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Factors Affecting Big Data Adoption:
An Empirical Study in Small and Medium Enterprises in Vietnam

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ABSTRACT

This study examined factors impacting the big data adoption of small and medium enterprises (SMEs) in Vietnam. The mixed method study was used. The qualitative research was applied by a group discussion with 15 participants and a cross-sectional survey with 372 representatives of SMEs. The results show that perceived benefit, simplicity, compatibility, data quality, security and privacy, vendor support, management support, financial investment, perceived usefulness, and attitudes toward adoption. This research extended the academic framework and examined causal relationships by adopting new characteristics from the integrated perspective of TOE with TAM beyond the existing research models.

KEYWORDS

Adoption of Big Data, Attitude Toward Adoption, Big Data, Factors Affecting, Integrated TOE With TAM, Perceived Usefulness, SMEs, Vietnam

INTRODUCTION

The adoption of big data (AB) is often considered a firm's key asset. It has reflected the interactions among firms and customers and furnishes descriptive, predictive, actionable, and prescriptive outcomes (Baig et al., 2021; Shirdastian et al., 2019). AB helps decision-makers get timely information to make the right decisions and increase revenue (Wahab et al., 2021). The global AB market was valued at USD 66.2 billion in 2020 and is anticipated to develop at an average annual rate of USD 157.2 until 2026 (IDC, 2020). SMEs play an important role in the economy of both developed & developing countries. SMEs in the United States account for 28% of direct exports while accounting for about 41% of the total value added domestically included in U.S. exports (Chong et al., 2019). In Europe, SMEs contribute significantly to the value-added in exported products (Piacentini & Fortanier, 2015). Tang et al. (2016) argue that SMEs in China contribute much higher value added to export products than direct exports. In Vietnam, SMEs comprise 97% of all businesses, contribute 45% of the GDP, and 31% of the country's overall budget revenue, and draw over 5 million workers (Vietnam MPI, 2021). Many firms view the implementation of AB as being crucial and think it has great potential (Staegemann et al., 2021). However, because of the high volume and velocity and various information assets, valuable knowledge, and information extraction from it remain full of complexity (Volk et al., 2020). Lately, the AB has been reasonably low (Nam et al., 2019). Many firms have not yet incorporated use beyond the initial adoption procedure (Choi et al., 2022).

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Firms adopting DB have gained many advantages in improving their operational efficiency (Mikalef et al., 2019; Dubey et al., 2020; Raguseo & Vitari, 2018). Large firms used AB to predict new market trends, evaluate customer behavior and experience to identify new enhancement opportunities and achieve good results. Due to limited resources, SMEs' AB is still limited (Ghasemaghaei 2019; O'Connor & Kelly, 2017). Studies of SMEs AB are few and limited (Dubey et al., 2020; Al-Sai et al., 2020; Munawar et al., 2020). While some research used Technology-Organization-Environment (TOE) or Technology Acceptance Model (TAM) models, others used an extended TOE model to study technology/innovation adoption (Althunibat et al., 2021; Lutfi et al., 2020). However, the elements of the TOE model are affected and dictated by the technology used, the size of the company, and the study's setting (Al-Sai et al., 2020; Sun et al., 2020).

The primary factors of the extent of TOE effects include various environmental circumstances and national settings. Given that AB drivers are a new subject with little empirical validation, it is necessary to undertake additional studies and develop a systematized body of information. Therefore, a new paradigm is needed to clarify the motivations for SMEs' AB (Al-Sai et al., 2020).

This study contributes by developing and testing an integration of TOE and TAM models to evaluate AB by SMEs in Vietnam, a country progressing through an economic transition. The integrated TOE with the TAM model is justified for three reasons driven by the literature review presented by Al-Sai et al. (2020). First, there are few studies on AB, and they are predominantly conceptual, which necessitates more empirical research and further clarification. Second, most of the AB research has been conducted in developed countries in Europe and North America (Frizzo-Barker et al., 2016), with few studies addressing AB barriers in other developing countries, such as the Middle East (Hashem et al., 2016). Third, several authors emphasized the necessity of thinking about AB in different contexts (Wahab et al., 2021; Sun et al., 2018), especially to improve the body of existing material in developing nations (Choi et al., 2022; Al-Sai et al., 2020).

The study's findings will assist SME decision-makers in understanding the precursors to successful AB and suppliers' key decision-makers in advancing their customers' AB. Considering the recommendations, this investigation adds to the body of knowledge regarding the TOE elements that affect SMEs' acceptance of business developments in a developing nation like Vietnam. Furthermore, the conceptual model can be used as the basis for related research in digital transformation and the application of new technologies.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Theoretical and Conceptual Framework

Over the past few decades, many models have been used in the research and application of new technologies. Two models that are widely used and have proven to be relevant for technology acceptance are TAM and TOE (Nguyen et al., 2022). These two models do, however, have some drawbacks. TAM has the limitation of looking at upcoming behavior, not current behavior (Wu, 2011). The external variables in the extended models of TAM are not well defined. The TOE proposed by Tornatzky and Fleischer (1990) is acceptable for innovative internet-based explanations of organizational behavior in terms of new technology (Paris et al., 2016; Abualrob & Kang, 2016). TOE is more suitable for organizational research but suffers from unclear and general structures (Wang et al., 2010). In SMEs, the top manager is often also the owner with a very important role in strategic decisions. The AB in SMEs has both the individual and the organization's role, so integrating TOE and TAM models is appropriate. Therefore, this research integrated TAM and TOE to increase the predictive capability of the conceptual framework, as well as some individual limitations of TAM and TOE. We developed the hypotheses of this research based on TOE, TAM, previous research, and the current SME context.

