological acceptance practices (Alsheibani et al., 2018) theory of reasoned action (TRA) provides profound insight into how a person's conduct is influenced and led by their attitudes and norms. Ajzen advances TRA by proposing the theory of planned behavior (TPB) (Ajzen, 2012), which asserts that an individual's behavioral intents and behaviors are shaped by his or her attitude toward behavior, subjective norms, and perceived behavioral control (Davis, 1985) offers the technology acceptance model (TAM) based on TRA to discover the factors that influence people's adoption or rejection of information technology. It implies that when users encounter new technology, a variety of factors impact their decision regarding how and when to use it (Davis, 1989). Mobile healthcare systems (Lumsden & Gutierrez, 2013; McCarthy & Hayes, 1981), as well as electronic banking (Picoto et al., 2014; Tornatzky et al., 1990), offer the technology-organization-environment (TOE) paradigm to describe how technical and environmental elements influence companies' technological innovation adoption decisions.

As a result of the TOE, some scholars have begun to investigate the elements that influence an organization's IT adoption (Quaddus & Xu, 2005), perform a qualitative field study, and find four elements that influence the adoption and spread of knowledge management systems (KMS) in organizations: organizational culture, managerial support, individual advantages, and the KMS dream. (Co et al., 1998) conduct an analysis of 27 management variables related to human factors affecting enterprises' adoption of modern manufacturing technologies (AMT). According to Kosaroglu and Hunt (2009), technical, leadership, managerial, and administrative capabilities all contribute to the success of new product development (NPD) projects in the telecommunications industry (Oliveira & Martins, 2008) review the research on IT adoption at the organizational level, including the TOE framework (Rogers, 1995; Tornatzky et al., 1990) diffusion of innovation (DOI) theory, (Schalkoff, 1990) institutional theory, and electronic data interchange (EDI) framework reviewed by (Iacovou et al., 1995).

2.2. The Contexts of AI Adoption

TAM, TPB, and UTAUT have all been extensively used in research on AI adoption. They are, nonetheless, applicable to particular research. By comparison, the DOI and the TOE framework are two frequently used theories in organizational-level IT adoption research (Oliveira & Martins, 2011; Venkatesh et al., 2003; Rogers, 1995). DOI Theory is one of the earliest social science theories. It originates in communication and is used to describe how an idea or product gains traction and spreads over time within a particular demographic or social system. Rogers

defines diffusion as the process of disseminating innovation through time among social system actors (Rogers, 2010). According to the thesis, widespread adoption of innovation is necessary for progress and sustainability. Rogers observes that those who accept an innovation early exhibit distinct characteristics from those who acquire it later. He divides adopters into five groups: innovators, early adopters, early majority, late majority, and laggards. Additionally, when it comes to fostering innovation, methods for different groups of adopters should be distinct.

Several studies are now being conducted to evaluate the uses of artificial intelligence in specific fields (Alsamhi et al., 2018; Macleish, 1988; Oliveira & Martins, 2011; Wang et al., 2016). Other works examine the theoretical underpinnings of AI (Mitka, 2012; Zou, 2015) as well as its applications (Kouziokas, 2017; Xu & Jia, 2021). However, few studies have been conducted on the adoption of artificial intelligence, particularly at the organizational level. For instance, (Alsheibani et al., 2018) present a study framework for AI adoption, but this framework is not validated across a sample of enterprises to discover the elements affecting AI adoption. Additionally, their study lacks hypothesis tests and empirical validation.

As a result, the study is required to examine the aspects that influence the proclivity of AI to adopt, as well as an organization's specific organizational competence and environmental circumstances. According to the evaluation of studies on AI adoption, the TOE framework is an excellent starting point for investigating AI adoption not only because it emphasizes the unique context in which the adoption process occurs but also because it can be used to evaluate the elements affecting AI adoption. As a result, this study uses the TOE framework as its theoretical framework. Additionally, because scholars have combined the TOE framework and the DOI theory to evaluate IT adoption (Oliveira & Martins, 2011), this study takes the same method with AI adoption. As previously stated, the TOE framework is comprised of three components: the technology context, the organizational context, and the environmental context.

