International Journal of Electronic Commerce Studies
Vol.13, No.2, pp.01-26, 2022
doi: 10.7903/ijecs.2013

Impact Of Competitive Strategy on Big Data Analytics Adoption: An Information Processing Perspective

Wei-Hsiu Weng
National Chengchi University
Department of Management Information Systems
wilsonw.weng@msa.hinet.net

ABSTRACT

Recent advancements in big data analytics have invoked tremendous attention from both academics and industries. Many researchers refer that the adoption of big data analytics could lead to performance impact to organizations. However, few research study the association between business strategy and big data analytics adoption. Furthermore, the role of firms' functional activities, such as supply chain operations, has not been clarified in the adoption considerations of big data analytics. In this research, empirical data from enterprises were collected and analyzed to assess the linkage between business strategy and big data analytics adoption, and the possible effect of supply chain competence in the linkage. The results supported our hypotheses, and the implications for management decisions are elaborated.

Keywords: business strategy, big data analytics, supply chain competence, technology adoption, information processing view

1. INTRODUCTION

Big data is characterized by scholars and practitioners with three Vs: Volume, or the amount of data that either consume massive storage or entail of a large number of data records; Velocity, which is the frequency or the speed of data generation, data delivery, and data change; and Variety, to highlight the property that data are generated from a large variety of sources and formats, and contain multidimensional data fields including structured and unstructured data [1-3]. Big data analytics refers to the methods, algorithms, middleware, and systems to discover, retrieve, store, analyze, and present big data to generate the fourth V: Value for business.

The development of big data analytics responds to the world of fast accumulating data, such as social media data, electronic commerce data, geographical data, multimedia streaming data, and many others generated from personal and organizational applications [4, 5]. Other emerging technologies, such as cloud computing and the internet of things, also enhanced the need for big data analytics [6-8]. For example, with the rapid pace of development in cloud computing, data centers of both public clouds and private clouds are continuing to accumulate enormous volumes of data. Thus, big data analytics and its applications are becoming ever more noticed [3, 9].

While the influences of big data analytics on enterprise performance were explored in previous studies [2], the question of whether firms will adopt big data analytics remains unresolved. Factors influencing enterprise adoption intention of big data analytics have not been comprehensively investigated.

Studies of organizational information processing theory [10, 11] have shown that the uncertainty that firms encounter when formulating and executing business strategy is an essential factor for firms' adoption of innovative information technologies [12-14]. This result leads to the speculation that business strategy pursuit is associated with big data analytics adoption intention. However, studies of possible relationships between big data analytics adoption and firms' business strategies are rare in the literature so far.

Moreover, a business strategy needs to be implemented and realized with functional activities such as human resource management, research and development, production, marketing, sales, customer services, and supply chain management [15]. Among these functional level activities, supply chain management is particularly noticeable as a possible factor for big data analytics adoption [16, 17]. Therefore, this research intends to investigate the linkage between business strategy and big data analytics adoption and the effect of supply chain competence in this linkage.
The paper begins with reviewing the relevant literature about the relationships between business strategy, supply chain competence, and big data analytics. Then it proposes a model which links these variables. Following that, the model is tested using a sample of large Taiwanese companies with global operations. Finally, the findings are presented along with the managerial implications of the study, its limitations, and our recommendations for future work. An earlier version of this paper has been presented at the 20th International Conference on Electronic Business.

2. LITERATURE AND HYPOTHESES

2.1 Information Processing Theory and Big Data Analytics

Studies of organizational information processing theory [10, 11] have revealed that the uncertainty that firms confront when pursuing and developing business strategy is an essential factor for firms' adoption of innovative information technologies [12-14]. Information processing theory views firms as information processing systems dealing with uncertainty in business decisions. Nowadays, organizations face more significant challenges in decision making than before, as the information to be processed is overgrowing in volume, velocity, and variety. This challenge motivated the study and utilization of big data analytics [18-20].

Big data analytics is used to store, convert, transmit and analyze large quantities of dynamic, diversified business data which may be structured or unstructured [21, 22]. Big Data processing requires tools and techniques that leverage the combination of various IT resources: processor, memory, storage, network, and end-user devices. Analytical tools are developed to process the large amounts of unstructured and heterogeneous data collected continuously in various formats such as text, picture, audio, video, log file, and others [23]. Current examples of such tools include the Hadoop Distributed File System (HDFS) [24], the parallel processing system MapReduce [25], the non-relational database system NoSQL [26], and others. These tools provide processing functionality for big data beyond the application scope of conventional data mining and business analytics [27].

2.2 Business Strategy and Supply Chain Competence

Porter's framework for business strategies of competition is a widely accepted typology of business competition [28, 29]. Porter's study in industrial economics suggested two fundamental types of generic business strategies for achieving above average rates of return: cost leadership and differentiation [28, 30]. Porter proposed that to succeed in business, a firm must pursue one of these generic business strategies. A firm's strategic choice eventually determines its competitiveness and profitability [31]. Other scholars argued that the two types of business strategies are not mutually exclusive. Firms adopting a cost leadership strategy may seek to deliver distinctive products or services under the central theme of cost efficiency. Firms with a differentiation strategy could also attempt cost performance while achieving the uniqueness of products or services [32, 33].

