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The Adoption of Big Data to Achieve Firm Performance of Global Logistic Companies in Thailand

Krisana KITCHAROEN[1]

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Abstract

Purpose: Big Data analytics (BDA) has been recognized to improve firm performance because it can efficiently manage and process large-scale, wide variety, and complex data structures. This study examines the determinants of Big Data analytics adoption toward marketing and financial performance of global logistic companies in Thailand. The research framework is adopted from the technology–organization–environment (TOE) model, including technological factors (relative advantages), organizational factors (technological infrastructure and absorptive capability), environmental factors (industry competition and government support), Big Data analytics adoption, marketing performance, and financial performance. **Research design, data, and methodology:** A quantitative method is applied by distributing the survey to 450 employees at the manager's level and above. The sampling methods include judgmental, stratified random, and convenience sampling. The data were analyzed by Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM). **Results:** The results showed that all factors significantly influence Big Data analytics adoption, except technological infrastructure. In addition, Big Data analytics adoption significantly influences marketing and financial performance. Conversely, marketing performance has no significant influence on financial performance. **Conclusions:** The findings of this study can contribute to the strategic improvement of firm performance through Big Data analytics adoption in the logistics, distribution, and supply chain industries.

Keywords : Big Data Analytics, Technology Adotion, Logistic, Supply Chain, Firm Performance

JEL Classification Code : M10, M31, L61, L62, O30

1. Introduction

Globalization has accelerated digitalization, transforming today's businesses (Maroufkhani et al., 2020). Modern technologies bring the importance of data processing in different industries. The advancement of new Information Technology (IT) has been applied to strengthen operational effectiveness, market advantages, and firm performance (Bresnahan & Yin, 2017). Hence, adopting innovative technologies can elevate business opportunities (Ghobakhloo et al., 2012). According to Alsghaier et al. (2017), the emergence of smartphones and social media has accelerated the boom of digital technologies. Nolin (2020) stated, "Data is the new oil of the digital economy." Thus, Big Data as a digital record has been generated enormously worldwide and recognized as a core element of various technologies, potentially granting firms new value propositions and business models (Raguseo & Vitari, 2018).

Ekbia et al. (2015) explained that Big Data is "the information generated from social media, data from internet-enabled devices including smartphones and tablets, machine data, video and voice recording, and structured and unstructured data preservation and logging." Wibowo et al.

1 First Author and Corresponding Author. Associate Professor, DBA, Full-Time Lecturer, Department of Innovative Technology Management, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand. Email: krisana@au.edu

(2021) referred Big Data as "dynamic volume data, large and different data made by humans, tools, and machines" In the light of this, Big Data requires "new, innovative, and scalable technologies to collect, host, and analytically process the vast amounts of data collected for real-time business insights relating to enhanced consumer, risk, profit, performance, productivity management, and shareholder value" (Sen et al., 2016). In globalization, Big Data analytics are effective methods to develop and improve a firm's market position (Talebi et al., 2012).

Big Data integrates technological tools with structured, unstructured, and semi-structured data, which can be managed and implemented for business analysis in various areas such as finance, customers, marketing, and operation (Wibowo et al., 2021). The impact of Big Data in businesses leads to the ability to adjust the strategy to achieve business goals and maintain firms' sustainability. The value creation from Big Data can maximize profits and increase a company's revenue (Rehman et al., 2016). Additionally, Big Data has been addressed to create business value in the aspect of innovation capabilities for the improvement of marketing and financial performance (Wibowo et al., 2021).

Mikalefa et al. (2019) stated that many firms struggle to leverage value from Big Data adoption to enhance performance through such technology. It has been seen that inadequate understanding and contradictory points of view about how businesses can leverage firm performance with Big Data analytics (Wamba et al., 2017). More precisely, the current problem is that there need to be more studies on adopting Big Data analytics (BDA) and how companies can exploit it to strengthen marketing and financial performance in a developing country. Hence, this research aims to examine the determinants of Big Data analytics adoption toward marketing and financial performance of global logistic companies in Thailand. The technology–organization–environment (TOE) model is adopted, including technological factors (relative advantages), organizational factors (technological infrastructure and absorptive capability), and environmental factors (industry competition and government support).