3. Research Model and Hypotheses

This study presents a research methodology based on the TOE framework and DOI theory to gain an insight deeper into the success variables influencing AI adoption at the organizational level. This study categorizes success variables into three categories of artificial intelligence, including technological context, organizational context, and external environment. As shown in Figure 1, Compatibility, relative advantage, and complexity are all factors in the category of technological features of AI. The organizational context category includes the following variables: managerial support, organizational size, managerial capability, and organizational readiness. External environment factors include government involvement, market uncertainty, competitive pressure, and vendor partnerships. This section proposes a framework for the modified technology acceptance model to aid in characterizing the study's existing research problem and implementing a research model.

3.1. Technological Context

From a technological perspective, technology demonstrates the important components in AI decision-making. Numerous studies have been conducted on the effect of innovative traits on the innovation process (Chau & Tam, 1997; Kwon & Zmud, 1987; Rogers, 1995), although list five qualities of innovation in DOI theory, namely compatibility, relative advantage, complexity, trialability, and observability, only the first three are reliably associated with innovation adoption at the organizational level (Tornatzky et al., 1990; Wu et al., 2007).

Technical Compatibility (CPA):
Technical compatibility is a critical factor in determining whether an innovation gets adopted (Azadegan & Teich, 2010; Chong & Bauer, 2000; Dedrick & West, 2004; Oliveira et al., 2014). It refers to the extent to which innovation and its capacity to deliver value and experience while satisfying the requirements of potential users are compatible (Rogers, 1995). Compatibility on a high level can result in better adoption. Artificial intelligence applications, particularly machine learning, require vast amounts of data (et al., 2015). If AI technology is compatible with existing IT environments, its installation will likely be less expensive and time-consuming. As a result, AI may be more readily adopted. As a result, the following hypothesis is formed.

H1a: *Technical compatibility is significantly and positively related to AI applications adoption.*

Relative Advantage (RAD):
The relative advantage of innovation is the degree to which it is seen as being superior to the strategy it substitutes (Yang et al., 2013; du Plessis & Smuts, 2021), emphasizing an organization's propensity to adopt new technology is influenced by the perceived advantage of innovation. As a result, new technologies that provide unambiguous benefits in terms of strategic and operational effectiveness are more likely to be accepted (Greenhalgh et al., 2004). Recently, AI has been used in customer service chatbots, customer-facing speech and voice services, and automated network operations (El Khatib et al., 2019). These applications help businesses cut operational expenses, improve service quality, enhance client experiences, and increase efficiency. This leads to the following hypothesis.

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H1b: Relative advantage is significantly and positively related to AI applications adoption.

Technical Complexity (CPL):

The technical complexity of innovation represents the extent to which it is considered as being comparatively difficult to comprehend and use (Yang et al., 2013). The complexity of AI stems from its lack of maturity, a lack of technical competence and IT specialists, as well as its lengthy development period and high cost (Attewell, 1992), observes that enterprises postpone in-house adoption of a complex technology until they have accumulated sufficient technical knowledge to successfully deploy and operate it. Currently, AI is relatively new to many businesses, which lack a good comprehension of AI applications. This leads to the following hypothesis.

H1c: Technical complexity is significantly and negatively related to AI applications adoption.

3.2. Organizational Context

Organizational capabilities encompass the leadership, management, and managerial support resources available to facilitate an innovation's adoption. These qualities are typically organization-specific, non-transferable, and ingrained inside an organization. The resource-based view (RBV) theory can be used to determine which organizational competencies contribute to AI adoption. According to RBV, corporations gain a competitive edge by combining economically valued, difficult to copy, and nontransferable resources (Garrison et al., 2015; Hannan & McDowell, 1984).