The successful implementation of the business strategies relies on making the right decision on core functions of a firm, such as human resource management, production, marketing, research and development, sales, information systems, and supply chain management. These functions form a value chain, and all have a role in lowering the cost structure and increasing the value of products through differentiation [30]. A firm's ability to acquire superior functional efficiency, including supply chain competence, will determine if its product is differentiated from its competitors and if it has a low-cost structure simultaneously. Firms that increase the utility consumers get from their offerings through differentiation, while at the same time lowering their cost structure, can create more value than their rivals and will acquire a competitive advantage, superior profitability, and profit growth [32, 34].

A cost leadership strategy is pursued through low-cost operations in each segment of supply chain activities, including production scheduling, demand management, sourcing and procurement, inventory management, distribution, and delivery [35, 36]. Differentiation may eventuate in unique methods or channels of sourcing or delivery, innovative manufacturing processes, or inventory operations in a supply chain [37]. Thus, the following two hypotheses are proposed:

H1a. Cost leadership strategy is positively associated with supply chain competence.

H1b. Differentiation strategy is positively associated with supply chain competence.

2.3 Business Strategy and Big Data Analytics Adoption

A business strategy of a firm includes the competitive positioning, market segmentation, and industry environment [28]. To survive, grow and sustain, a firm needs to monitor its internal and external status. The formulation and execution of a business strategy rely on the collection, extraction, analysis, and interpretation of internal and external status data [1, 38].

From the information processing view [10], an organization is an imperfect decision-making system because of uncertainty. Therefore, a firm needs the support for decision-making when facing uncertainty. Uncertainty is associated with inadequate information related to decision-making. The information extracted from big data can mitigate uncertainty [11]. This information can be processed and analyzed by using big data analytics. Moreover, the business strategies of most organizations are frequently a combination of their intended strategies and emergent strategies [39]. Firm leaders need to analyze the process of emergence and make strategy adjustments when appropriate [40]. For this purpose, big data analytics could also serve as the tool to facilitate strategic decisions to be accurately aligned with competition changes [41, 42].

Big data analytics with the 3Vs (Volume + Velocity + Variety) provides a clear picture of product use, showing which features customers prefer or dislike by means of the big data collected from customer. An example is the effects of word of mouth generated by consumers [43, 44]. By analyzing and comparing more dimensions of usage patterns, firms can do much precise customer segmentation. Decision-makers can apply more profound knowledge to tailor special offers or after-sale service packages, create features for specific segments, and develop more sophisticated pricing strategies that better match price and value at the individual customer level [45]. These price and value analytics further forms the basis for decisions of differentiation and cost structure.

For a firm pursuing a cost leadership strategy, cost analytics of all levels can facilitate a viable leading cost structure. For a firm pursuing a differentiation strategy, customer preference analytics helps differentiate the offerings at a competitive price [43].

In summary, we propose the following hypotheses:

H2a. Cost leadership strategy is positively associated with big data analytics adoption.

H2b. Differentiation strategy is positively associated with big data analytics adoption.

2.4 Supply Chain Competence and Big Data Analytics

Supply chain operations generate and utilize large-scale heterogeneous data with time-varying nature [46]. The timely and accurate flow of information is a necessity for successful supply chain operations [47]. The evolution of big data analytics is expected to transform enterprises' managerial paradigm, including supply chain management [17]. Previous studies suggest that IT advancement and IT alignment can facilitate the development of supply chain competence [48-51]. These results lead to the further investigation of the association between supply chain competence and big data analytics [17, 52]. The association between supply chain competence and big data analytics adoption has become a crucial topic to both academics and practitioners [16]. For enterprises, big data analytics adoption may facilitate and enhance information processing and exchange. Big data analytics can undertake real-time and complex analytics of vast amounts of operational data to help enterprises perform decision-making within a critical timeframe [53]. The 3Vs capability of big data analytics can respond to the requirement of supply chain operations [1, 17]. Therefore, big data analytics adoption in a firm is expected to produce significant results for supply chain competence enhancement.

The competence of supply chain operations mainly centers around time efficiency, cost efficiency, and flexibility [54, 55]. The time efficiency in the supply chain includes reducing lead time, response time, and delivery time. The cost efficiency in the supply chain comprises lowering the costs of materials, inventory, distribution and transportation, and information exchange among various sites. The flexibility of the supply chain is enhanced by instant adjustment to changes of customer requirements, supplier and distributor conditions, and contingent events such as natural disasters [54, 55].

The 3Vs capability of big data is desired for efficient supply chain operations. The efficiency in supply chain operations is supported by the prompt interchange of status data among parties participating in the supply chain. As the supply chain competence keeps enhancing, data volume may grow from more detailed information regarding price, quantity, items sold, time of day, date, customer data, and inventory at more locations and a more dispersed level. Data velocity also increases because of the frequent updates of sales orders, inventory status, and transportation time. Data variety is amplified since the attributes of products, channels of procurement, and methods of delivery become more versatile [56]. The 3Vs of big data are further magnified by other emerging technologies such as cloud computing, RFID, and the Internet of Things adopted for supply chain competence [57-59]. Thus to pursue supply chain competence, firms will intend to use big data analytics.

Therefore, the hypothesis of this research suggests that:

H3. Supply chain competence is positively associated with big data analytics adoption.

2.5 Research Model

Based on the hypotheses proposed above, the research model is illustrated in Figure 1.

