EMPIRICAL STUDY ON INFLUENCING FACTORS OF BIG DATA ADOPTION IN SME BASED ON TOE THEORY

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ABSTRACT

Leading the future development of Information Technology (IT), Big data technology is recognized as a disruptive change in information systems. In the face of the hot big data technology, many large enterprises have already adopted big data technology and benefited from it. SMEs, another main body of the market, which have the functions of creating employment opportunities, promoting economic growth, and improving social benefits, however, have not followed suit. Thus, the factors that SMEs consider when making adoption decisions are the focus of research scholars. However, there is limited research concerning the reasons which SMEs adopt big data analytic technology. To address this gap, the present study employs the technology-organization-environment theory and resource-based view theory to elucidate the influence factor that SMEs' BDA adoption in China. We tested the research hypothesis using primary data collected from 226 questionnaires in Chinese SMEs.This study uses SPSS 19.0 to analyze data, and under the premise of verifying the reliability and validity of the data, multiple linear regression is used to test the correlation between various factors and the willingness to adopt. The results of data analysis show complexity, trialability, and organization have the greatest impact on the adoption intention of SMEs. The second is observability and market disturbance. Market competition, relative advantage, and compatibility have a general influence on SMEs' adoption intention. On the other side, resource readiness, high-level leader support, and government policy have no significant impact on adoption intention. Based on the results, a few suggestions were proposed pertaining to business strategies for SMEs and big data providers. The proposed findings and suggestions offer valuable input for BDA technical adoption researchers in building a more reliable and accurate model.

Keyword: Big Data, IT Adoption, Chinese SMEs, Multiple Linear Regression, SPSS

I. INTRODUCTION

Today's enterprises are challenged with high competition, shortage of talent, technological change, shortage of funds, and backward management and governance. (Jeble et al., 2018) In such an unstable environment, enterprises need to strengthen their flexibility and keep up with the changing trends. Therefore, they need efficient tools to continuously scan for opportunities and risks to make quick business decisions based on the available data. At the same time, under the phenomenon of Industry 4.0, everyone is inseparable from new digital technologies such as smartphones and social media, and everyone is adding digital records, commonly termed big data, all over the world every moment. Computerization in different industries and the data processing industry has attracted a lot of financing, and a large amount of data has been obtained in various fields, which makes the technology of raw data become mainly mastered, stored, analyzed, and used at a lower cost. Therefore, companies tend to choose big data analysis (BDA) practices as an ideal tool to gain a competitive advantage. (Sanchez and Ramos, 2019). By leveraging big data, managers are able to make more informed decisions based on evidence rather than relying on guesswork. (McAfee and Brynjolfsson, 2012)

At the same time, big data has become a major development of IT and national strategy in many countries (Jin et al. 2015). In 2012, the US launched Big Data Research and Development Plan and 82 projects (Zhao et al. 2018), while Australia and the UK released strategies to promote service reform and data exploration, respectively. Current BDA revenue is estimated at $215 billion, with Statista (2021) predicting it will reach $270 billion by 2022. Global big data is in a stage of rapid development (El-Haddadeh et al. 2021), and countries need to adopt this new technology to seize development opportunities and remain competitive under limited resources.

With the rapid development of global big data, large corporations have seized the opportunity of the policy and used big data analysis technology to gain a competitive advantage (Raguseo & Vitari 2018). However, the SMEs who are also innovators and risk takers (Dana and Dana 2005), have unique entrepreneurial thinking (Dana 1995), and are the main factors of economic growth are on the sidelines (Singh 2019). They are eager to get the help of big data analysis technology, but they are worried that big data cannot adapt to the current situation of SMEs and fail to achieve the expected results (Maroufkhani et al. 2020). In order to make big data more widely used, it’s important to understand the influencing factors of small-middle enterprises’ big data adoption. Finding out the key influencing factors can help big data technology providers make an accurate market position, conduct accurate promoting, and speed up big data popularization. It can also help enterprises choose appropriate big data technology, enhance their own competitive advantage, achieving informatization more efficiently.