Managerial Support (MSU):

Managerial support is crucial for any significant organizational transformation because it directs resource allocation and service integration (Co et al., 1998). Scholars have discovered that managerial support is critical for both the implementation of information systems (Fui-Hoon et al., 2001; Müller & Jugdev, 2012; Sanders & Courtney, 1985) and the acceptance of information technology (Chong et al., 2009; Kim et al., 2015; Teo et al., 2006; Elbanna, 2013) contends that managerial support must be consistent and continuous throughout a project's implementation, or even the project would fail. This leads to the following hypothesis.

H2a: Managerial support is significantly and positively related to AI applications adoption.

Managerial Capability (MCP):

The term "managerial capability" refers to a manager's ability to influence, motivate, and empower employees to contribute to the organization's performance and success (House et al., 2002). It entails decision-making, establishing a solid workplace and culture, efficiently accomplishing goals and objectives, and cultivating creativity and innovation. In information technology, managerial competency encompasses both project coordination and education & training. Firms with good management capabilities can overcome these impediments and quickly adopt new technologies. As a result, the business may quickly implement AI technologies and boost its performance, gaining a competitive edge. This leads to the following hypothesis.

H2b: Managerial capabilities are significantly and positively related to AI applications adoption.

Organization Size (ORS):

According to Lin and Lin (2008), the size of an organization has a significant impact on its ability to accept new innovations. Numerous studies have discovered that large organizations invest in AI more quickly and at a greater scale than other forms of investments. We propose that organization size is related to the organizational context, which has a direct impact on AI adoption. This leads to the following hypothesis.

H2c: Organizations' size is significantly and positively related to AI applications adoption.

Organizational Readiness (ORE):

Organizational readiness is also important when it comes to adopting AI. According to a Narrative Science survey, 59 percent of firms that are proficient in big data also use AI technologies (King & He, 2018). As previously mentioned, AI adoption implementations are related to the organization's technical readiness and the skill of its people resources. As a result, we believe that the availability of AI expertise, data required to train personnel in the use of AI, and technical understanding promote the spread of AI. This leads to the following hypothesis.

H2d: Organizational readiness is significantly and positively related to AI applications adoption.

3.3. Environmental Context

The role of institutional contexts in defining organizational structure and behaviors is emphasized by institutional theory (Scott, 2008). Firms are influenced by their external environment, according to (Hutajulu et al., 2021). As a result, organizational decisions are influenced not just by rational efficiency goals but also by social and cultural issues, as well as concerns about legitimacy.

The external environment can both induce and dissuade enterprises from adopting new technologies. External isomorphic pressures from the government, competitors, and customers are likely to drive firms to adopt and use AI (Gibbs & Kraemer, 2004).

Government Involvement (GIV):

Government involvement is critical in promoting IT innovation (Wang et al., 2022). The government could implement supportive strategies and policies to encourage the commercialization of new technology, as well as new rules for their development. According to Al-Hawamdeh and Alshaer (2022), the adoption of new technology is a complex process, and the framework established by the government is extremely important. This leads to the following hypothesis.

H3a: *Government involvement is significantly and positively related to AI applications adoption.*

Market Uncertainty (MUC):

Market uncertainty factors, such as product demand, market competition, and consumer loyalty, are beyond the control of enterprises but can have an impact on their performance (Hao et al., 2018). Many AI applications and applications are still in their infancy at the moment, and suitable professional and technical experts are scarce, but AI has already demonstrated significant vitality and provides enterprises with additional competitive prospects. Also, some complicated activities, such as fingerprint identification and fact detection, are only suitable for being performed by AI programs. This leads to the following hypothesis.

H3b: *Market uncertainty is significantly and positively related to AI applications adoption.*

Competitive Pressure (CPR):

Competitive pressure is a motivator for technological innovation. Adopting new technology is frequently a strategic necessity to compete in the market (Dutton, 2018; Lippert, 2006). Firms' competitive advantages are not permanent and long-lasting, but rather transient. According to (Porter & Millar, 1985), IT innovation can change industry structure, change competition rules, exploit new approaches to outperform rivals, and transform the competitive environment. Firms that successfully use emerging AI applications to improve their products and services will gain a competitive advantage. This leads to the following hypothesis.