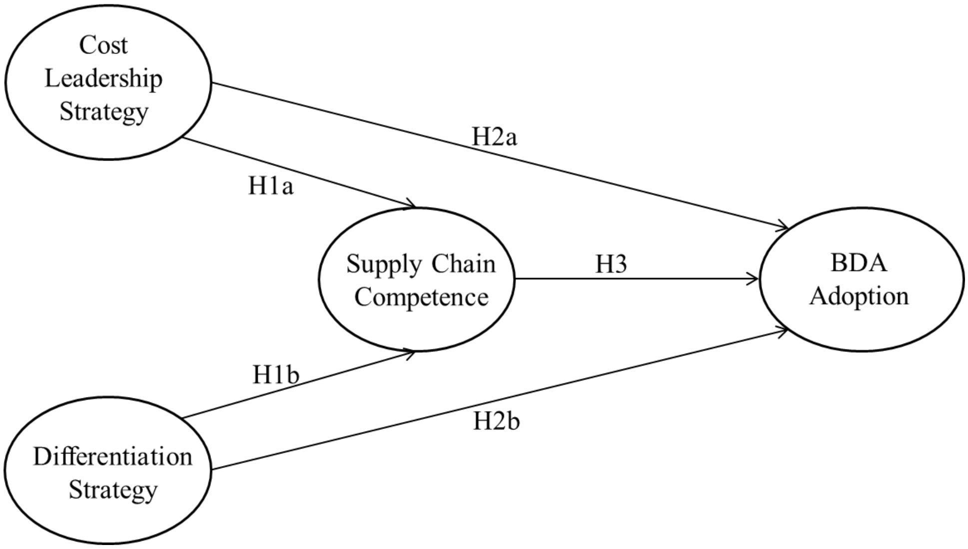

Figure 1. Research model

3. RESEARCH METHOD

3.1 Survey Instrument

The survey instrument was developed using questions derived from the literature on Porter's competitive strategies, the supply chain competence framework, and big data analytics utilization discussed previously. We operationalized the study variables by using multi-item reflective measures on a 7-point scale [60].

The construct of cost leadership strategy pursuit was measured using four items that reflect the extent to which a firm pursues a cost-oriented strategy. First, cost leadership refers to higher margins than those of competitors by achieving lower operation costs. Firms with a cost leadership strategy often have highly stable product lines and a strong emphasis on profit and budget controls [31]. Second, pursuing cost leadership is often reflected in price competitiveness [61, 62]. The third item was the economic scale. A firm can gain a cost advantage through economies of scale or superior manufacturing processes [28, 30]. Finally, larger firms with greater access to resources are more likely to take advantage of cost leadership strategy through lower-cost products. In contrast, smaller firms are often forced to compete using highly differentiated products and services in a niche market [63].

The differentiation strategy pursuit construct was measured using four items that reflect the extent to which a firm pursues a differentiation strategy. Differentiation entails being unique or distinct from competitors, for example, by providing superior information, prices, distribution channels, and prestige to the customer [28]. Differentiation prevents a business from competitive rivalry, insulating it from competitive forces that reduce margins [64]. Extending Porter's competitive strategy discussions, Miller [31] distinguished differentiation based on innovation from marketing. These propositions provide two items in the construct. Moreover, differentiation strategies based on innovation may create a dynamic environment for a distinct business model that is difficult for competitors to predict and react. This item may provide the innovator a substantial advantage over its competitors [31, 62].

The construct of supply chain competence was measured using six items. Respondents rated their intensity of pursuing supply chain competence over the time frame of the past few years. Beamon [54] proposed a framework for measuring supply chain competence. The framework included measuring resources, output, and flexibility as the strategic goals of supply chain operations. The key measuring variables included cost, activity time, customer responsiveness, and flexibility. These variables are direct and observable measures of supply chain competence. Firms achieve supply chain competence by lowering operational costs, reducing inventory, promoting flexibility, ensuring on-time deliveries, and minimizing critical resources shortages. These items therefore provide the measures of supply chain competence [46, 55].

The big data analytics adoption construct served as the dependent variable and was measured using three items by the subjects' responses to whether they would adopt big data analytics for their respective firm within one year. To facilitate this measurement, we followed the guidelines established by Ajzen [65] and adapted items employed by Venkatesh and Bala [66]. These items measure user intention in the context of the technology acceptance model [67].

All items for this study were assessed with a 7-point Likert scale ranging from "strongly disagree" to "strongly agree." Moreover, we use firm size, IT department size, and industry sector as control variables, as these factors have been noted in previous studies to affect intention to adopt information technologies [68, 69]. Table 1 presents the items used to measure each of the independent and dependent construct variables.

Table 1. Constructs and items used in the survey

Construct and item description (1 – strongly disagree; 7 – strongly agree)
CLS: Cost leadership strategy
CLS1: We provide low-cost products or services based on operational efficiency.
CLS2: We deliver products or services at lower prices than competitors.
CLS3: We provide products or services with an economy of scale.
CLS4: We develop our products or services at a lower cost than our competitors.
DFS: Differentiation strategy
DFS1: We deliver products or services with a distinctive business model.
DFS2: We differentiate our products or services based on innovation.
DFS3: We deliver products or services with superior functionality to our competitors.
DFS4: We differentiate our products or services based on effective marketing.
SCC: Supply chain competence
SCC1: We deliver products or services on time.
SCC2: Reducing lead time is crucial to us in our supply chain operations.
SCC3: We respond promptly to changes in customer requirements.
SCC4: Lack of critical resources is effectively avoided in our supply chain operations.
SCC5: Inventory and logistics flexibility is above average in our supply chain operations.
SCC6: Reducing the cost of our supply chain operations is vital to us.
BDA: Big data analytics adoption
BDA1: If we can adopt any big data analytics for our company, we will do so.
BDA2: If we have access to any big data analytics, we will use it.