Adoption of Big Data

Mashey (1999) first used the AB term, and it has become associated with three key concepts: big volume, large variety, and high velocity (Zikopoulos et al., 2011). AB refers to the trend of using the results of predictive analytics, consumer behavior analytics, or other progressive data analytics methods. According to Günther et al. (2017), AB enables innovation to change a technology platform. It offers new opportunities for firms to use information in their favor and achieve a competitive edge (Ur Rehman et al., 2019; Al-Qirim et al., 2017). The AB includes advanced information process techniques and technologies that improve the decision process (Raguseo, 2018). Big budgets may make AB tedious, but they can pave the way for long-term success (Al-Qirim et al., 2017). Almost every industry produces big data (Moat et al., 2014). The results of a Zoom survey in 2017 showed that 41% of firms are currently using big data, 46% have plans to use it in the future (Zoomdata, 2017) and organizations are expecting more AB (Zhao et al., 2019). Based on Surbakti et al. (2019) and Weerasinghe et al. (2018), AB can be improved if the elements influencing affectation are properly utilized in the appropriate theoretical, assessed, and addressed. Several factors of TOE and TAM models have been identified based on the literature. They are organized into three categories: organizational, technological, and environmental, perceived usefulness, and attitude toward adoption.

Technological Context

The research literature identified how AB can be influenced by technological aspects such as perceived benefits of AB, ease of use, and use systems, data accuracy, and compatibility with already-existing systems. Positive outcomes of extensive research show the extent to which businesses identify advantages such as time savings, cost reductions, and decision support (Gartner, 2014). That AB saves time and effort is one of its primary characteristics (Lytras & Visvizi, 2019). AB enables firms to gather trillions or billions of real-time data points on their clients, goods, and resources to repackage that fact to improve the client experience quickly. Using big data services could significantly influence reducing costs, gaining business insight and strategic intelligence, and then driving quality, efficiency, and business decisions (Kwon et al., 2014; Gandomi & Haider, 2015). According to Lutfi et al. (2016), SMEs are more likely to embrace technology if they see its benefits over competing options existing technology.

We refer to the ease with which a big data system can be implemented and used to its simplicity of usage. Usability, accessibility, or ease of use are all related to its simplicity. According to Davis (1993), one of the key determinants of users' acceptance of new information technology is its simplicity of use. Thus, the simplicity of implementation and use will drive large corporate details and databases (Gangwar et al., 2015; Lian et al., 2014). Compliance with the current compatibility with existing systems is the degree to which big data is compatible with the existing system; the degree to which big data is compatible and consistent with current data systems (Accenture, 2014). In this study, the degree to which a company's current security and control methods meet the security requirements of big data platforms is referred to as compatibility. Borgman et al. (2013) argued that compatibility has a very beneficial and significant positive impact on the acquisition option of new technologies. Firm-level system compatibility drives big data adoption (Yang et al., 2014; Cao et al., 2015). If the technology and structure of the organization are inconsistent, this should affect the firm's success (Wickramasinghe & Alawattage, 2007). Data quality reflects how well the data is analyzed by the system engaged in large-scale data applications and integrated with the collected data (Gartner, 2014; IBM, 2012). Depending on the underlying data, the type and quality of the data derived from big data can vary. Therefore, ensuring data quality and integrating different data types are important tasks (Kwon et al., 2014). The following influencing factors related to the technical context are therefore hypothesized:

H1: The perceived benefits of AB have a positive effect on perceived usefulness.

H2: The simplicity of use systems has positively influenced perceived usefulness.
H3: Compatibility with existing systems has positively influenced perceived usefulness.
H4: Data quality has positively influenced perceived usefulness.

Context of Organization

Organizational characteristics directly influence the availability and utilization of internal resources. Tan et al. (2007) characterized organizational readiness for adopting new technology as a function of resource readiness, commitment, and governance, as well as the assistance of managers. Salwani et al. (2009) explain it as the perceptions and actions of top management about the use of new technology in creating sustainable firm values. It guarantees enduring vision and management support, reinforces values, commits resources, and supports removing obstacles, resistance, and opposition to change (Salleh and Janczewski, 2016; Wang et al., 2010; Ramdani et al., 2009). Borgman et al. (2013) suggest that support from high management ensures the successful deployment of new technology. AB must be aligned with the upper company's guiding principles. The role of management in AB and utilization is significant. Hence, top leader support is likely to drive the AB, like other information systems (Cao et al., 2014; Lian et al., 2014; Low et al., 2011).

Besides, the firm's financial investment is an important factor that affects AB. Financial investment is required for technology, infrastructure, and consulting AB (Gartner, 2014; Accenture, 2014). The data collection, storage, safety, mining, insight, and security processes all require enormous financial resources and expenses that obstruct the use of big data. Therefore, financial investment capacity will influence firms to the acquisition AB. Generally, financial readiness (financial investment in AB) affects big data adoption. The literature and the above arguments show that support of top management and money investment is closely associated with influencing AB. Therefore, the hypotheses are proposed:

H5: Management support has positively impacted the AB.
H6: Financial investment has positively affected AB.