2. Literature Review

2.1. Technology–Organization–Environment (TOE) Model

Technology–Organization–Environment (TOE) Model was developed by Tornatzky et al. (1990). TOE is predominant in inspecting issues related to technology or innovation adoption. It is a "fundamental adoption/diffusion of technology model and generally measures internal and external features, including technological, organizational, and environmental factors that assist the adoption/ diffusion of various technologies" (Maroufkhani et al., 2020). TOE is an ideal model for BDA adoption in the current study because it incorporates the Innovation Diffusion Theory and how its three elements impact the firm performance (Baker, 2012). Many scholars have recognized the model in the topic of frequently-used technology adoption (Alshamaila et al., 2013; Grant & Yeo, 2018; Hsu et al., 2014; Maduku et al., 2016; Maroufkhani et al., 2020; Wahab et al., 2021). Therefore, the TOE model is the most applicable theory in this study's context of BDA. TOE plays a vital role to explain the technology adoption and measure the firm's performance (Ling & Wahab, 2019).

2.2. Technological Factors

2.2.1. Relative Advantages

Rogers (2003) referred to relative advantage as "the degree to which an innovation is perceived as being better than the idea it supersedes." The advancement of new technology allows firms to maximize the efficiency of business operations, offer solutions, and improve productivity (Wahab et al., 2021). Relative advantage is the most prominent factor in technology adoption (Alshamaila et al., 2013; Grant & Yeo, 2018; Hsu et al., 2014; Maduku et al., 2016; Maroufkhani et al., 2020; Wahab et al., 2021). It is how a firm perceives the benefits of the new technology adoption, especially in the warehousing sector of the logistics, distribution, and supply chain industries. There has been an increasing demand for Big Data analytics to analyze current business trends and changes. In this context, Cao et al. (2009) posited that "BDA is very useful in assisting firms to efficiently manage warehouse operations by reducing asymmetric information inferiority." Agrawal (2015) indicated that the relative advantages of BDA can improve business operations effectiveness and reduce lead times and labor costs. Francisco and Swanson (2018) highlighted that BDA enables data transparency in warehouse operations and the entire supply chain process and can assist firms in predicting possible business risks, tracking and tracing the inventory flow, improving efficacy, and providing real-time data. Based on these assumptions, the relative advantage is an influential factor that affects BDA adoption among logistic companies. Consequently, the following hypothesis is proposed:

H1: Relative advantages have a significant influence on Big Data analytics adoption.

2.3. Organizational Factors

2.3.1. Technological Infrastructure

According to Nkhoma and Dang (2013), technological infrastructure is "a major business resource for firms to maintain their competitive advantage in the long term." Integration of the new technology empowers firms to leverage and strengthen their unique selling propositions over competitors. The current business environment has accelerated firms to invest and exploit technological infrastructure to respond promptly to customers' demands (Tan et al., 2015). Kumar and Kumar (2015) acknowledged that technological infrastructure is vital to assimilate innovations and to improve operational transactions. Technological infrastructure offers the technical foundation for data analysis, allowing firms to develop business strategies. The adopt BDA relates to the degree of technological infrastructure in the firm (Lai et al., 2018). Wahab et al. (2021) pointed out that technological infrastructure greatly impacts BDA adoption. Thus, the following statement is hypothesized:

H2: Technological infrastructure has a significant influence on Big Data analytics adoption.

2.3.2. Absorptive Capability

Absorptive capability is "the capability and capacity of the firm to discover valuable information adopted from its external environment, including competitors" (Wahab et al., 2021). Addo-Tenkorang and Helo (2016) posited that absorptive capability can be done by integrating, revolutionizing, and enhancing existing business procedures toward competitive advantage. Absorptive capability is a vital strategy for firms to enquire new knowledge and critically manage information flows to achieve greater levels of innovation (Govindana et al., 2018). Liu et al. (2013) demoted that a level of absorptive capability relies on the firms' existing knowledge applied to their products and processes. Liu et al. (2021) indicated that knowledge could assist firms in achieving growth and gaining a competitive advantage. Hence, adequate knowledge and experience for logistic firms lead to a high degree of BDA adoption (Wahab et al., 2021). Subsequently, this study proposes the following hypothesis:

H3: Absorptive capability has a significant influence on Big Data analytics adoption.