BDA3: My company is using or plans to use big data analytics within one year.

Control Variables (rescaled)

Firm Size: Total number of employees.

IT Size: Total number of IT staff.

Industry: Industry sectors of firms. 1 for service firms and 0 for manufacturing firms.

3.2 Sample and Data Collection

Empirical data for testing the hypothesized relationships were obtained by surveying large Taiwanese companies. A questionnaire developed following Table 2 was implemented as the survey instrument. It was pretested iteratively among a sample of 15 executives and managers. The questionnaire items were revised based on the results of the expert interviews and refined through pretesting to establish content validity. The pretesting focused on instrument clarity, wording, and validity. During the pretesting, participants were invited to comment on the questionnaire. The comments of these respondents then provided a basis for revisions to the construct measures.

A Taiwanese market research organization publishes comprehensive data of the 1,000 largest corporations in Taiwan with international operations. Most of these companies are publicly listed corporations with global transactions. After the pretesting and revision, survey invitations and the questionnaires were mailed to these 1,000 companies. Follow-up letters were sent approximately 15 days after the initial mailing. Data were collected through responses from executives and managers of the companies. Data collection was completed in two months.

In total, 209 valid questionnaires were obtained, with a valid response rate of 20.9%. We compared respondent and non-respondent firms in terms of industry, size (number of employees), and revenue. These comparisons did not show any significant differences, suggesting no response bias. Table 2 shows the profile of the final sample list.

Table 2. Profile of the final sampling firms

	Sample size	Percentage
Industry		
Manufacturing	108	51.7
Services	101	48.3
Total	209	100.0
	Sample size	Percentage
Under 100	48	23.0
100-199	49	23.4
200-499	66	31.6
500 and above	46	22.0
Total	209	100.0
IT department size		
Under 5	71	30.0
5-19	84	40.2
20 and above	54	25.8
Total	209	100.0

4. RESULTS

The collected data were compiled and analyzed using the SPSS software package. Partial least square structural equation modeling (PLS-SEM) was performed using the SmartPLS package for hypothesis testing [70].

4.1 Reliability and Validity

Table 3 summarizes the descriptive statistics and results of the reliability and validity tests. The reliability of the instrument was examined using composite reliability estimates by employing Cronbach's α. All the coefficients exceeded Nunnally's recommended level (0.70) of internal consistency [71]. Moreover, factor analysis was performed to confirm the construct validity. The results supported the constructs of our research model. The discriminant validity was confirmed since items for each construct loaded on to single factors with all loadings greater than 0.8. These results demonstrate that each construct in our hypothesized model is unidimensional and factorially distinct.

Table 3. Descriptive statistics with reliability and validity

Construct	Item	Mean	SD	Cronbach's alpha	Cronbach's alpha if item deleted	Factor loading on single factor
CLS	CLS1	3.732	1.518	0.868	0.816	0.851
	CLS2	3.598	1.445		0.844	0.842
	CLS3	3.900	1.402		0.862	0.817
	CLS4	3.804	1.346		0.801	0.875
DFS	DFS1	4.574	1.371	0.873	0.843	0.836
	DFS2	4.416	1.342		0.860	0.818
	DFS3	4.335	1.585		0.831	0.858
	DFS4	4.225	1.462		0.811	0.893
SCC	SCP1	4.517	1.445	0.911	0.898	0.819
	SCP2	4.789	1.321		0.902	0.797
	SCP3	4.632	1.324		0.889	0.867
	SCP4	4.579	1.328		0.892	0.849
	SCP5	4.445	1.457		0.898	0.828
	SCP6	4.550	1.400		0.894	0.842
BDA	BDA1	3.766	1.450	0.734	0.675	0.801
	BDA2	4.455	1.337		0.585	0.859
	BDA3	4.421	1.521		0.686	0.767

Table 4 summarizes the correlations among different factors. We also assessed discriminant validity based on the construct correlation that Campbell and Fiske [72] proposed. The diagonal values are the square root of AVE (average variance extracted), which should exceed the inter-construct correlations for adequate discriminant validity. The tests indicated acceptable results concerning discriminant validity.

Table 4. Construct correlation

Construct	1	2	3	4	5	6	7
1. CLS	**0.846**						
2. DFS	0.616	**0.852**					
3. SCC	0.619	0.671	**0.834**				
4. BDA	0.781	0.712	0.724	**0.810**			
5. Industry	-0.124	-0.099	-0.099	-0.076	1.000		
6. Firm Size	0.028	0.002	-0.013	0.111	-0.028	1.000	
7. IT Size	-0.011	-0.020	-0.021	0.037	-0.246	0.302	1.000

4.2 Tests of Hypotheses

Table 5 lists the quality indicators of the PLS model. The AVE (average variance extracted) values of the four variables are all above 0.50, indicating the acceptable explanation powers of the four latent variables towards their measuring items [73]. The composite reliability values are all above 0.7. The values of R^2 of the two endogenous latent variables show medium predictability. The VIF (variance inflation factor) values of CLS and DFS are both less than 5.0, indicating low collinearity between the two variables [73].

The computation results of the PLS model using the partial least square algorithm is shown in Figure 2.