H3c: *Competitive pressure is significantly and positively related to AI applications adoption.*

Vendor Partnership (VPA):

According to Assael (1992), vendor participation can considerably influence the rate of adoption and diffusion of innovative products. Vendors require a massive quantity of data to train their AI technologies, including sensitive consumer information. As a result, vendors are frequently unable to market AI solutions that are ready to use; instead, they must collaborate closely with businesses (their clients) to do AI training both during and after deployment. Partnerships between vendors can have a significant impact on the AI adoption process. As a result, AI providers can effectively sell AI applications. This leads to the following hypothesis (Figure 1).

H3d: *Vendor partnership is significantly and positively related to AI applications adoption.*

4. Research Methodology

4.1. Sample and Data Collection

To empirically test the suggested framework, we first conducted a thorough review of the literature, followed by a quantitative approach that collected data via a survey. A detailed analysis of scholarly works on technology readiness and AI was performed. Items accepted and tested in earlier studies were utilized to assist cumulative research (Ahmadi et al., 2015; Cruz-Jesus et al., 2017; Lai, 2017). Items assessing management hurdles and organizational preparedness factors were created specifically for this study by taking earlier research into account (Picoto et al., 2014; Wright et al., 2017). To the best of our knowledge, although the TOE has been employed in multiple IT adoptions at the company level, none of the constructs used in these studies were focused on AI adoption. As a result, a pre-test survey was conducted to check that the items were appropriate for evaluating framework dimensions in the context of this study.

To reach a wide number of possible participants, this study conducted a mail survey of significant Vietnamese enterprises. To verify content validity, the questionnaire items were changed based on the results of the expert interviews and polished by thorough pre-testing. Eleven constructs (Compatibility, Relative advantage, Complexity, Managerial support, Organization size, Managerial capability, Organizational readiness, Government involvement, Market uncertainty, Competitive pressure, and Vendor partnership) were operationalized as indicators of a total of 37 items. To measure these items and collect most responses, a 7-point Likert scale ranging from "I strongly agree" (7 points) to "I strongly disagree" (1 point) is utilized. Senior managers, particularly those directly in charge of information systems in both private and public companies
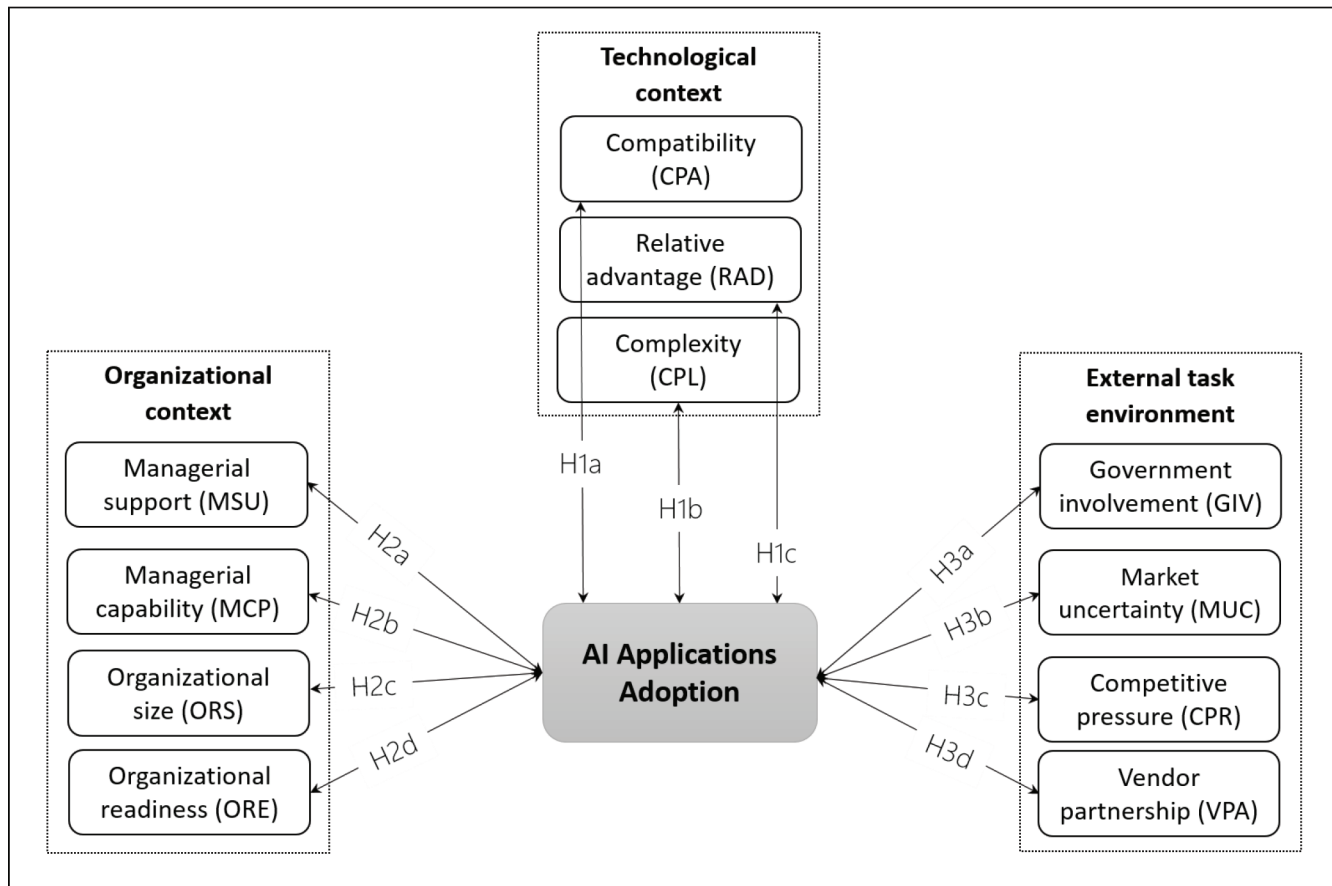
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Figure 1: Research Model