2.4. Environmental Factors

2.4.1. Industry Competition

Competitive pressure is under environmental factors influencing BDA adoption (Maroufkhani et al., 2020). Oliveira et al. (2014) defined *competition* as "competitive pressure influenced by the external environment that prompt the firm to adopt BDA." Competitive pressure can come from its customers, suppliers, and competitors. This study points out the competition that majorly lies in the logistics industry. Accordingly, Industry competition refers to "the dynamic rivalries among business competitors within the identical market" (Wahab et al., 2021). BDA adoption activates a highly competitive advantage to the firm in unpredictable business circumstances and assists businesses in improving their overall supply chain business performance (Gunasekaran et al., 2017). Sangari and Razmi (2015) posted that a competitive advantage of a firm can enhance business sustainability and facilitate their return on investment. Hence, the adoption of Big Data is influenced by industry competition. Based on the above discussions, a hypothesis can be developed:

H4: Industry competition has a significant influence on Big Data analytics adoption.

2.4.2. Government Support

A prominent factor of the TOE model is government support, which has also been realized as another influential factor in BDA adoption (Wahab et al., 2021). Maroufkhani et al. (2020) implied the government's support as government regulations imposed by authorities of governments yield firms to look for technological alternatives. Government regulations may encourage firms to adopt innovation and new technology through promotion and restrictions. To some extent, some measures may endorse or prohibit firms from adopting new technology (Weigelt & Sarkar, 2009). Raut et al. (2019) emphasized that government support enables business expansion, particularly in the competitive logistics industry, due to the government being a responsible party to expediting policies about the usage and investment of new technology. Thus, BDA adoption in both logistic sectors is critically essential to accelerate the growth of the countries' digital economy (Wahab et al., 2021). Based on these arguments, a hypothesis is suggested:

H5: Government support has a significant influence on Big Data analytics adoption.

2.5. Big Data Analytics Adoption

Most firms utilize Big Data analytics to make data-driven decisions that enhance marketing and firm performance. BDA adoption's benefits include improving operational efficiency, effective marketing, customer personalization, and new revenue opportunities (Vela et al., 2022). Dai et al. (2019) provide a sample of global businesses that adopt BDA, such as Amazon, eBay, Groupon, and Etsy. BDA directly impacts firm performance, as supported by numerous studies (Alshamaila et al., 2013; Maduku et al., 2016; Maroufkhani et al., 2020; Mikalefa et al., 2019; Wahab et al., 2021). The firm performance consists of the financial and market performance, including the optimization of price, sales and profits maximization, financial productivity, and market share and returns on investment (Wibowo et al., 2021). McAfee et al. (2012) stressed that Big Data is an innovation capability that enhances marketing and financial performance. Hence, this study hypothesizes that:

H6: Big Data analytics adoption has a significant influence on marketing performance.
H7: Big Data analytics adoption has a significant influence on financial performance.

2.6. Marketing Performance

Marketing performance refers to "upgrading the position of firms in the market place to gain their completive advantage" (Ren et al., 2017). Lamprinopoulou and Tregear (2011) regarded that good marketing performance can contribute to profit margins, brand reputation, and sustainability. Marketing performance determines firms' competitive advantages and market share over their competitors (Wibowo et al., 2021). In addition, marketing performance is the evaluation of the effectiveness of the overall collaboration (Zhao & Priporas, 2017). The TOE model illustrates the influence of innovation adoption on firm performance. BDA can be a technological tool to produce new products, services, and processes, which can enhance marketing performance, which is expected to impact firms' financial performance (Teguh et al., 2021). Sett (2018) found a linkage between marketing and firm performance, whereas some studies may group both variables as overall firm performance. Therefore, this study will be based on the following hypothesis:

H8: Marketing performance has a significant influence on financial performance.

2.7. Financial Performance

Financial performance is determined as "the grade of financial goals that have been accomplished, which is used to evaluate a firm's total financial health, which is the process of determining a company's profitability, growth, and market value in monetary terms." Successful adoption of Big Data analytics leads to effective business performance (Maroufkhani et al., 2020). Several studies emphasize that adopting BDA positively correlates with firm performance (Maroufkhani et al., 2020; Meroño-Cerdan & Soto-Acosta, 2007; Sett, 2018; Yeo, 2016). Ren et al. (2017) confirmed that BDA could raise the performance of firms. In addition, Raut et al. (2019) implied that BDA adoption could sustain business performance.