Table 5. Quality indicators of the PLS model

Variable	AVE	Composite Reliability	R Square	VIF
CLS	0.717	0.910		1.610
DFS	0.725	0.913		1.610
SCC	0.695	0.932	0.518	
BDA	0.656	0.851	0.745	

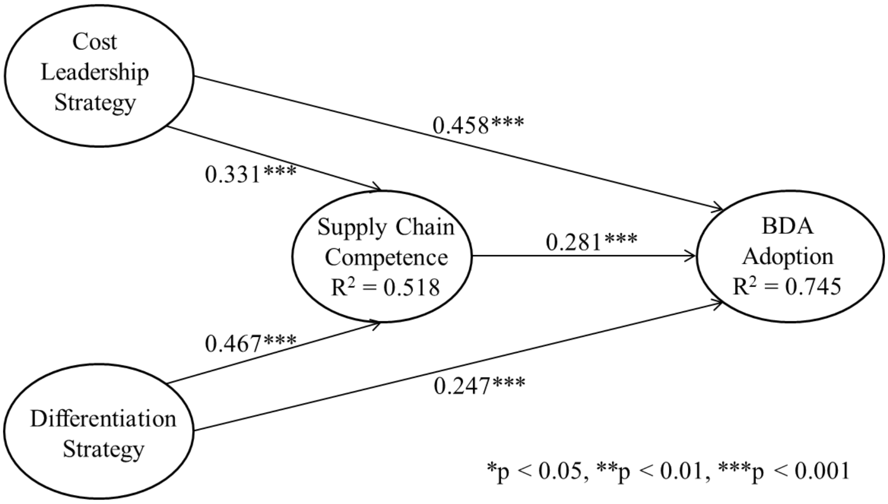

Figure 2. PLS-SEM computation result

Table 6 shows the significance test results of the path coefficients in the PLS model using bootstrapping. All of the path coefficients in the PLS model are tested as significant.

Table 6 Significance tests of path coefficients

Path	Path coefficient	t value	p value
CLS → SCC	0.331	5.351	0.000***
DFS → SCC	0.467	6.778	0.000***
CLS → BDA	0.458	9.228	0.000***
DFS → BDA	0.247	3.823	0.000***
SCC → BDA	0.281	3.643	0.000***

*p < 0.05, **p < 0.01, ***p < 0.001

The causal effects of paths in Figure 1 are summarized in Table 7.

Table 7. Causal effects of paths in the hypothesized model

Hypothesis	Path	Test results
H1a	CLS → SCC	Direct effect supported
H1b	DFS → SCC	Direct effect supported
H2a	CLS → BDA	Direct effect supported
H2b	DFS → BDA	Direct effect supported
H3	SCC → BDA	Direct effect supported

5. DISCUSSION AND CONCLUSIONS

5.1 Research Implications

This study investigated the impact of a firm's business strategy on big data analytics adoption and the role of supply chain competence. Supporting the research hypotheses, the first critical insight we obtained from our empirical results is that the link between a firm's business strategy and its big data analytics adoption was significant. This result is observed for both cost leadership strategy and differentiation strategy. This result provides a valuable reference for firms making strategic decisions in adopting innovative information technologies.

Our findings also provide evidence that for both cost leadership strategy and differentiation strategy, there is a positive relationship between the business strategy and supply chain competence. This result provides the empirical evidence on the relationship between business strategies and functional competences [74-76]. A managerial interpretation is that a firm's business strategy pursuit leads its functional-level operations with an extensive competence objective, clear motivation, and planned strategic goal [77, 78]. This goal could be cost oriented or differentiation oriented, or a combination of the two [32, 33, 79]. To reach this goal, functional-level operations will pursue competence through adopting decision-support tools such as big data analytics.

The third observation is that the direct effect of supply chain competence on big data analytics adoption intention was positive and significant. This result suggests that supply chain competence also has a direct impact on big data adoption. From the information processing view [10, 11], this finding indicates that the perceived complexity and uncertainty for supply chain operations are significant for firms [17]. The information requirement involved may impel firms for big data analytics adoption. A managerial implication here is that a supply chain operation unit of a firm is good at understanding the outside environment because of its collaboration with the other organizations participating in the supply chain. Therefore, a supply chain operation unit is vital for a firm to make its strategic decisions fit with its surroundings, including technology adoption decisions. The supply chain competence is thus a significant factor for big data analytics adoption.

In conclusion, innovative information technologies are essential to the success of business strategies and operational competences. However, past studies have not provided sufficient analysis of the interrelationships among them. Moreover, big data analytics has emerged in recent years and its adoption decision factors remain unclear. Through the analysis performed, this study has made contributions in the following perspectives: (1) linking competitive strategy theory, core competence theory, and organizational information processing theory with big data analytics adoption; (2) defining the measurable variables for the linked abstract constructs; (3) investigating the interrelationship among business strategies, supply chain competence, and big data analytics; (4) demonstrating information processing view for strategic uncertainties as an effective thinking in supporting the exploration of the cause and effect relationship in a technology adoption decision problem; (5) interpreting the empirical results based on the theories and providing insightful implications accordingly.

5.2 Study Limitations and Further Research

This study reported meaningful implications regarding the development of multidimensional measures of factors that influence big data analytics adoption. However, it should be realized that the validity of an instrument cannot be firmly established based on a single study. In this study, empirical data used for tests were collected from large firms based in Taiwan with worldwide operations. Therefore, practitioners and researchers are suggested to interpret our findings as a reference model and be cautious when generalizing our measures to other emerging technologies or industry circumstances.