With regard to SMEs, the best way to overcome poverty and inequality in developing countries is moving toward the development of a private sector, in which SMEs play a central part (Hubner 2000). It is crucial for developing countries to improve and develop the position of SMEs in their market in order to promote the development of SMEs. (Talebi et al. 2012).BDA is a new way to help SMEs grow, and SMEs can rely on analytical tools to make more accurate decisions on market and customer needs. This undoubtedly improves their competitive position within the industry (Sen et al. 2016). Therefore, the adoption of BDA within SMEs may be one of the key strategies to enhance their market position (Singh 2019). Hence, it is important to comprehend the influencing factors of SMEs’ big data adoption in developing countries.

As the largest developing country in the world - China, the informatization level of China’s SMEs (China's Regulations 2011) is generally lower than that of other countries. Though SMEs are constantly constructing informatization and construction, deploying their information-based solutions in the past ten years and the informatization level has been greatly improved, there are still many problems in the process of China's SME informatization. Firstly, SME informatization is at a low level, which only replaces manual work. Secondly, the SMEs' adoption process is too blind, there are no appropriate informatization projects selective at the objective level. Thirdly, the informatization project started too fast, and there are not sufficient human resources for support. As a result, the organizational human, financial and material resources aren't coordinated with the new system in the implementation process so the project made slow progress, causing the waste of resources, and even influencing the development of the SMEs themselves. This concept of "production paradox" has significantly affected the adoption intention of information technology for SMEs who become cautious in facing the new information technology. Therefore, it's extremely important to understand what factors can affect the adoption intention of enterprises.

Previous studies have investigated big data analysis technology, and only a few articles pay attention to the adoption of BDA. Moreover, few previous studies have focused on SMEs, whose needs vary from that of the big enterprises that have the strong financial strength and a high level of management. The objective of this study is to minimize this existing gap by conducting an in-depth investigation into the concerns and apprehensions of SMEs when they prepare to adopt the BDA. In addition, it seeks to identify the industry type, size, revenue of SMEs, and the attitude they adopt when faced with this technology. Based on this information, the study aims to present some detailed suggestions on business strategies for SMEs and BDA providers. The proposed advice could serve as a guide for BDA technical demands and providers in building more sustainable and durable enterprises.

This paper consists of six (6) sections. Section I discuss the background of this study including the issues and problems of SME BDA adoption. Section II discusses the adoption of BDA by SMEs and the basic theory of IT adoption (individual level and organizational level). Section III introduces the research model and research questions. Section IV elucidates the methodology used in the study. Section V presents the findings of the work and discussion. Lastly, section VI concludes the paper with a summary of the findings and recommended future work.

II. LITERATURE REVIEW

A. Adoption of BDA by SME

In the academic world, Nature (2008) published the special issue "Big Data", and Science (2011) published the special issue of "Dealing with Data", in which the challenges that big data has brought to Internet technology, Internet economics, supercomputing, and environmental science are introduced technically. McKinsey (Manyika et al. 2011), a consultancy, published an exhaustive report on big data-"Big Data: Innovation, Competition and the Next Frontier of Production", which expounds on the concept of big data and how to achieve social benefits through various data. Global Information Technology and Business Solutions Company IBM released “Analytic: Real-world Application of Big Data” which introduced how innovative companies can obtain value from uncertain data (Schroeck et al. 2013).

The current research on big data focuses on two fields; one field is big data technology itself. In detail, articles in this field mainly study big data from a technical perspective. For example, the distributed file system (Google File System, GFS) (Ghemawat et al. 2003), distributed parallel computing (MapReduce) (Dean & Ghemawat 2008), and distributed data (BigTable) (Chang et al. 2008). These technologies have laid a foundation for the current big data technology. The scope of this field is very broad, so it has a huge literature. Another field is the commercial application of big data. Precisely, its focuses on whether to adopt big data and the challenges of big data (Maroufkhani et al. 2022). For example, Akter et al.(2016) emphasized the importance of BDA in large companies. Mandal (2018) found big organizations enhance their competitive advantage in the market by adopting the BDA for a long time.