3. Research Methods and Materials

3.1. Research Framework and Hypotheses

The research framework is adopted from the theoretical models of four previous studies (Maroufkhani et al., 2020; Sett, 2018; Wahab et al., 2021; Wibowo et al., 2021). The technology–organization–environment (TOE) model is the foundation theory to develop the conceptual framework in this research, including technological factors (relative advantages), organizational factors (technological infrastructure and absorptive capability), environmental factors (industry competition and government support), Big Data analytics adoption, marketing performance, and financial performance. Accordingly, the following framework and hypotheses are proposed as shown in Figure 1, and the summary of previous research used to construct the model is explicated in Table 1:

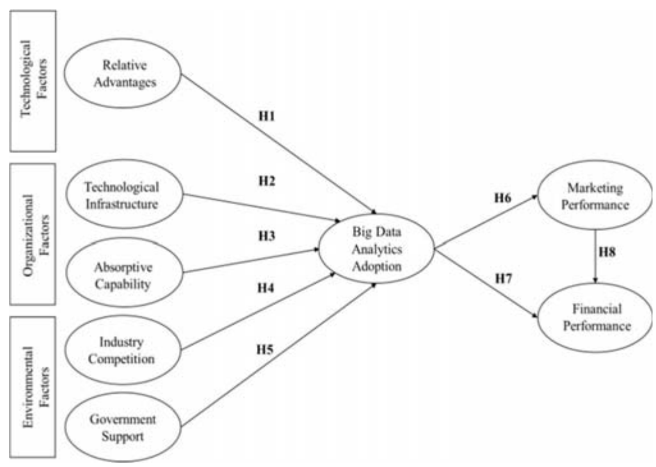

Figure 1: Conceptual Framework

H1: Relative advantages have a significant influence on Big Data analytics adoption.
H2: Technological infrastructure has a significant influence on Big Data analytics adoption.
H3: Absorptive capability has a significant influence on Big Data analytics adoption.
H4: Industry competition has a significant influence on Big Data analytics adoption.
H5: Government support has a significant influence on Big Data analytics adoption.
H6: Big Data analytics adoption has a significant influence on marketing performance.
H7: Big Data analytics adoption has a significant influence on financial performance.
H8: Marketing performance has a significant influence on financial performance.

Table 1: Summary of Previous Research

Author & Year	Key Variables	Research Finding
Maroufkhani et al. (2020)	Technological Context, Organizational Context, Environmental Context, Big Data Analytics Adoption, Financial Performance, Market Performance	The results offer evidence of a BDA mediation effect in the relationship between technological, organizational and environmental contexts, and SMEs performance.
Sett (2018)	Market Orientation, Financial Performance, Market Performance	Market orientation can sustain superior firm performance in a rapidly changing environment.
Wahab et al. (2021)	Relative Advantages, Technological Infrastructure, Absorptive Capability, Environmental Factors, Industry Competition, Government Support, Big Data Analytics Adoption	The empirical results revealed that relative advantage, technological infrastructure, absorptive capability and government support influence the levels of BDA adoption, whilst industry competition appeared to be of no significant influence.
Wibowo et al. (2021)	Big Data, Value Creation, Innovation Capability, Marketing Performance	The most significant influence is found on the relationship of Big Data to value creation. The lowest effect was obtained from the relationship between Big Data and marketing performance through the mediation variable and innovation capability.

3.2. Methodology

The research methodology is quantitative, using the questionnaire distribution. A questionnaire is administered in three parts; screening questions (2), the five-point Likert scale questions (33), which ranged from “strongly disagree” (1) to “strongly agree” (5), and demographic information (5), including gender, age, income, educational level, and positions. Before collecting the data, the Item–Objective Congruence (IOC) index was applied by rating four experts who are Ph.D. and c-level in logistic companies, resulting in all scale items being passed at a score of 0.5. Cronbach’s Alpha coefficient values were tested in the pilot test of 50 participants, and all constructs were validated at 0.70 and above (Nunnally & Bernstein, 1994). Afterward, the survey was distributed on a large scale to 450 employees at the manager’s level and above of five global logistic companies in Thailand. The SPSS and SPSS AMOS were used to analyze the statistical data. Confirmatory Factor Analysis (CFA) was conducted for the data analysis with reliability, validity, and goodness of fit indices. Furthermore, Structural Equation Model (SEM) was used to test the model’s goodness-of-fit and hypothesis.

3.3. Population and Sample Size

The target population is 450 employees at the manager’s level and above of five global logistic companies in Thailand. Kline (2011) determines the minimum sample size of a complex model to be at least 200. After the survey distribution was made to around 1,000 participants, 450 responses were received as passed the data screen process for the data analysis of this study.