in Vietnam, are the intended participants. The goal was to recruit a representative sample of the Vietnamese industry from a wide range of levels, backgrounds, gender and age groups, and geographical areas. The usage of the LinkedIn.com database gives advantages such as the ability to reach a large number of respondents with extremely diversified characteristics such as position, educational level, and geographical location within Vietnam, allowing the results to be more generalizable. In total, 500 invitations were sent to all industries in Vietnam. The total number of LinkedIn responses was 203, with 10 missing data points. By excluding these responses, the number of valid responses was reduced to 193, which is still suitable as a valid sample for informing the quantitative analysis (Chen, 2018).

4.2. Data Analysis

To investigate sample data and assess model fit, this study employs structural equation modeling (SEM). SEM is a technique for performing high-quality statistical analysis on multivariate data that was developed in the second generation (Chin & Marcolin, 1995). SEM is carried out using Analysis of Moment Structures (AMOS), a covariance-based technique for analyzing models incorporating variables with measurement error (Gefen & Straub, 2000). The study employs a combination of multivariate and regression analysis to analyze factor analysis and idea linkages. SmartPLS version 3.3 is used in this work to examine the measurement model and structural model. The measurement model depicts the relationships between constructs (latent variables) and their indicators (observed variables), whereas the structural model depicts the latent variables' potential causal relationships (Chin et al., 2003).

5. Results and Discussion

5.1. The Measurement Model

The measurement model's adequacy is determined by examining the reliability of individual items, construct validity, convergent validity, and discriminant validity of the measuring instrument. The proposed model measures

eleven latent constructs (factors) and associated observable variables (indicators). Then, factor analysis is performed to discover and corroborate the indicators under each construct about AI adoption success factors. Some signs are eliminated because their factor loadings are too low (0.4) or they are part of crossing loadings. The KMO coefficient is 0.829 (more than 0.5). The outcome of Bartlett's testing (Sig. = 0.000) suggests that the factors analysis is appropriate. From the 37 observation variables, eleven factors are extracted. The extracted variance is 72.168 percent (more than 50%). Confirmatory factor analysis (CFA) results show that all routes connecting the remaining observable variables and the constructs are significant at $p < 0.001$. According to Fornell and Larcker (1981), the percentage of extracted variance explains a model's construct validity. The overall variance explained by each indicator ranges between 50% and 80%.