As mentioned earlier, BDA technology, which has extensive research literature, is currently recognized as one of the important technology in the future and can provide a potential competitive advantage to enterprises (Raguseo and Vitari, 2018). However, there is less research literature in the area of BDA adoption, thereby leaving untapped potential in terms of how companies can adopt BDA and create business value from such a technology. In light of this, El-Haddadeh et al. (2021) utilize a technology ‑ organization ‑ environment framework to examine the role of top management support in facilitating value creation from BDA adoption for the realization of SDGs. Data was collected from 320 UK managers. The study found that the high-level support coupled with the technological driver of BDA can significantly promote the adoption process. Also, Wang et al. (2018) examine the historical development, architectural design, and component functionalities of big data analytics. Data was collected from content analysis of 26 BDA cases in healthcare. The study provides five strategies for healthcare organizations that are considering adopting BDA.

Similarly, Bag et al. (2021) mentioned the reasons why large firms engaging in manufacturing activities adopt BDA technology. Data was collected from 219 automotive and allied manufacturing companies operating in South Africa. The work results showed that institutional theory and resource-based view theory affect the adoption of BDA. Based on the above literature, it is clear that previous BDA adoption studies have mainly looked at large enterprises. Only a few have focused on SMEs, possibly because they are less impact on the economy and society. In fact, SMEs have fewer resources and influence in society compared to large firms.

For the areas where further research is needed, Wamba et al. (2017) examine the value of the model by survey managers and business analysts in the IT industry. Bag et al. (2021) lie in the statistical validation of the theoretical framework by investigating automotive companies which belong to the manufacturing industry. Wang et al. (2018) paid attention to the content analysis of BDA cases in the industry of healthcare. That literature provides an idea for further research that the scope of the investigation could be controlled in a specific field such as IT, manufacturing, and healthcare that have their Industry characteristics.

B. Basic theory of IT adoption

Tornatzky & Flescher (1990) put forward the Technology-Organization-Environment model (TOE) based on the Innovation Diffusion Theory. According to the model, when enterprises adopt new information technologies, they should consider three aspects of factors including technology, organization, and environment. Technical factor refers to the feature of new technology itself, including complexity, compatibility, relative advantage, observability, and trialability. Organizational factor refers to organizational features, including organizational scale and scope, organizational information infrastructure, etc. The environmental factor means considering the economic and cultural condition, including the competition intensity, market uncertainty, government policy, culture, etc. For the TOE model, the internal factors, external factors, and technology factors that influence information technology adoption are fully considered. It’s the basic framework to study IT adoption.

Resource-based View (RBV) examines the connection between resources and competitive advantage from the perspective of resources that belong to businesses. Wernerfelt (1984) found that the RBV offers a technique for observing the organizational-level characteristics of a company and maintains that valuable, replicable resources and irreplaceable are what allow an enterprise to obtain a competitive edge. Additionally, coordination skills and knowledge management skills are intangible resources for businesses that will have a big impact on how well they function when resources are integrated into daily operations.

III. RESEARCH MODEL AND RESEARCH QUESTIONS

The objective of this study is to identify and examine the factors that influence SMEs in China to adopt BDA. Therefore, based on the conceptual study and the research literature, a model based on the TOE theory by (Tornatzky & Flescher 1990) has been developed.The model contains 13 factors affecting the BDA adoption for Chinese SMEs. The associated factors are explained as follows.

A. Relative advantage

Relative advantage refers to the degree to which the adoption individual thinks that the new technology is superior to the old one compared with the original technology. Chau & Tam (1997) emphasized that relative advantage is positively correlated with the adoption intention. As a systematic information technology, big data technology can optimize business processes, improve customer service, increase customer value, increase business opportunities, and improve the level of enterprise information.

B. Compatibility

When Zmud et al. (1990) studied the application of Material Requirement Planning (MRP) in enterprises, they found that the compatibility of MRP with the organization can well predict MRP adoption in the organization. If big data is consistent with the enterprise’s current values and operation philosophy, and the enterprise has experience in implementing similar information technology, big data is compatible with the enterprise’s information infrastructure, they will adopt the big data system to great extent.