3.4. Sampling Technique

In this study, the sampling methods are multi-step for the data collection, including judgmental, stratified random, and convenience sampling. First, judgmental sampling was conducted per the judgment of the researcher to choose the group of employees at the manager’s level and above of five global logistic companies in Thailand. Second, stratified random sampling was carried out to calculate sample size in proportion, as shown in Table 2. The company name cannot be disclosed due to the consent issue. Last, convenience sampling was employed to distribute offline through the human resources department and online questionnaires via email, social media, and chat applications from May to September 2022.

Table 2: Stratified Random Sampling

Company	Number of Employee	Sample Size (425)
Company 1	1,400	34
Company 2	10,000	244
Company 3	1,000	25
Company 4	5,000	122
Company 5	1,000	25
Total	**18,400**	**450**

4. Results and Discussion

4.1. Demographic Profile

In Table 3, the results of demographic information are based on 450 respondents. Most respondents were males, 57.3 percent (258), whereas females were 42.7 percent (192). For the age group, most respondents were between 36 to 45 years old at 37.8 percent (170), whereas the least group was less than 25 years old at 12.2 percent (55). Most respondents earned THB 50,001-80,000 per month, or 36.7 percent (165). For educational level, Bachelor’s degree or below was 65.8 percent (296), followed by a Master’s degree at 27.1 percent (122) and a Doctorate Degree at 7.1 percent (32). Most respondents were at the manager level of 67.3 percent (303).

Table 3: Demographic Profile

Demographic Results (N=450)		Frequency	Percentage
Gender	Male	258	57.3%
	Female	192	42.7%
Age	25 years old or below	55	12.2%
	26 to 35 years old	123	27.3%
	36 to 45 years old	170	37.8%
	Above 45 years old	102	22.7%

Demographic Results (N=450)		Frequency	Percentage
Income per Month	Below THB 50,000	134	29.8%
	THB 50,001-80,000	165	36.7%
	THB 80,001-120,000	94	20.9%
	Above THB 120,000	57	12.6%
Educational Level	Bachelor's or below	296	65.8%
	Master's	122	27.1%
	Doctorate	32	7.1%
Position Level	Manager	303	67.3%
	Director	119	26.5%
	C-Level	28	6.2%

4.2. Confirmatory Factor Analysis (CFA)

CFA is a multivariate analysis validated by the measurement model. In Table 4, CFA was measured by Cronbach's Alpha, factor loadings, composite reliability (CR), and average variance extraction (AVE). The results show that Cronbach's Alpha coefficient values were validated at 0.70 and above (Nunnally & Bernstein, 1994). The acceptable values of factor loadings are 0.5 or higher. Composite reliability (CR) and average variance extraction (AVE) are acceptable at 0.7 or above and 0.4 or higher, respectively (Fornell & Larcker, 1981). In summary, CFA analysis results were significant and can approve this study's convergent and discriminant validities.

Table 4: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
1. Relative Advantages (RA)	Agrawal (2015)	5	0.837	0.690-0.740	0.838	0.509
2. Technological Infrastructure (TI)	Kumar and Kumar (2015)	4	0.880	0.736-0.870	0.883	0.656
3. Absorptive Capability (AC)	Agrawal (2015)	4	0.816	0.644-0.801	0.817	0.530
4. Industry Competitive (IC)	Mikalefa et al. (2019)	5	0.817	0.636-0.732	0.817	0.472
5. Government Support (GS)	Hsu et al. (2014)	5	0.821	0.638-0.761	0.823	0.483
6. Big Data Analytics Adoption (BDA)	Tu (2018)	3	0.887	0.815-0.904	0.886	0.722
7. Marketing Performance (MP)	Ren et al. (2017)	4	0.811	0.696-0.759	0.812	0.519
8. Financial Performance (FP)	Raguseo and Vitari (2018)	3	0.898	0.848-0.859	0.898	0.745

Note: CR = Composite Reliability, AVE = Average Variance Extracted

The square root of the average variance extracted determines that all the correlations are greater than the corresponding correlation values for that variable, as shown in Table 5 (Jaruwanakul, 2021). Furthermore, multicollinearity's problem can be evaluated through the correlation coefficient which the factor correlations did not surpass 0.80. As a result, this study has no multicollinearity issues (Studenmund, 1992).