Environment Context

The variables relate to the external environment in which an organization operates include data privacy and security concerns and vendor support. Security in big data adoption is about authenticity and authorization, data protection, data recovery, and ensuring business continuity (Katzan, 2010). Privacy awareness and ethical and risk considerations related to big data adoption are necessary for both firms and customers (Motomarri et al., 2017). Because of the wide variety of unstructured and semi-structured data and large volumes, access and sharing of data, data protection, and security and privacy are challenges. Traditional data protection methods are unsuitable for growing amounts of AB, increasing security and privacy risks. In addition, AB also depends on many external factors, which can increase the probability of risk and hinder big data application.

The variables relate to the external environment in which an organization operates include data privacy and security concerns and vendor support. Security in big data adoption is not limited to authenticity and permission but is also concerned with data protection, data recuperation, and ensuring firm continuity (Katzan, 2010). Privacy awareness and ethical and risk considerations related to AB are necessary for companies and clients (Motomarri et al., 2017). Because of the wide variety of unstructured and semi-structured data and large volumes, access and sharing of data, data protection, and security and privacy are challenges. Growing companies cannot use traditional data protection techniques for specific big data, increasing security and privacy risks. In addition, big data application also depends on many external factors, which can increase the probability of risk and hinder AB.

Because of the vast volume and variety, access, data encoding, analytics, and data sharing are challenging and difficult (Chen et al., 2014). Many firms depend on vendors to collect, maintain, and analyze big data. Big data application vendors include software providers, cloud service providers, and data collection and analysis specialists. Vendors are required to make sure big data is always available when they need it. Support is the fundamental need to solve the problem with big data that firms pay the support vendors. Therefore, big data service vendors recruit and provide proper training teams to provide their customers with the best assistance possible (Kim & Suwon, 2009). Vendors' support drives big data adoption of firms. Consequently, the following influencing factors related to the environmental context are hypothesized:

H7: Security and privacy have negatively impacted attitudes toward AB.
H8: Vendor support has positively influenced attitudes toward the adoption of big data.

Perceived Usefulness (PU)

The importance of perceived usefulness has been an extensively acknowledged variable in influencing the intention of technology adoption. Davis (1993) defined PU as a person's belief that using new technology will improve or increase their work. The thought to be useful of technology is the degree to which someone believes using technology would improve their work capacity (Mathwick et al., 2001). In the TAM model, PU is an important measure of attitude influencing technology. Regarding big data research, AB allows the automatic utilization of both models and algorithms that support procedures for decisions in organizations (Abbasi et al., 2016). The primary factor in user acceptance of technology is its PU (Joshi et al., 2005). This study focuses on users' trust and their intention adoption their big data analytics context to decide. Venkatesh et al. (2016) recommended this synthesis strategy with the unified theory of acceptance and use of technology (UTAUT) model. Therefore, the hypothesis proposed is:

H9: PU has positively affected AB.

Attitude Toward the Adoption of Big Data (AT)

Attitude is defined as an individual's positive or negative feelings about performing the target behavior (Fishbein and Ajzen, 1977). There is an opinion that attitude is a multi-structure, including the primary structures of PU and PE (Taylor & Todd, 1995). According to the TPB and TAM models, consumers' decisions and attitudes are predictable. In the study of new technology using the TAM model, studies have shown that businesses have a positive attitude, and the TAM structure has a positive meaning which affects mentality and desire to make new technology systems (Davis, 1989). Through these studies, we found that the enterprise's AB intention was determined by its attitude. Therefore, we propose the hypothesis:

H10: Attitude toward adoption has positively affected big data adoption.

METHODOLOGY

Research Design

This study employed a mixed methodology. Jogulu and Pansiri (2011) stated that mixed techniques are commonplace across many academic fields, including marketing, strategic management, people or human resources, organizational behaviors, and knowledge management. A group discussion with 15 participants includes two sections that answer 'what' and 'why' questions regarding AB in SMEs. First, a discussion was based on an unstructured questionnaire to clarify the fundamental concerns with the AB for SMEs and review variables and measurement items inherited from previous studies. Second, we evaluated the content reliability of the variables and measurement items from the questionnaire.

Content validity is essential in any development process variables and measurement items (Benson & Clark 1983) and has been widely employed in various fields of study (Wilson et al., 2012). According to Ayre and Scally (2014), CRVcritical=([(zÖN)+1])/N. Where N is the overall composition of the panel participants, ne is the participants concurring that it is "essential," p is the likelihood that each item will be agreed upon = ½, 0.5 whether is the continuity correction, z is the binomial's standard deviation approximation, z=((ne-Np-0.5))/(Ö([Np(1-p))])~(N(0.1). The variables and measurement items were accepted in this group discussion with 15 participants if CVRCritical ^{3} 0.6 were accepted (Ayre & Scally, 2014). Convenience and non-probability sampling techniques were applied when conducting the quantitative study.

Questionnaire Survey

Besides the introduction, the survey questionnaire had three parts. The first part included two screening questions identifying survey respondents representing SMEs and SMEs with AB. We arranged the second part with each variable's five measurement items. Measurement items of variable were modified from the previous research as follows in order: Five measurement items of each independent variable belonging to the context: "technological, organizational, and environmental" were adaption from Chen et al. (2015); Salleh and Janczewski (2016); and Sun et al. (2018). Five measurement items of PU and AT were adaptions from Davis (1989), Nguyen and Luu (2020), and Truong (2018). The AB items were adaptions from Palmatier and Martin (2019) and Nguyen and Luu (2020). The questionnaire used the 5-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree). The third part of the questionnaire addressed information about a firm, including the number of employees, the age of the firm, the main business sector, and the firm's market.