C. Complexity

Complexity refers to the difficulty that adopters shall feel in using new technology. Zmud et al. (1990) studied the application of MRP to enterprises and showed that the complexity of enterprises is negatively correlated with the adoption intention. The complexity of big data technology relative to the enterprise is related to the enterprise information level, the higher the complexity is, the more difficult it will be adopted.

D. Trialability

Trialability refers to the degree to which new technology can be tested based on existing resources. It’s generally believed that enterprises would be more inclined to adopt such IT systems if they could try new systems on a small scale before making the decision on the adoption.

E. Observability

Observability refers to the degree to which the results of a new technology application can be observed. Companies are more inclined to adopt big data technologies if they can easily observe the application effect, or if they can easily observe the situation of big data applied by other enterprises.

F. Business scale

A study by Thong (1999) states that even in small enterprises, adoption intentions were higher in relatively large enterprises than in small ones. In general, the organization scale can significantly influence the adoption intention of the enterprise.

G. Business scale

High-level leader support has been considered a key factor for implementing information systems successfully(JIMMIESON et al. 2004). The decision of adoption behavior is influenced by the High-level leader, especially when the enterprise organization system is not complete. On one hand, high-level leader support can motivate the staff to participate in implementing the new system. On the other hand, it can provide a resource for implementing the new system, and the most obvious performance is to increase the investment in big data adoption.

H. Business scale

According to the scholars’ analysis, enterprise information technology resources are divided into three categories in this paper: information infrastructure, human resources, and organizational resources. The high level of the enterprise’s information infrastructure represents that it has the sufficient technical foundation to implement big data. The high level of human resources means that staff can grasp new technology through training and better complete the arrangement of big data systems according to experience. In the shortest time, big data technology is internalized into the enterprise’s conventional technology. The rich business resources mean that under the unified information platform, the enterprise and the supplier, the enterprise and the customer establish good business relations. Once the new information system is implemented, the suppliers and customers can respond and coordinate positively.

I. Market competition

The intense market competition is the direct environmental factor that the enterprise adopts the new information system. The greater the market competition pressure the organization faces, the stronger the intention of adopting information technology will be(Xu et al. 2004). Both theoretical and empirical studies have shown that market competitive pressures promote enterprises to adopt new information technologies(Grover & Goslar. 1993)(Iacovou et al. 1995).

J. Market turbulence

Market disturbance mainly means that consumer demand changes over time, and new customers often have different demands. It means the uncertainty of the enterprise’s external environment. The more uncertainty is, the less effective the strategy will be. The benefit of big data technology is to help enterprises recognize the environmental advantages and disadvantages, insight into consumer preferences timely, and adjust and launch product combinations to meet consumers’ preferences, thereby expanding market share and winning competitive advantage.

K. Government policy

Government policy is a key factor in the adoption of enterprises’ new information systems. When studying the construction of informatization in Singapore enterprises. Teo et al. (1997) found that government policies can promote the adoption of new information technology in Singapore. At present, the earnest concern about big data by China’s enterprises comes from the governmental support for big data too much extent.

According to the above conceptual study and research literature, the influencing factors of a SMEs' big data adoption are analyzed from the technical characteristics, organizational level, and environmental level. 13 influencing factors are put forward in this study. The model is built as shown in figure 1.