Table 5: Discriminant Validity

	BDA	RA	TI	AC	IC	GS	MP	FP
BDA	**0.850**							
RA	0.554	**0.713**						
TI	0.278	0.228	**0.810**					
AC	0.558	0.530	0.275	**0.728**				
IC	0.609	0.587	0.199	0.632	**0.687**			
GS	0.449	0.326	0.300	0.461	0.452	**0.695**		
MP	0.698	0.507	0.277	0.567	0.630	0.659	**0.721**	
FP	0.777	0.551	0.259	0.486	0.523	0.425	0.643	**0.863**

Note: The diagonally listed value is the AVE square roots of the variables

The measurement model was used to test the goodness of fit in the CFA. This study uses the criteria of CMIN/DF, GFI, AGFI, NFI, CFI, TLI, RMSEA, and RMR, as illustrated in Table 6. As a result, all values were acceptable fit without an adjustment. Accordingly, convergent and discriminant validities of this study were approved.

Table 6: Goodness of Fit of Measurement Model

Index	Acceptable Values	Measurement Model
		Statistical Values
CMIN/DF	≤ 3.00 (Kline, 1998)	1.443
GFI	≥ 0.90 (Kline, 2005)	0.919
AGFI	≥ 0.90 (Tabachnick & Fidell, 2007)	0.903
NFI	≥ 0.90 (West et al., 2012)	0.916
CFI	≥ 0.90 (West et al., 2012)	0.972
TLI	≥ 0.90 (West et al., 2012)	0.969
RMSEA	≤ 0.05 (MacCallum et al., 1996)	0.031
RMR	≤ 0.05 (Steiger, 2007)	0.014
Model summary		**Acceptable Model Fit**

Remark: CMIN/DF = ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residual

4.3. Structural Equation Model (SEM)

The structural model was applied to ensure the acceptable fit value of SEM, as presented in Table 7. The initial model showed that the fit results must harmonize with empirical data. After the model adjustment, the fit values are acceptable, including CMIN/DF = 1.467, GFI = 0.917, AGFI = 0.902, NFI = 0.913, CFI = 0.971, TLI = 0.967, RMSEA = 0.032, and RMR = 0.019.

Table 7: Goodness of Fit of Structural Model

Index	Acceptable Values	Structural Model	
		Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	≤ 3.00 (Kline, 1998)	2.470	1.467
GFI	≥ 0.90 (Kline, 2005)	0.849	0.917
AGFI	≥ 0.90 (Tabachnick & Fidell, 2007)	0.826	0.902
NFI	≥ 0.90 (West et al., 2012)	0.849	0.913
CFI	≥ 0.90 (West et al., 2012)	0.904	0.971
TLI	≥ 0.90 (West et al., 2012)	0.896	0.967
RMSEA	≤ 0.05 (MacCallum et al., 1996)	0.057	0.032
RMR	≤ 0.05 (Steiger, 2007)	0.073	0.019
Model summary		**Unacceptable Model Fit**	**Acceptable Model Fit**

Remark: CMIN/DF = ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residual

4.4. Research Hypothesis Testing Result

The research hypothesis testing results are measured from the standardized coefficients (β) with t-values, as shown in Table 8 and Figure 2. The significance level is supported at p = 0.05. Big Data analytics adoption has the strongest significance on financial performance (β = 0.898), followed by marketing performance (β = 0.745). Big Data analytics adoption is significantly influenced by industry competition (β = 0.276), followed by relative advantages (β = 0.254), government support (β = 0.189), and absorptive capability (β = 0.160). On the contrary, technological infrastructure does not significantly influence Big Data analytics adoption (β = 0.075). Furthermore, marketing performance does not significantly influence financial performance (β = -0.022).

Table 8: Hypothesis Result of the Structural Model

H	Paths	(β)	S.E.	t-Value	Tests Result
H1	RA ---> BDA	0.254	0.068	4.446*	Supported
H2	TI ---> BDA	0.075	0.047	1.777	Not Supported
H3	AC ---> BDA	0.160	0.080	2.342*	Supported
H4	IC ---> BDA	0.276	0.087	4.052*	Supported
H5	GS ---> BDA	0.189	0.073	3.705*	Supported
H6	BDA ---> MP	0.745	0.047	13.122*	Supported
H7	BDA ---> FP	0.898	0.066	13.580*	Supported
H8	MP ---> FP	-0.022	0.073	-0.367	Not Supported