Data Collection and Analysis

According to the ten-times rule for PLS-SEM (Hair et al., 2011), this model has at most ten-referring links into one variable, so the minimal sample size suggested was 100. With 372 reliable collected questionnaires, this study met the minimum sample size. Non-probability sampling method with a convenience technique was used. The questionnaire was distributed on both direct survey and online platform procedures in June 2022. SPSS and SmartPLS software were used to analyze the data collected. According to Hair et al. (2021), the model was fit if SRMR < 0.7. The CR ranged from 0.70 to 0.90, illustrating inherent consistency and dependability. If the outer loading indicator was > 0.708 and AVE was > 0.50, the convergent validity of the variable was attained. The discriminant validity is achieved if the threshold level statistic should not include the value 1 for combinations of variables and HTMT < 0.85.

RESULTS

Qualitative Research

The conceptual model was developed from theories, and previous research comprised 11 variables and 55 measurement items. We deleted seven measurement items (DQ5; MS5; AT4; FI4; SP4; SP5; and AB4) based on the focus group results, as the validation CVRCritical < 0.6 was invalid. The remaining 48 measurement items were then used in the cross-sectional survey.

Descriptive Analysis

This study collected 372 valid questionnaires from 372 respondents who represent SMEs. There are 142 SMEs established less than 2 years earlier (38.17%), 99 SMEs established from two to five years earlier (26.61%), 72 SMEs from five to ten years earlier (19.35%), and 59 SMEs established more than ten years earlier (15.86%). For the main business sector of the firm, 21 SMEs operated in the agriculture sector (5.65%), 95 SMEs in the industrial sector (25.54%), 156 SMEs in the service sector

(41.94%), and the other 100 SMEs span two or three industries (26.88%). Regarding the market of the firm, the result showed that 16 SMEs (4.3%) were open in an international (export) market, 301 SMEs (80.91%) business in the domestic Vietnam market and 55 SMEs (14.78%) business were in both the Vietnamese and the global market. As for the number of employees, the result showed that 27 SMEs had less than ten employees (7.26%), 219 SMEs had 10-49 employees (58.87%), and 126 SMEs had 50-100 employees (33.87%).

Exploratory Factor Analysis (EFA)

The EFA was carried out by a Promax rotation with the principal axis factoring. Seven measurement items – PB3, AB2, MS4, FI5, PU4, VS1, and VS2 – were eliminated because of the analysis because their factor loadings were below 0.5. The Kaiser-Meyer-Olkin value = 0.709; $\chi2$ = 9287.816; df = 820; and Sig = 0.000. The Cumulative Extraction Sums of Squared Loadings = 63.635%. Indicators for each construct were therefore valid. For the subsequent analytical step, the conceptual framework with 41 measurement items and 11 variables (Table 1) was appropriate.

Table 1. Measurement model reliability and validity

Variable/ measurement item		Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Adoption of big data		0.872	0.922	0.797
AB1	AB aligns with the firm strategy.			
AB5	We think the adoption of big data is good.			
AB3	We will continue to apply big data.			
Attitude toward adoption		0.866	0.907	0.710
AT3	We are glad that AB can be a good solution.			
AT2	We trust AB because it is supported by the vendor.			
AT1	We desire the AB for its sake.			
AT5	We like AB because the staff is happy to do it.			
Compatibility with the existing system		0.851	0.893	0.625
CS5	AB is consistent with firms' practices.			
CS3	AB fits our firm culture.			
CS2	It is easy to incorporate AB into our business.			
CS4	AB characteristics are consistent with existing IT.			
CS1	Big data characteristics are better than existing ones.			
Data Quality		0.871	0.911	0.720
DQ1	DQ is essential to our firm.			

Table 1 continued on next page

Table 1 continued

Variable/ measurement item		Cronbach's Alpha	Composite Reliability	Average Variance Extracted
DQ3	Data quality and integration are useful for our firm.			
DQ2	DQ enables the firm to manage a business.			
DQ4	DQ would enable our business to respond faster.			
Financial investment		0.755	0.857	0.667
FI2	The firm has adequate financial resources for AB.			
FI3	We have financial resources for training humans.			
FI1	We know how to invest financially to support AB.			
Management support		0.824	0.895	0.739
MS1	Our management supports the use of AB.			
MS2	Our management creates improvements for AB.			
MS3	Our management promotes AB as a strategy.			
Perceived benefit		0.827	0.884	0.659
PB2	AB reduces the cost of unproductive activities.			
PB1	The adoption of big data saves us time.			
PB4	AB enables one to accomplish tasks more quickly.			
PB5	AB improves our workflow process.			
Perceived usefulness		0.843	0.895	0.682
PU1	AB addresses my job-related needs.			
PU2	Using AB increases our productivity.			
PU3	AB improves our job performance.			
PU5	Overall, we find the BD useful in our business.			
Security and privacy		0.865	0.916	0.785
SP2	Big data causes security and privacy concerns.			
SP1	Concerns about risk related to AB.			
SP3	The firm believes that it will be not safe for AB.			