Further research efforts which focus on collecting more empirical evidence for assessing and validating firm data are recommended to overcome the limitations of the present study. Such research is suggested to address how other emerging technologies are related to business strategies and functional operations. For example, mobile big data has received inadequate attention from strategic considerations and technology adoption theories [7, 8, 80]. These efforts should involve studies identifying the factors which affect business operations, information processing, and strategy formation. The analysis of such data may enable conclusions to be drawn about more generalized relationships among business strategies, functional competences, and innovative technology adoption.

6. REFERENCES

[1] A. McAfee, and E. Brynjolfsson, "Big data - The management revolution," *Harvard Business Review,* vol. 90, no. 10, pp. 60-68, 2012.

[2] S. Fosso Wamba, S. Akter, A. Edwards, G. Chopin, and D. Gnanzou,

"How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study," *International Journal of Production Economics,* vol. 165, pp. 234-246, 2015.

[3] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, and S. Ullah Khan, "The rise of "big data" on cloud computing: Review and open research issues," *Information Systems,* vol. 47, pp. 98-115, 2015.

[4] W. H. Weng, and W. T. Lin, "Development trends and strategy planning in big data industry," *Contemporary Management Research,* vol. 10, no. 3, pp. 203-214, 2014.

[5] W. H. Weng, and W. T. Lin, "A Big Data technology foresight study with scenario planning approach," *International Journal of Innovation in Management,* vol. 1, no. 2, pp. 41-52, 2013.

[6] W. H. Weng, and W. T. Lin, "Development assessment and strategy planning in cloud computing industry," *International Journal of Electronic Commerce Studies,* vol. 5, no. 2, pp. 257-266, 2014.

[7] W. H. Weng, and W. T. Lin, "A mobile computing technology foresight study with scenario planning approach," *International Journal of Electronic Commerce Studies,* vol. 6, no. 2, pp. 223-232, 2015.

[8] W. H. Weng, and W. T. Lin, "A scenario analysis of wearable interface technology foresight," in The International Conference on Electronic Business (ICEB), Taipei, 2014, pp. 8-15.

[9] D. Agrawal, S. Das, and A. E. Abbadi, "Big data and cloud computing: Current state and future opportunities," in ACM EDBT, Uppsala, Sweden, 2011.

[10] J. R. Galbraith, "Organization design: an information processing view," *Interfaces,* vol. 4, no. 3, pp. 28-36, 1974.

[11] M. L. Tushman, and D. A. Nadler, "Information processing as an integrating concept in organizational design," *Academy of Management Review,* vol. 3, no. 3, pp. 613-624, 1978.

[12] H. A. Smith, J. D. McKeen, and S. Singh, "Developing information technology strategy for business value," *Journal of Information*

Technology Management, vol. 18, no. 1, pp. 49-58, 2007.

[13] C. M. Koo, C. E. Koh, and K. Nam, “An examination of Porter's competitive strategies in electronic virtual markets: A comparison of two on-line business models,” *International Journal of Electronic Commerce,* vol. 9, no. 1, pp. 163-180, 2004.

[14] M. E. Porter, and V. E. Millar, “How information gives you competitive advantage,” *Harvard Business Review,* vol. 63, no. 4, pp. 61-78, July/August, 1985.

[15] S. Li, B. Ragu-Nathan, T. S. Ragu-Nathan, and S. Subba Rao, “The impact of supply chain management practices on competitive advantage and organizational performance,” *Omega,* vol. 34, no. 2, pp. 107-124, 2006.

[16] B. T. Hazen, C. A. Boone, J. D. Ezell, and L. A. Jones-Farmer, “Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications,” *International Journal of Production Economics,* vol. 154, pp. 72-80, 2014.

[17] M. A. Waller, and S. E. Fawcett, “Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management,” *Journal of Business Logistics,* vol. 34, no. 2, pp. 77-84, 2013.

[18] P. Bharati, and A. Chaudhury, “Assimilation of big data Innovation: Investigating the roles of IT, social media, and relational capital,” *Information Systems Frontiers,* vol. 21, no. 6, pp. 1357-1368, 2019.

[19] J. Shirish, D. Rameshwar, C. S. J., P. Thanos, R. David, and P. Anand, “Impact of big data and predictive analytics capability on supply chain sustainability,” *The International Journal of Logistics Management,* vol. 29, no. 2, pp. 513-538, 2018.

[20] Y. Wang, L. Kung, W. Y. C. Wang, and C. G. Cegielski, “An integrated big data analytics-enabled transformation model: Application to health care,” *Information & Management,* vol. 55, no. 1, pp. 64-79, 2018.

[21] V. Borkar, M. Carey, and C. Li, “Inside "big data management":

Ogres, onions, or parfaits?," in ACM EDBT/ICDT Joint Conference, Berlin, Germany, 2012.

[22] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quarterly,* vol. 36, no. 4, pp. 1165-1188, 2012.

[23] R. F. Babiceanu, and R. Seker, "Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook," *Computers in Industry,* vol. 81, pp. 128-137, 2016.

[24] J. Shafer, S. Rixner, and A. L. Cox, "The hadoop distributed filesystem: Balancing portability and performance," in Performance Analysis of Systems & Software (ISPASS), 2010 IEEE International Symposium on, White Plains, NY, USA, 2010, pp. 122-133.

[25] D. Glushkova, P. Jovanovic, and A. Abelló, "Mapreduce performance model for Hadoop 2.x," *Information Systems,* vol. 79, pp. 32-43, 2017.