Note: *p<0.05

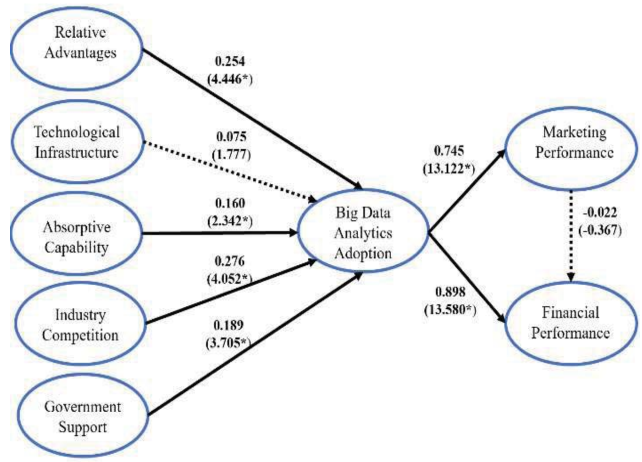

Figure 2: The Results of Structural Model

Remark: Dashed lines, not significant; solid lines, significant. *p<0.05

The hypothesis results from Figure 2 can be refined per followings;

H1 approves the significant relationship between relative advantages and Big Data analytics adoption, with the standardized path coefficient value of 0.254 (t-value = 4.446*). Many scholars confirm that relative advantage is an influential factor in technology adoption (Alshamaila et al., 2013; Grant & Yeo, 2018; Hsu et al., 2014; Maduku et al., 2016; Maroufkhani et al., 2020; Wahab et al., 2021).

H2 fails to confirm the significant influence of technological infrastructure on Big Data analytics adoption, reflected in the standardized path coefficient value of 0.075 (t-value = 1.777). The results contradict previous studies that technological infrastructure is vital to assimilate innovations and improve operational transactions (Kumar & Kumar, 2015; Tan et al., 2015; Wahab et al., 2021).

H3 indicates the standardized path coefficient value of 0.160 (t-value = 2.342*), which supports the relationship between absorptive capability and Big Data analytics adoption. Wahab et al. (2021). Posited that adequate knowledge and experience for logistic firms lead to a high degree of BDA adoption

H4 supports the significant relationship between industry competition and Big Data analytics adoption, resulting in a standardized path coefficient value of 0.276 (t-value = 4.052*). In light of this, industry competition is a business pressure that influences BDA adoption (Maroufkhani et al., 2020; Oliveira et al., 2014; Wahab et al., 2021). BDA adoption can elevate the competitive advantage of logistic firms (Gunasekaran et al., 2017).

H5 demonstrates that government support significantly influences Big Data analytics adoption, representing a standardized path coefficient value of 0.189 (t-value = 0.073*). The results aligned with numerous empirical studies that government regulations may encourage firms to adopt Big Data through promotion (Maroufkhani et al., 2020; Raut et al., 2019; Wahab et al., 2021; Weigelt & Sarkar, 2009).

H6 signifies the support relationship between Big Data analytics adoption and marketing performance. The hypothesis testing results show the standardized path coefficient value of 0.745 (t-value = 13.122*). Thus, Big Data analytics adoption can determine firms' market share over their competitors (Lamprinopoulou & Tregear, 2011; Wibowo et al., 2021; Zhao & Priporas, 2017).

The results of H7 show that Big Data analytics adoption strongly influences financial performance, representing the standardized path coefficient value of 0.898 (t-value = 13.580*). As aligned with many studies, the successful adoption of Big Data analytics leads to the financial performance of firms (Maroufkhani et al., 2020; Meroño-Cerdan & Soto-Acosta, 2007; Sett, 2018; Yeo, 2016).

Finally, H8 reveals that marketing performance does not influence financial performance, demonstrating the standardized path coefficient value of 0.022 (t-value = -0.367). The results contradicted earlier studies that marketing performance is expected to impact firms' financial performance (Sett, 2018; Teguh et al., 2021).

5. Conclusions and Recommendation

5.1. Conclusion and Discussion

The research objectives have been fulfilled to identify factors influencing Big Data analytics adoption toward marketing and financial performance of global logistic companies in Thailand. Technology–organization–environment (TOE) model was adopted to construct the study's conceptual framework. The data were collected from 450 employees at the manager's level and above. Furthermore, the data were analyzed by Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM). The results showed that all factors significantly influence Big Data analytics adoption, except technological infrastructure. In addition, Big Data analytics adoption significantly influences marketing and financial performance. Conversely, marketing performance has no significant influence on financial performance.