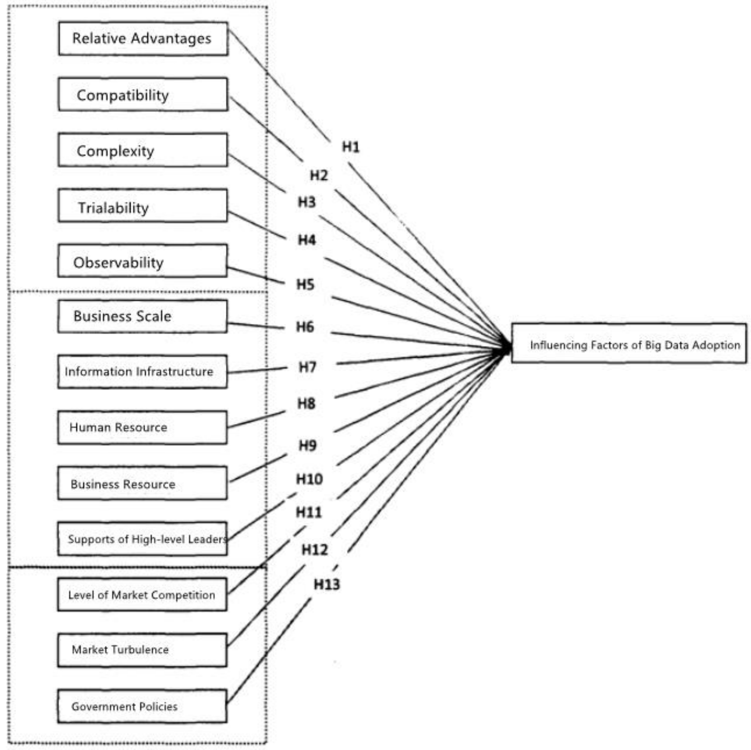

Figure 1 Theoretical model of influencing factors SMEs' BDA adoption

The case for this study comprise the selected Chinese SMEs that in adoption phase of big data analytics technology technology. In general, the study aims to answer the following research questions:

i) RQ1: What are the factors that influence SMEs in China to adopt BDA?
ii) RQ2: Do the identifying factors play a significant role in the current Chinese SME BDA adoption?

IV. METHODS: PARTICIPANTS AND DATA COLLECTION

The participants of the study were 226 staffs from various SMEs department which are Accounting and Finance, Human Resources, Information Systems, Marketing, R&D, and Others.

In terms of the number of employees, 9.7% had a 1-10,31% had a 10-100,28.3% had a 100-300,15% had a 300-1000,15.9% had a more than 1000. Moreover,18,1% of enterprise age were less than 10 years, 36.3% had 11-20 years, 30.1% had 21-40 years and 15.5% had over 41 years; also 11.9% of enterprises had an annual income of less than 500K RMB, 16.4% had 500K-10M RMB, 20.8% had 10M-30M RMB, 28.3% between 30M-50M RMB, 22.6% had more than 50M RMB. In terms of the Industry type, 24.3% of the enterprise was software and IT service, 9.7% of the enterprise was

Engineering, 5.3% of the enterprise was construction, 22.6% of the enterprise was transportation, 18.6% of the enterprise was financed, 6.6% of the enterprise were catering and entertainment service, 6.6% of the enterprise were others.

Besides that, 16,8% of respondents were high-level managers, 30.5% of respondents were middle-level managers, 21.2% of respondents were first-line managers and 31.4% of respondents were others. In terms of the current big data implementation stage of the enterprise, 23.0% of enterprises are still non-adopt, 23.0% were aware of adopting, 8.8% were considering to adopt, 2.2% were planned to adopt, 9.7% were already adopted and adapted and 33.2% were already adopted and internalized.

For the validity and reliability of the instrument, two (2) test have been conducted which is a) Cronbach's α coefficient test for reliability, and b) factor analysis for measuring structural validity.

V. RESULTS & DISCUSSION

The evaluation system of the questionnaire is embodied in the form of a scale, and the rationality of the compilation determines the usability and credibility of the evaluation results. The reliability and validity of the scale directly show the data's reliability and validity (Taherdoost 2016).The reliability of the questionnaire using Cronbach's Alpha (CA) score between 0.898 and 0.963. Therefore, this shows the questionnaire's reliability value is at an excellent level above the minimum level of 0.70 set (Gliem & Gliem 2003).

The reliability of the questionnaire using factor analysis. The value of KMO are between 0.802 and 0.924.Beside that the significance level of Bartlett's sphere test results is close to 0.000. all of which passed the correlation test, and factor analysis can be conducted. According to the factor variance contribution which obtained by principal component analysis, it's feasible to represent the Technology-Organization-Environment (TOE) feature factors with the 11 factors.Based on the rotation component matrix, The extracted factor is consistent with the factor of scale design, therefore, they have higher structural validity.