[26] M. Stonebraker, "SQL databases vs NoSQL databases," *Communications of the ACM,* vol. 53, no. 4, pp. 10-11, 2010.

[27] M. Gupta, and J. F. George, "Toward the development of a big data analytics capability," *Information & Management,* vol. 53, no. 8, pp. 1049-1064, 2016.

[28] M. E. Porter, *Competitive strategy*, New York: Free Press, 1980.

[29] A. Miller, and G. G. Dess, "Assessing Porter's (1980) model in terms of generalizability, accuracy, and simplicity.," *Journal of Management Studies,* vol. 30, no. 4, pp. 553-585, 1993.

[30] M. E. Porter, *Competitive advantage*, New York: Free Press, 1985.

[31] D. Miller, "Relating porter's business strategies to environment and structure: analysis and performance implications," *Academy of Management Journal,* vol. 31, no. 2, pp. 280-308, 1988.

[32] C. V. L. Hill, "Difierentiation versus low cost or differentiation and low cost: A contingency framework," *Academy of Management Review,* vol. 13, no. 3, pp. 401-412, 1988.

[33] A. I. Murray, “A contingency view of Porter's "generic strategies",” *Academy of Management Review,* vol. 13, no. 3, pp. 390-400, 1988.

[34] B. Huo, Y. Qi, Z. Wang, and X. Zhao, “The impact of supply chain integration on firm performance,” *Supply Chain Management: An International Journal,* vol. 19, no. 4, pp. 369-384, 2014.

[35] A. Lockamy, and K. McCormack, “Linking SCOR planning practices to supply chain performance,” *International Journal of Operations & Production Management,* vol. 24, no. 12, pp. 1192-1218, 2004.

[36] S. H. Huan, S. K. Sheoran, and G. Wang, “A review and analysis of supply chain operations reference (SCOR) model,” *Supply Chain Management: An International Journal,* vol. 9, no. 1, pp. 23-29, 2004.

[37] S. M. Wagner, P. T. Grosse-Ruyken, and F. Erhun, “The link between supply chain fit and financial performance of the firm,” *Journal of Operations Management,* vol. 30, no. 4, pp. 340-353, 2012.

[38] E. Claver-Cortés, E. M. Pertusa-Ortega, and J. F. Molina-Azorín, “Characteristics of organizational structure relating to hybrid competitive strategy: Implications for performance,” *Journal of Business Research,* vol. 65, no. 7, pp. 993-1002, 2012.

[39] H. Mintzberg, “Strategy formation in an adhocracy,” *Administrative Science Quarterly,* vol. 30, no. 2, pp. 160-197, 1985.

[40] H. Mintzberg, and J. A. Waters, “Of strategies, deliberate and emergent,” *Strategic Management Journal,* vol. 6, no. 3, pp. 257-272, 1985.

[41] M. Janssen, H. van der Voort, and A. Wahyudi, “Factors influencing big data decision-making quality,” *Journal of Business Research,* vol. 70, pp. 338-345, 2017.

[42] S. Akter, S. F. Wamba, A. Gunasekaran, R. Dubey, and S. J. Childe, “How to improve firm performance using big data analytics capability and business strategy alignment?,” *International Journal of Production Economics,* vol. 182, pp. 113-131, 2016.

[43] K. Xie, Y. Wu, J. Xiao, and Q. Hu, "Value co-creation between firms and customers: The role of big data-based cooperative assets," *Information & Management,* vol. 53, no. 8, pp. 1034-1048, 2016.

[44] A. H. Wien, and S. O. Olsen, "Producing word of mouth – a matter of self-confidence? Investigating a dual effect of consumer self-confidence on WOM," *Australasian Marketing Journal (AMJ),* vol. 25, no. 1, pp. 38-45, 2017.

[45] J. Qi, Z. Zhang, S. Jeon, and Y. Zhou, "Mining customer requirements from online reviews: A product improvement perspective," *Information & Management,* vol. 53, no. 8, pp. 951-963, 2016.

[46] A. Gunasekaran, C. Patel, and E. Tirtiroglu, "Performance measures and metrics in a supply chain environment," *International Journal of Operations & Production Management,* vol. 21, no. 1/2, pp. 71-87, 2001.

[47] A. White, E. M. Daniel, and M. Mohdzain, "The role of emergent information technologies and systems in enabling supply chain agility," *International Journal of Information Management,* vol. 25, no. 5, pp. 396-410, 2005.

[48] F. Wu, S. Yeniyurt, D. Kim, and S. T. Cavusgil, "The impact of information technology on supply chain capabilities and firm performance: A resource-based view," *Industrial Marketing Management,* vol. 35, no. 4, pp. 493-504, 2006.

[49] L. R. Vijayasarathy, "An investigation of moderators of the link between technology use in the supply chain and supply chain performance," *Information & Management,* vol. 47, no. 7-8, pp. 364-371, 2010.

[50] S. Qrunfleh, and M. Tarafdar, "Supply chain information systems strategy: Impacts on supply chain performance and firm performance," *International Journal of Production Economics,* vol. 147, pp. 340-350, 2014.

[51] S. E. DeGroote, and T. G. Marx, "The impact of IT on supply chain agility and firm performance: An empirical investigation,"

International Journal of Information Management, vol. 33, no. 6, pp. 909-916, 2013.