Table 1 displays the Cronbach's alpha (CA) value for each construct. They are all greater than 0.7, the usually accepted cutoff (Kline, 2013). The internal consistency of the scales is measured by composite reliability (CR). It is a more precise measure of dependability (Chin & Gopal, 1995). For developing appropriate model reliability, the recommended value of CR is 0.7 (Gefen et al., 2000). All of the CR values for each construct are more than the threshold. As a result, the model's build reliability is established. Convergent validity measures the consistency of many items. The Average Variance Extracted is used to calculate it (AVE).

Table 2 represents the AVE values for each construct. They are all greater than the acceptable cutoff of 0.50 (Fornell & Larcker, 1981). This suggests that the latent constructs capture at least 50% of the measurement variation of the indicators on average (Chin & Gopal, 1995). Furthermore, all computed standard loadings are statistically significant at $p < 0.001$, which is greater than the allowed magnitude of 0.50 (Chin & Marcolin, 1995). As a result, the model's measurements show significant convergent validity. The Fornell-Larcker criterion is used to determine the discriminant validity of constructs, which states that the square root of AVE should be greater than the correlations between the components (Fornell & Larcker, 1981). As illustrated in Table 2, the square root of the AVE of each latent construct, which is bolded on the diagonal, is greater than the correlations between the latent constructs in the corresponding columns and rows. As a result, the constructs' discriminant validity is established.

Additionally, the inter-item correlations are less than 0.90 (Bagozzi et al., 1991), demonstrating that each concept is different. While certain constructs have a marginally low level of construct validity, the majority of constructions have adequate levels of validity and reliability. Thus, the model's constructs' validity and reliability are established.

Multicollinearity occurs when there is a significant correlation between predictor variables, resulting in unreliable and unstable regression coefficient estimations. The variance inflation factor (VIF), which is defined as the amount by which the standard error increases due to collinearity, is used to diagnose multicollinearity. Examining the correlation table (Table 3) for indications of multicollinearity amongst the eleven latent variables reveals that all VIF values are less than the threshold value of 5.0 (Tabri & Elliott, 2012). VIF values vary from 1.155 to 2.659. This indicates that the predictor variables are not multicollinear.

5.2. Assessing the Structural Model and Hypotheses Testing

To validate the hypothesized relationships, an examination of the structural model was conducted. The structural model was then evaluated using the structural equation model SEM-PLS. The path coefficients, coefficient of determination, and predictive significance of the measurement model were evaluated to examine and validate it. The method of path coefficients encapsulates the relationships between the constructions.

As shown in Table 4, 11 hypotheses (H1a, H1b, H1c, H2a, H2b, H2c, H2d, H3a, H3b, H3c, and H3d) have significant paths leading to the endogenous variable, whereas two hypotheses (H2c, and H3c) are rejected (path coefficients < 0.20). R^2 is the coefficient of determination, and f^2 denotes the size of variation explained by all external constructs in the endogenous construct. (Leguina, 2015) if the results of a value greater than 0.670 are considered "significant," 0.330 are considered "moderate," and 0.190 are considered "weak." Our findings indicate that the R^2 value is 0.872, which indicates a high level of prediction accuracy. (Leguina, 2015) final define f^2 values greater than 0.35 as "high", values between 0.15 and 0.35 as "medium," values between 0.02 and 0.15 as "low," and values less than 0.02 as "weak". Our research found that the f^2 of (CPA, ORE, MCP, and MSU) is high and the f^2 of OS is weak (less than 0.02); however, the f^2 of CPR and GIV is less than 0.02.