In order to study the causality among variables, many methods can be adopted such as regression analysis and Structural Equation Model (SEM). Regression analysis is a statistical analysis method to study whether there is a linear or nonlinear relationship between one or more dependent variables and an independent variable. When the structural model is relatively simple, there is a clear causal order and the regression analysis is available. The SEM is a method to establish, estimate and test causality models, which is suitable for analyzing models with uncertain causality order, potential variables, and complex structures. What is to be discussed in this paper is the relationship between many independent variables and one dependent variable. Therefore, with the help of SPSS software, the regression analysis theory model is adopted.

In this paper, it’s assumed that there are 11influencing factors of enterprise big data adoption, including the relative advantage (RA), compatibility (COMP), complexity (CXTY), trialability (T), observability (O), business scale (BS), resource readiness (RR), supports of high-level leaders (SH), market competition(MC), market disturbance (MD) and government policy (GP), the dependent variable is adoption intention (AI).

Figure 2 shows the fitting effect of the regression equation. The complex correlation coefficient R is a measurement of the relationship closeness between variables. When there is a strong linear correlation between two variables, the correlation coefficient is close to -1(negative correlation) or 1(positive correlation). When the two variables are less linearly correlated, the correlation coefficient will approach 0. The fitting degree of determination coefficient R2 is the degree to which the independent variable explains the change in the dependent variable percentage. The greater the determination coefficient is, the higher the interpretation of independent variables to dependent variables will be, and the higher the variance percentage caused by independent variables will be. The decision coefficient of the modified freedom does not lose the freedom, so it’s more objective to evaluate the fitting effect than R 2, the closer it’s to 1, the better the fitting effect will be. In the table, R2 was 0.438 and 0.409, indicating that the model fitting effect is good, 11 independent variables can explain the variation of 40.9% of dependent variables.

Model	R	R^2	Adjusted R^2	Std. Error
1	.662[a]	.438	.409	4.38249
a. Predictive variables: (constant), RA, COMP, CXTY, T, O, BS, RR, SH, MC, MD, GP. b. Dependent variable: AI				

Figure 2 Summary of regression equation fitting effect

Figure 3 shows that the significance of the regression equation is 0.000, showing that the independent and dependent variables are significantly correlated.

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	3197.912	11	290.719	15.137	.000[a]
	Residual	4110.128	214	19.206		
	Total	7308.040	225			
a. Predictive variables: (constant), RA, COMP, CXTY, T, O, BS, RR, SH, MC, MD, GP. b. Dependent variable: AI						

Figure 3 Analysis of variance of the regression equation

There may be a correlation between the independent variables and the model may be distorted. Therefore, it’s necessary to test the collinearity of independent variables when conducting the regression analysis. Multicollinearity refers to the multicollinearity or high correlation among the independent variables in a multi-regression model, causing distortion or difficulty in estimating the model accurately. The multi-collinearity can be estimated by Variance Inflating Factor (VIF) and tolerance. The larger the variance inflation factor is, the more serious the multicollinearity between independent variables will be. It’s generally believed that the model has serious multicollinearity when the variance inflation factor is greater than 5. Tolerance is the reciprocal of the variance inflation factor, so the smaller the tolerance is, the more serious the multicollinearity will be. In Table 4.26, the variance inflation factors of the 11 independent variables were less than 2 and the tolerances were greater than 0.5, indicating that the correlation between independent variables is lower and the regression analysis can be conducted.

Model		Denormalization coefficient		Standard coefficient	t	Sig.	Collinearity statistics	
		B	Standard error				Tolerance	VIF
1	(Constant)	-11.440	2.155		-5.307	.000		
	RA	.131	.031	.225	4.220	.000	.927	1.079
	COMP	.093	.046	.115	2.046	.042	.828	1.208
	CXTY	.256	.065	.216	3.914	.000	.860	1.162
	T	.252	.062	.223	4.084	.000	.878	1.139
	O	.194	.071	.150	2.737	.007	.873	1.145
	BS	.214	.066	.174	3.271	.001	.931	1.074
	RR	.007	.016	.024	.453	.651	.926	1.080
	SH	.007	.047	.008	.144	.885	.934	1.071
	MC	.139	.054	.138	2.574	.011	.919	1.088
	MD	.189	.077	.147	2.444	.015	.731	1.368
	GP	.081	.062	.078	1.308	.192	.736	1.358
a. Dependent variable: AI								