Table 1 continued on next page

Table 1 continued

Variable/ measurement item		Cronbach's Alpha	Composite Reliability	Average Variance Extracted
The simplicity of system usage		0.886	0.917	0.688
SS1	AB characteristics are perceived as being easy.			
SS2	The timing of the AB is advantageous.			
SS3	AB characteristics are adopted with no difficulty.			
SS4	Knowledge of employees fit use big data.			
SS5	The compatibility of AB is useful to our company.			
Vendor support		0.783	0.874	0.698
VS4	The vendor encourages us to adopt big data.			
VS5	Vendors providing related service support AB.			
VS3	Vendors provide incentives for adopting AB.			

Valuation of the Measurement Model

Reliability and Validity

According to Hair et al. (2021), the construct achieves internal consistency reliability when a factor's Cronbach's Alpha, Rho-A, and composite reliability (CR) > 0.7. The results revealed that the range of Cronbach's Alpha was from 0.755 to 0.886, CR from 0.857 to 0.922, and roh A from 0.783 to 0.890 (Table 1). As a result, the internal consistency reliability for all 11 variables was verified.

Convergent Validity

The researchers considered the outer loadings of the indicators and AVE to assess the convergent validity of reflective variables. To assess the construct as having convergent validity, the AVE must be above 0.50, the outer loading over 0.6, and the reliability indicator greater than 0.5 (Hair et al., 2021). Regarding the research figures, the outer loading of 41 measurement items ranged from 0.682 (PB4) to 0.933 (AB1) > 0.60, and the AVE of 11 variables ranged from 0.625 to 0.797, which was > 0.5. Hence, 11 variables were deemed to have convergent validity (Table 1).

Discriminant Validity

The results demonstrated that all HTMT values fell below the 0.85 conservative thresholds, ranging from 0.063 to 0.592. The HTMT values, on the other hand, were considerably different from 1 when looking at the HTMT ratios. As a result, all 11 variables had discriminant validity (Table 2).

Table 2. Heterotrait-Monotrait Ratio (HTMT)

	AB	AT	CS	DQ	FI	MS	PB	PU	SP	SS
AT	0.263									
CS	0.309	0.083								
DQ	0.211	0.063	0.248							
FI	0.429	0.487	0.271	0.079						
MS	0.378	0.096	0.368	0.190	0.294					
PB	0.201	0.130	0.568	0.264	0.255	0.444				
PU	0.257	0.091	0.451	0.372	0.116	0.105	0.492			
SP	0.073	0.126	0.139	0.106	0.085	0.103	0.108	0.067		
SS	0.290	0.074	0.358	0.388	0.119	0.391	0.592	0.518	0.106	
VS	0.333	0.226	0.403	0.298	0.498	0.356	0.418	0.291	0.071	0.404

Structural Equation Modeling (SEM)

Collinearity Test

The variance inflation (VIF) factor served as a comparable indicator of collinearity. Hair et al. (2021) stated that VIF values must be below 5. The results show that the VIF ranged from 1.431 to 3.593 (from FI3 to SS1, respectively). Thus, all 41 measurement items had VIF values < 5. Researchers might continue to assess the report results, as collinearity among the predictor variables was not a significant issue in the structural model.

Model Fit

The fit of a model is assessed using the Standardized Root Mean Square Residual (SRMR) metric, which is the dissimilarity between the observed correlation and the model-implied correlation matrix. According to Hu and Bentler (1999), if a value was less than 0.10 or 0.08, it was considered a good fit. As our model showed an SRMR of 0.063 (0.08), we assessed the model as having a good fit.

Hypotheses Testing

In bootstrapping with 5,000, the conceptual model and ten hypotheses were evaluated, and the p-value was supposed < 0.05. The results show that all p-values ranged from 0.000 to 0.022, supporting the ten hypotheses. All the hypotheses concerning path coefficients ranged from -0.111 to 0.269 (Table 3 and Figure 1). The variables' R2 values differ from 0.049 to 0.314, showing a medium level of interpretation of the independent factors' effects on the dependent variables' perceived usefulness (PU), attitude toward adoption (AT), and adopt big data (AB) (Figure 1). The F2 values showed a small to medium level an exogenous construct had on an endogenous construct, ranging from 0.013 (H7) to 0.089 (H5), respectively (Table 3).