This indicates that managerial capability is significantly related to the innovation attributes of AI. Stronger managerial capability creates a better IT environment for AI adoption and reduces the difficulty of applying AI technologies. These results suggest that organizational size and competitive pressure do not play a role in the process of AI adoption, but government involvement and vendor partnership are critical factors for AI adoption. This means that good vendors and supplier partnerships can help firms adopt AI, and government involvement can influence AI adoption. However, there is no positive relationship between AI adoption and market uncertainty, and competitive pressure, respectively.

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Table 1: Items and Descriptive Statistics

Critical	Sub-Critical	Code	CA	*R*-square	Loading
Technological context	Technical compatibility	CPA	0.926		
		CPA1		0.753	0.868***
		CPA2		0.791	0.890***
		CPA3		0.837	0.915***
		CPA4		0.755	0.869***
	Relative advantage	RAD	0.935		
		RAD1		0.549	0.741***
		RAD2		0.548	0.740***
		RAD3		0.695	0.834***
		RAD4		0.725	0.851***
	Technical complexity	CPL	0.831		
		CPL1		0.744	0.863***
		CPL2		0.839	0.916***
		CPL3		0.733	0.856***
		CPL4		0.749	0.865***
Organizational context	Managerial support	MSU	0.808		
		MSU1		0.708	0.841***
		MSU2		0.681	0.825***
		MSU3		0.716	0.846***
	Managerial capability	MCP	0.911		
		MCP1		0.751	0.866***
		MCP2		0.812	0.901***
		MCP3		0.696	0.834***
	Organization size	ORS	0.831		
		ORS1		0.596	0.702***
		ORS2		0.689	0.816***
		ORS3		0.682	0.866***
	Organizational readiness	ORE	0.869		
		ORE1		0.695	0.834***
		ORE2		0.725	0.851***
		ORE3		0.708	0.841***
		ORE4		0.681	0.825***
External environment	Government involvement	GIV	0.875		
		GIV1		0.716	0.689***
		GIV2		0.602	0.825***
		GIV3		0.735	0.789***
	Market uncertainty	MUC	0.892		
		MUC1		0.689	0.737***
		MUC2		0.682	0.896***
		MUC3		0.593	0.744***
	Competitive pressure	CPR	0.901		
		CPR1		0.786	0.769***
		CPR2		0.753	0.920***
	Vendor partnership	VPA	0.809		
		VPA1		0.493	0.702***
		VPA2		0.786	0.887***
		VPA3		0.753	0.868***
		VPA4		0.787	0.887***

Note: ***, ** and *indicates significant at 1%, 5% and 10% level of significance based on *t*-statistics.

Table 2: Result of Measurement Model

Construct	Composite Reliability (CR)	Variance Inflation Factor (VIF)	Average Variance Extracted (AVE)
Technical compatibility (CPA)	0.926	1.155	0.757
Relative advantage (RAD)	0.936	2.659	0.784
Technical complexity (CPL)	0.841	1.741	0.641
Managerial support (MSU)	0.929	1.275	0.766
Managerial capability (MCP)	0.813	1.546	0.593
Organization size (ORS)	0.901	2.293	0.752
Organizational readiness (ORE)	0.837	1.522	0.633
Government involvement (GIV)	0.871	2.205	0.629
Market uncertainty (MUC)	0.876	2.326	0.701
Competitive pressure (CPR)	0.852	2.490	0.677
Vendor partnership (VPA)	0.904	1.755	0.705

Table 3: Latent Variable Correlations

Construct	1	2	3	4	5	6	7	8	9	10	11
CPA	**0.883**										
RAD	0.720**	**0.895**									
CPL	0.311**	0.323**	**0.823**								
MSU	−0.441**	−0.329**	−0.108	**0.866**							
MCP	0.192**	0.289**	0.442**	0.018	**0.791**						
ORS	0.512**	0.571**	0.535**	−0.211**	0.379**	**0.876**					
ORE	0.259**	0.258**	0.545**	−0.07	0.463**	0.411**	**0.785**				
GIV	0.541**	0.590**	0.504**	−0.144*	0.404**	0.591**	0.443**	**0.802**			
MUC	0.576**	0.669**	0.390**	−0.281**	0.270**	0.585**	0.296**	0.544**	**0.835**		
CPR	0.644**	0.688**	0.312**	−0.264**	0.283**	0.547**	0.286**	0.519**	0.654**	**0.819**	
VPA	0.554**	0.568**	0.240**	−0.285**	0.208**	0.476**	0.213**	0.379**	0.501**	0.601**	**0.839**