Figure 4 Regression coefficients of model-independent variables

The regression coefficients for the model-independent variables are shown in Figure 4. It can be found that of 11 variables, the significance level of the 8 variables including the relative advantage (RA), compatibility (COMP), complexity (CXTY), trialability (T), observability (O), business scale (BS), market competition (MC) and market disturbance (MD) is less than 0.05. That is, the influence of these 8 factors on the adoption intention of the dependent variable is significant. The significance level of resource readiness (RR) is 0.651, that of High-level leader support (SH) is 0.885, and that of government policy (GP) is 0.192, greater than 0.05, that is, resource readiness, High-level leader support, and government policy have no significant impact on adoption intention. Therefore, the hypothesis corresponding to three variables is invalid. From the table, the regression coefficients of relative advantage (RA), compatibility (COMP), complexity (CXTY), trialability (T), observability (O), business scale (BS), market competition (MC) and market disturbance (MD) are all positive, so the hypothesis is valid. The regression coefficients of complexity, trialability, and organizational scale are 0.256,0.252, and 0.214, respectively. The second is observability and market disturbance, the regression coefficient is 0.194,0.189. The regression coefficients of market competition, relative advantage, and compatibility are 0.139,0.131, and 0.093 respectively, which had a general influence on the adoption intention of enterprises.

The data in this study are all from SMEs in various fields in China. This study statically found that technical, organizational, and environmental contexts do affect the adoption of enterprise applications by SMEs, which is consistent with the conclusion of Ramdani et al. (2013). The findings show that compatibility has both direct and indirect effects on the extent to which Chinese SMEs adopt BDA. This finding is consistent with the findings of Yadegaridehkordi et al. (2020), who found a similar pattern for Malaysian SMEs. Nonetheless, Maroufkhani et al. (2020) do not support this relationship in their study. They believe that compatibility needs to be combined with high-level leaders' support as a significant influencing factor. The results further indicated that an association between high-level leaders' support and BDA adoption was not supported. This finding is consistent with Mangla et al. (2021). However, numerous previous studies have highlighted the critical role of high-level leaders' support for BDA adoption in Malaysian hotel SMEs (Yadegaridehkordi et al., 2020), UK SMEs (El-Haddadeh et al., 2021) and Indian companies (Verma and Bhattacharyya, 2017). Obviously, this study contradicts them, the factor of top management support is not significant for BDA adoption.

This study also shows that the technical complexity of BDA causes Chinese SMEs to show hesitation and concern before implementing and using BDA. This finding is consistent with El-Haddadeh et al. (2021), who support the negative impact of complexity on the BDA of UK SMEs.However, this negative association was not statistically supported in Chinese (Lai et al. 2018) and Egyptian/UAE firms (Youssef et al., 2022). The results also show that the relationship between resource readiness and DBA adoption is negligible. This finding is consistent with Lai et al. (2018), who also considered resource readiness as an independent factor. However, this contradicts the findings of Verma and Bhattacharyya (2017) and Yadegaridehkordi et al. (2020), who found that having the necessary resources and infrastructure at hand was an important driver of BDA adoption.

VI. CONCLUSION

This study was designed to identify influence factors that SMEs in the pre-implementation phase for big data analysis technology in China. The published Technology-Organization-Environment model (TOE) by Tornatzky & Flescher (1990) has been adopted in this study and supported by a literature review from previous studies. This analysis confirmed that compatibility, relative advantage, complexity, trialability, business scale, observability, market competition, and market disturbance are influence factors for SMEs in the adoption phase for BDA technology. In addition, this study also found that resource readiness, High-level leader support, and government policy do not significantly influence the BDA adoption intention of SMEs.In the future, If SMEs have adopted big data technology, further studies can be conducted on whether the influencing factors are consistent with those before adoption needs. In particular, further studies need to verify whether technical complexity and market disturbance influence the new adoption behavior by SMEs.In addition, studies can also be focused on the factors for big data adoption by different industry backgrounds. We can select a specific industry to investigate the information construction of enterprises and observe the influencing factors of the adoption behavior.

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