TOE is a powerful and appropriate model to investigate the determinants of BDA adoption in this study because it can explain the impact of technology adoption on firm performance. The findings showed that relative advantages, absorptive capability, industry competition, and government support influence Big Data analytics adoption. Firstly, relative advantages are addressed to have a significant influence on Big Data analytics adoption due to BDA adoption assists firms in maximizing the efficiency of business operations, offering solutions, and gaining competitive advantages (Alshamaila et al., 2013; Grant & Yeo, 2018; Hsu et al., 2014; Maduku et al., 2016; Maroufkhani et al., 2020; Wahab et al., 2021). Secondly, absorptive capability has a significant influence on Big Data analytics adoption. According to Govindana et al. (2018), absorptive capability can enhance firms' strategy to enquire new knowledge and critically manage information flows. Thirdly, Maroufkhani et al. (2020) also stated that competitive pressure is under environmental factors influencing BDA adoption.

Fourthly, Raut et al. (2019) highlighted that government support could promote the adoption of BDA in the logistics industry. Fifthly, Big Data analytics adoption presents a strong significant influence on both marketing and financial performance. The firm performance consists of financial and market performance. Accordingly, Big Data is an innovation capability that enhances marketing and financial performance (McAfee et al., 2012; Wibowo et al., 2021). Next, this study disapproves of confirming the significant influence of technological infrastructure on Big Data analytics adoption. The results show that the importance of technological infrastructure needs to be more skeptical about endorsing BDA adoption in logistic firms. Several studies found no linkage between some organizational factors and BDA adoption (Gangwar, 2018; Ramanathan et al., 2017). Lastly, the findings reveal that marketing performance has no significant influence on financial performance, which scholars have debated widely (Sett, 2018; Teguh et al., 2021).

5.2. Recommendation

Big Data analytics can help logistic firms to exploit the data on the customer behavior of consumption, transportation, and travel for logistics planning, which will raise the level of entrepreneurs and increase the country's competitiveness. Leading logistics companies will focus on Big Data and use it to improve work efficiency. Based on available information by using Big Data analytics to assist in planning and decision making. Both in terms of cost reduction through various data collection within the business to be analyzed whether transport process fuel cost consumption data. This will make it possible to know what problems within the business need to be improved.

This study offers practical guidance for decision-makers in or in charge of defining the implementation strategy of Big Data analytics adoption in logistics, distribution, and supply chain firms. Relative advantages, absorptive capability, industry competition, and government support significantly influence Big Data analytics adoption. In a competitive environment, logistic firms can obtain a relative advantage through logistics by taking a superior position within the industry regarding cost reductions, diversification, flexibility and reliability, and customer satisfaction. Absorptive capacity can be promoted through technology transfer. It can connect innovation stakeholders and move inventions from creators to public and private users such as universities and private companies.

Industry competition is a major concern for logistics firms. Due to the fierce competition expected to occur, as professional multinational logistics, the firm needs to enhance its operations with the new technology. Therefore, BDA adoption is an alternative to ensure operational efficiency and determine a new business model. Furthermore, government support plays a crucial role in the adoption of BDA. Currently, the Thai government is pushing for a project to study the development of Big Data Analytics innovation for the transportation of goods by trucks and the travel of people in Bangkok and its vicinity. To take advantage of Big Data, data centers and cloud computing are created to achieve the use of analytical data to provide services that are appropriate to meet the needs of the people. Therefore, logistic companies should join forces with the government to integrate technology solutions for people.

Even though this study found no significant relationship between technological infrastructure and Big Data analytics adoption, logistic firms need to determine the right investment in Big Data technologies. However, Big Data is a complex technological infrastructure and requirements. The firm needs to focus on customer-centric outcomes, strategize a Big Data adoption strategy and use existing data to generate quick wins. Additionally, marketing performance can partly explain financial performance in this study. Overall financial performance can be driven by various factors, not just a good marketing plan. Therefore, the full Technology–organization–environment (TOE) model can be further investigated.

5.3. Limitation and Further Study

This research addresses the limited sample group of employees at the managers level and above of global logistic companies in Thailand. Therefore, the subject excludes local firms and SMEs, which can produce different results. Next, the comprehensive study can be further explored in the different methodologies, such as qualitative and mix-method, to provide an in-depth analysis and interpretation of the results. Last, the conceptual framework can be extended based on other variables in Technology–organization–environments (TOE) model, such as complexity, compatibility, top management support, and technological readiness.

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