Note: Bold numbers on the diagonal are the square root of the AVE. **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Table 4: Hypothesis Test Results

Hypothesis Paths		Standard Path Coefficient (β)	*p*-value	Results
H1a	Technical compatibility → AI adoption	0.803	***	Support
H1b	Relative advantages → AI adoption	0.157	0.019**	Support
H1c	Complexity → AI adoption	−0.223	***	Support
H2a	Managerial support → AI adoption	0.206	0.011**	Support
H2b	Managerial capability → AI adoption	0.416	***	Support
H2c	Organizational size → AI adoption	−0.028	0.703	Not support
H2d	Organizational readiness → AI adoption	0.758	***	Support
H3a	Government involvement → AI adoption	−0.304	***	Support
H3b	Market uncertainty → AI adoption	0.149	0.047**	Support
H3c	Competitive pressures → AI adoption	0.036	0.519	Not support
H3d	Vendor partnerships → AI adoption	0.113	0.048**	Support

Note: ***, ** and *indicates significant at 1%, 5% and 10% level of significance based on *t*-statistics.

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Given that the conceptual framework for AI acceptance is still in the early stages, one goal of this study was to investigate AI adoption from an organizational standpoint. In terms of organizational environment, the data show that managerial support is one of the most powerful predictors of AI adoption. The findings of this study are consistent with those of Leach (2021) and Zhu and Kraemer (2005), who found that managerial assistance had a considerable beneficial impact on new technology adoption. Furthermore, our findings provide additional evidence of the importance that individuals play in AI adoption. The importance of organizational preparedness implies that technological capabilities such as technology infrastructure, data structure, and human capital are crucial in determining whether or not a business adopts AI. According to the findings, organizations with a higher level of preparation tend to achieve a higher level of AI adoption. Hence, one of the characteristics of AI adopters is the attempt to develop hybrid capable abilities to support Artificial Intelligence technologies. In the instance of Vietnamese organizations, this may be explained by implying that they may have held sufficient related expertise to overcome AI obstacles.

Surprisingly, this study discovered that the relationship between organization size and AI adoption was not statistically significant. These findings contradict those of (Walczak, 2018), who discovered that organization size had a favorable effect on AI and the adoption of innovative innovations. This could be explained by the rise of smaller technology-inspired start-ups. Furthermore, large organizations may be hampered by structural inertia as a result of having several levels of bureaucracy. According to the findings of this study, AI adoption is not a phenomenon dominated by large organizations. Our findings show that using organization size as a significant factor to better understand AI adoption is insufficient. This could be explained by the rise of smaller technology-inspired start-ups.

6. Conclusion

This study is an early investigation of AI applications adoption at the organizational level, incorporating well-established theories into a novel innovation. Our research provides a foundation for future research on why and how organizations use AI. It can be used as a starting point for further study on AI adoption in various industries. This contribution demonstrated the importance of offering guidance and tools for investigating the topic of AI adoption. The levels of abstract ideas provide an overview of potential study topics. Our research makes significant contributions from both theoretical and practical perspectives, as well as offers up exciting future research options. The current study provides different insights into the underlying components that explain the AI-specific aspects that influence an organization's intention to adopt AI. This contribution begins with a definition of AI from an IS and organizational standpoint. Furthermore, this study adds to the current body of knowledge about technology adoption. To give an extended framework, this study blends known theories and in-depth research literature in AI. As the literature study demonstrated, little research has been conducted to identify what factors lead enterprises to adopt AI. As a result, this study supports the organizational context and innovative features that influence AI adoption. The findings confirm that IS theories (TOE and DOI) as a theoretical underpinning, as embedded in the AI adoption framework, can provide a more comprehensive understanding of successful AI adoption at the organizational level.

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