Figure 1. Structural equation model

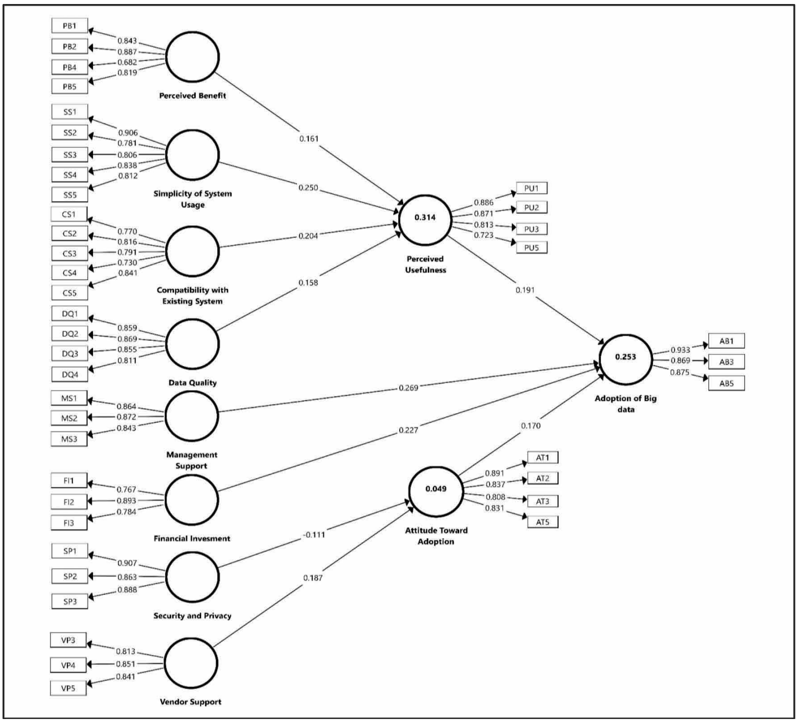

Figure 2. Importance-Performance map

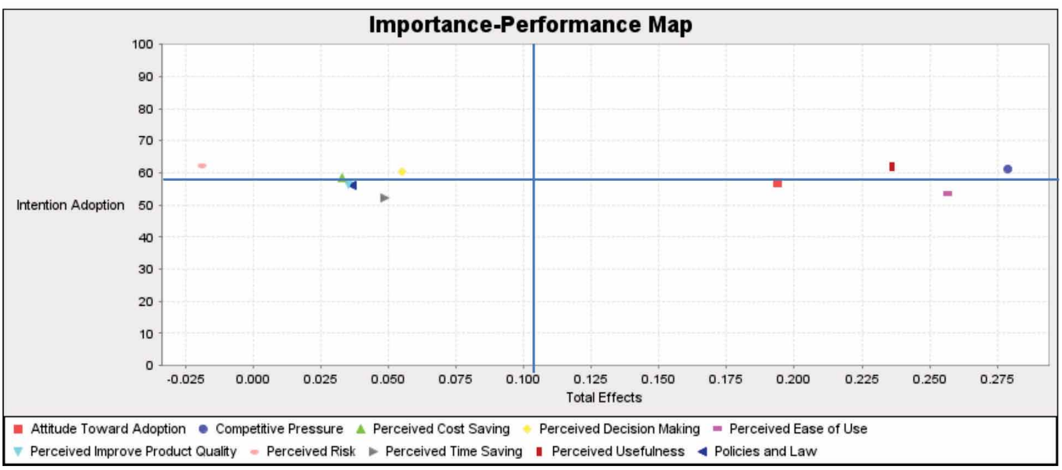

Table 3. Hypothesis tests

Relationship	Hypothesis	Original Sample (O)	T Statistics (|O/STDEV|)	P-Values	f^2	Hypothesis test
PB -> PU	H1	0.161	2.986	0.003	0.023	Supported
SS -> PU	H2	0.250	4.466	0.000	0.061	Supported
CS -> PU	H3	0.204	4.019	0.000	0.046	Supported
DQ -> PU	H4	0.158	3.888	0.000	0.031	Supported
MS -> AB	H5	0.269	4.790	0.000	0.089	Supported
FI -> AB	H6	0.227	4.044	0.000	0.054	Supported
SP -> AT	H7	-0.111	2.292	0.022	0.013	Supported
VS -> AT	H8	0.187	3.656	0.000	0.037	Supported
PU -> AB	H9	0.191	4.212	0.000	0.049	Supported
AT -> AB	H10	0.170	3.169	0.002	0.032	Supported

Predictive Relevance

The results show that all Q2 values > 0, showing that the exogenous variables had predictive relevance for the endogenous variable consideration. Furthermore, the Q2 of perceived usefulness (PU) has the largest value (0.205), the next adoption of big data (0.184), and the smallest attitude toward adoption (0.026). Therefore, perceived usefulness (PU), attitude toward adoption (AT), and adoption of big data (AB) support the model's predictive relevance regarding the endogenous latent variables.

The results, with the Q2 values being all greater than 0, suggested a predictive relevance under examination of the exogenous and the endogenous constructs. The Q2 of perceived usefulness (PU) has the highest value (0.205), followed by the adoption of big data (0.184) and the attitude toward adoption (0.026). Therefore, the model's predictive relevance for the endogenous latent variables is supported by perceived usefulness (PU), adoption of big data (AB), and attitude toward adoption (AT).

Indirect Effects

Analysis was done on the mediating influence of PU and AT to determine whether the two constructs trigger the impact of co-created value on AB, as shown in Table 5. The results point out the significant indirect influence because none of the 95% confidence intervals encompass zero, except for the p-values for SP at 0.070. Hence, the SP has no significant indirect effects on AB (p-value = 0.070). The empirical β of the indirect effect (0.032) of the VS$\rightarrow$ AT $\rightarrow$ AB yielded a p-value of 0.022. The p-value of 0.014 resulted from the indirect influence (0.031) of the PB $\rightarrow$ PU $\rightarrow$ AB. Likely producing a p-value of 0.003 is the indirect impact (0.048) of the CS $\rightarrow$ PU $\rightarrow$ AB. The p-value of 0.005 was obtained from the indirect link (0.030) of the DQ $\rightarrow$ PU $\rightarrow$ AB, and (0.039) of the SS $\rightarrow$ PU $\rightarrow$ AB resulting in a p-value of 0.005.

Table 4. Specific indirect effects

Relationship	β	Standard deviation	T Statistics	P-Values	2.50%	97.50%
SP -> AT -> AB	-0.019	0.010	1.813	0.070	-0.042	-0.003
VS -> AT -> AB	0.032	0.014	2.294	0.022	0.009	0.064
CS -> PU -> AB	0.039	0.014	2.803	0.005	0.015	0.069
DQ -> PU -> AB	0.030	0.011	2.811	0.005	0.012	0.054
PB -> PU -> AB	0.031	0.012	2.461	0.014	0.009	0.058
SS -> PU -> AB	0.048	0.016	2.961	0.003	0.020	0.083

Table 5. Results of hypothesis testing for labor groups

Hypothesis		Below 10 Labor		From 10 to 49 Labor		From 50 Labor over	
		β	P Values	β	P Values	β	P Values
H1	PB->PU	0.369	0.000	-0.047	0.477	0.253	0.026
H2	SS->PU	0.191	0.041	0.326	0.000	0.232	0.087
H3	CS->PU	0.098	0.316	0.307	0.000	0.131	0.200
H4	DQ->PU	0.235	0.000	0.147	0.009	0.140	0.164
H5	MS->AB	0.321	0.001	0.148	0.094	0.451	0.000
H6	FI->AB	0.164	0.085	0.292	0.000	0.311	0.002
H7	SP->AT	-0.142	0.213	-0.070	0.356	-0.094	0.573
H8	VS->AT	0.097	0.491	0.282	0.000	0.151	0.430
H9	PU->AB	0.198	0.014	0.142	0.052	0.218	0.021
H10	AT->AB	0.303	0.000	0.093	0.333	0.051	0.666

Table 6. Results of hypothesis testing for market groups

Hypothesis		Domestic and Export Market		Domestic Market		Export Market	
		β	P Values	β	P Values	β	P Values
H1	PB->PU	0.031	0.648	0.374	0.002	0.291	0.004
H2	SS->PU	0.320	0.000	0.273	0.012	0.087	0.513
H3	CS->PU	0.229	0.001	0.102	0.189	0.277	0.020
H4	DQ->PU	0.132	0.017	0.142	0.035	0.292	0.003
H5	MS->AB	0.240	0.000	0.342	0.001	0.126	0.466
H6	FI->AB	0.323	0.000	0.058	0.611	0.189	0.376
H7	SP->AT	-0.119	0.081	-0.130	0.255	-0.146	0.499
H8	VS->AT	0.148	0.043	0.333	0.001	0.222	0.235
H9	PU->AB	0.200	0.001	0.175	0.054	0.235	0.099
H10	AT->AB	0.092	0.201	0.350	0.003	0.239	0.195

Hence, the SP has no significant indirect effects on AB (p-value = 0.070). The empirical β of the indirect effect (0.032) for the VS→ AT → AB leads to a p-value of 0.022. The indirect relation (0.031) from the PB → PU → AB results in an 0.014 p-value. Likely is the indirect impact (0.048) for the CS → PU → AB producing a p-value of 0.003. The indirect effect with the DQ → PU → AB is (0.030), and for the SS → PU → AB is (0.039), sharing the same p-value, which stands at 0.005.

Importance-Performance Map Analysis (IPMA)

For further examination, the IPMA was categorized into four quadrants, following two main variables: importance and performance. It could be shown that the overall effects of all factors were 0.102, while the average performance of the construct scored 59.075. The SP variables in the upper left corner of the importance-performance map do well for the target AB construct but are not highly considerable. Therefore, the performance of the mentioned variables in this map area has a reasonably good chance of improvement. In contrast, the CP and PU variables are very prominent for the AB construct and exhibit great performance; therefore, preserving and maintaining the current positive outcome is important. The PB, VS, and CS variables in the lower left, with poor performance and minimal significance for the target construct, show a need for improvement, but with a lesser priority.

Multi-Group Analysis

The results of testing the group hypothesis by amount employees show a significant difference between the groups. The group of below ten employees accepted six hypotheses (H1, H3, H4, H5, H9, and H10), the group of 10 to 49 employees accepted five hypotheses (H2, H3, H4, H6, and H8), while the group of 50 employees or more accepted only four hypotheses (H1, H5, H6, and H9) (Table 5). No hypothesis was accepted in all three groups. Hypotheses H2 and H4 are accepted in both the group of below ten employees and the group of 10 to 49 employees; Hypothesis H1, H5, and H9 are approved simultaneously in groups of below 10 employees and groups of 50 or more employees, while hypothesis H6 is approved for both groups of 10 to 40 employees and groups of 50 employees. This result shows that many factors derive small businesses in their decision to apply big data, while medium enterprises have fewer influencing factors than small enterprises.

Regarding the market, these research results show there are quite obvious differences between groups by market. Only hypothesis H6 is accepted in all three groups; the remaining hypotheses are accepted in only one or two groups. The group domestic and export markets accept seven hypotheses (H2, H3, H4, H5, H6, H8, and H9), the domestic market group accepts six hypotheses (H1, H2, H4, H5, H8, and H10), while the group export markets accept only three hypotheses (H1, H3, and H4). This may be because fewer factors affect the AB than those with only the domestic market and those with both domestic and export markets. SMEs only export to follow orders and have a stable market, so adopting big data is more favorable. In contrast, businesses with a domestic market must consider more when applying big data.

DISCUSSION

Using perceived usefulness and attitude as mediating variables, the study identified the benefits of big data, simplicity of system usage, compatibility with the current system, data quality, security and privacy, and vendor support as important variables affecting the adoption of big data. Additionally, it was shown that financial investment and management support directly impact the adoption of big data. When confirming the determinants of business resources affecting the AB, these results are like those reported by Cabrera-Sánchez and Villarejo-Ramos (2019), Sam and Chatwin (2018), and Kyung and Lee (2015). These findings show that management support influences big data adoption favorably and strongly, but security and privacy negatively influence attitudes toward adoption.

Simplicity, compatibility, and data quality were found to have affected PU since big data was discovered to be compatible with current technology's format, look, structure, and quality. As big data can include all necessary capabilities and offer data interchange with other programs commonly used, compatibility could strongly be related. With PU in the application of big data, managers should change current procedures to take full advantage of the ease of use, infrastructure compatibility, and data quality of cloud solutions. Big data should also be incorporated into business needs, the IT development environment, and organizational policies (Lin & Chen, 2012). Every firm needs to approach data compatibility, simplicity, and quality data with the firm's culture, skill, management style, structure, and innovation. Accordingly, strategies must be developed to address those issues effectively.

The results also show that management support and financial commitment are necessary for AB. The AB is more likely in organizations with a high level of organizational preparation. Managers and policymakers should thus prioritize financial resources, including physical infrastructure, knowledge, and the acquisition of personnel with big data expertise. Additionally, because SMEs frequently have thin, flat leadership styles, technology adoption often follows a top-down approach. The top management plays a crucial role in convincing employees to improve their work behavior by using words of encouragement and rewards. To create a climate that supports the adoption of big data, management must continually show its commitment and support, for example, in employee education to assist them in grasping the functional and technical perspectives of big data and gaining knowledge and experience first-hand and strongly support the training of employees serving big data. Security and privacy concerns can still be associated with accepting big data. The inverse association between attitudes toward adoption and security and privacy suggests that to adopt big data, preserving competitive advantage should be built on security and privacy. As a result, several security mechanisms, management standards, access control, and process management are integrated into the big data system to safeguard it from security risks.

CONCLUSION

This study aims to determine the variables affecting the SMEs' AB in Vietnam, a developing nation with a transitional economy. The integrated TOE-TAM framework was used with TOE variables that are pertinent to the adoption of big data as external variables of TAM. For example, perceived benefit, simplicity of system usage, compatibility with the current system, data quality, security, and vendor support, which have a direct impact on either of the two variables of TAM and an indirect impact on adoption. As a result, the two TAM variables serve as mediating variables for the external TAM variables. The organizational context also comprises factors that enable financial management and investment toward big data adoption. The proposed hypotheses were tested, and the findings were analyzed. We established that the TOE-TAM integration model is appropriate for this study and addresses the same crucial areas connected to using big data. Additionally, this study's TOE and TAM integrated model may be suitable for research about digital transformation and new technology in SMEs or firms with similar characteristics.

This study contributes by offering evidence from an empirical survey and an objective analysis of the results. This paper's research findings and discussion confirmed that perceived benefit, simplicity of system usage, compatibility with the existing system, and data quality directly impact PU. This result confirms the findings in the studies of Lytras and Visvizi (2019), Lufti et al. (2016), Gangwar et al. (2015), and Cao et al. (2015). The variables which affect attitude toward adoption are security and privacy and vendor support. Management support, financial investment, attitude toward adoption, and perceived usefulness direct impact the adoption of big data. The research results presented in this paper serve as the basis for the implications of broadening the AB.

Implications

The study provides information for managers and businesses applying big data to consider and propose specific solutions to improve quality when adopting big data to SMEs in Vietnam. The component that influences people's attention to adopting big data is their attitude toward adoption (0.310). Therefore, it is crucial to improve the awareness of small and medium enterprises about how easy it is to understand and use big data as well as how simple it is to integrate big data into daily operations and master its system. Additionally, it is important to instill a positive mindset in SMEs that implementing big data would benefit them, including time and money savings and an improvement in the standard of work. We might achieve this outcome with techniques like offering additional details about the advantages of big data while also providing training and arranging seminars to assist organizations in learning about and being aware of these advantages.

Furthermore, the government must implement more regulations to promote and encourage enterprises to use big data, such as passing legislation to safeguard their interests. Finally, business solutions for AB would be provided to minimize competitive pressure from competitors and minimize potential risks when applying big data in the future. The results also confirm that trading partners and their needs influence attitudes toward AB. This is reinforced because big data cannot operate at its full potential without the cooperation and coordination of partners. Therefore, partners should establish networks to provide support and satisfy the demands of a broad range of consumers with quick-changing needs.

Limitations and Further Research

This study represents a contribution to big data adoption literature. The limitations include the use of a constrained number of variables and the exclusion of non-acceptors. Future research should confirm the results of the study in additional settings. Besides, the study's scope was restricted to SMEs in Vietnam, where the proportion of SMEs relative to major companies is enormous, and the use of big data is expanding quickly. Therefore, future studies should take the outcomes in other nations into account. We may also study big data adoption and efficacy using different methodologies, and these topics are candidates for further research.

AUTHOR NOTE

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