[52] T. Schoenherr, and C. Speier-Pero, "Data science, predictive analytics, and big data in supply chain management: Current state and future potential," *Journal of Business Logistics,* vol. 36, no. 1, pp. 120-132, 2015.

[53] R. E. Bryant, R. H. Katz, and E. D. Lazowska, "Big-data computing: Creating revolutionary breakthroughs in commerce, science, and society," in Computing Research Initiatives for the 21st Century, 2008.

[54] B. M. Beamon, "Measuring supply chain performance," *International Journal of Operations & Production Management,* vol. 19, no. 3, pp. 275-292, 1999.

[55] A. Gunasekaran, C. Patel, and R. E. McGaughey, "A framework for supply chain performance measurement," *International Journal of Production Economics,* vol. 87, no. 3, pp. 333-347, 2004.

[56] S. Robak, B. Franczyk, and M. Robak, "Applying big data and linked data concepts in supply chains management," in Proceedings of the 2013 Federated Conference on Computer Science and Information Systems, Krakow, Porland, 2013, pp. 1215 - 1221.

[57] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Computer Networks,* vol. 54, no. 15, pp. 2787-2805, 2010.

[58] C. G. Cegielski, L. Allison Jones-Farmer, Y. Wu, and B. T. Hazen, "Adoption of cloud computing technologies in supply chains: An organizational information processing theory approach," *The International Journal of Logistics Management,* vol. 23, no. 2, pp. 184-211, 2012.

[59] R. Angeles, "RFID technologies: Supply-chain applications and implementation issues," *Information Systems Management,* vol. 22, no. 1, pp. 51-65, 2005.

[60] C. B. Jarvis, S. B. MacKenzie, and P. M. Podsakoff, "A critical review of construct indicators and measurement model misspecification in marketing and consumer research," *Journal of*

Consumer Research, vol. 30, no. 2, pp. 199-218, 2003.

[61] G. G. Dess, and P. S. Davis, “Porter's (1980) generic strategies as determinants of strategic group membership and organizational performance,” *Academy of Management Journal,* vol. 27, no. 3, pp. 467-488, 1984.

[62] R. B. Robinson, and J. A. Pearce, “Planned patterns of strategic behavior and their relationship to business-unit performance,” *Strategic Management Journal,* vol. 9, no. 1, pp. 43-60, 1988.

[63] P. Wright, “A refinement of Porter’s generic strategies,” *Strategic Management Journal,* vol. 8, pp. 93-101, 1987.

[64] S. Kotha, and B. L. Vadlamani, “Assessing generic strategies: An empirical investigation of two competing typologies in discrete manufacturing industries,” *Strategic Management Journal,* vol. 16, no. 1, pp. 75-83, 1995.

[65] I. Ajzen, “The theory of planned behavior,” *Organizational Behavior and Human Decision Processes,* vol. 50, no. 2, pp. 179-211, 1991.

[66] V. Venkatesh, and H. Bala, “Technology acceptance model 3 and a research agenda on interventions,” *Decision Sciences,* vol. 39, no. 2, pp. 273-315, 2008.

[67] F. D. Davis, “Perceived usefulness, perceived ease of use, and user acceptance of information technology,” *MIS Quarterly,* vol. 13, no. 3, pp. 319-340, 1989.

[68] H. Liu, W. Ke, K. K. Wei, J. Gu, and H. Chen, “The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems,” *Journal of Operations Management,* vol. 28, no. 5, pp. 372-384, 2010.

[69] H. H. Teo, K. K. Wei, and I. Benbasat, “Predicting intention to adopt interganizaitonal linkages: An institutional perspective,” *MIS Quarterly,* vol. 27, no. 1, pp. 19-49, 2003.

[70] C. M. Ringle, S. Wende, and A. Will, *SmartPLS 2.0. M3. Hamburg: SmartPLS*, 2005.

[71] J. C. Nunnally, and I. H. Bernstein, *Psychometric Theory*, 3 ed., New York: McGraw-Hill, 1994.

[72] D. Campbell, T., and D. Fiske, W., “Convergent and discriminant validation by the multitrait-multimethod matrix,” *Psychological Bulletin,* vol. 56, no. 2, pp. 81-105, 1959.

[73] J. F. Hair Jr, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*: Sage publications, 2016.

[74] M. Pagell, and D. R. Krause, “Strategic consensus in the internal supply chain: Exploring the manufacturing–purchasing link,” *International Journal of Production Research,* vol. 40, no. 13, pp. 3075-3092, 2002.

[75] F. P. Williams, D. E. D'Souza, M. E. Rosenfeldt, and M. Kassaee, “Manufacturing strategy, business strategy and firm performance in a mature industry,” *Journal of Operations Management,* vol. 13, no. 1, pp. 19-33, 1995.

[76] M. K. Nandakumar, A. Ghobadian, and N. O'Regan, “Generic strategies and performance - evidence from manufacturing firms,” *International Journal of Productivity and Performance Management,* vol. 60, no. 3, pp. 222-251, 2011, 2011.

[77] Y. H. Kim, F. J. Sting, and C. H. Loch, “Top-down, bottom-up, or both? Toward an integrative perspective on operations strategy formation,” *Journal of Operations Management,* vol. 32, no. 7, pp. 462-474, 2014.

[78] P. R. Varadarajan, S. Jayachandran, and J. C. White, “Strategic interdependence in organizations: Deconglomeration and marketing strategy,” *Journal of Marketing,* vol. 65, no. 1, pp. 15-28, Jan 2001, 2001.

[79] C. B. Li, and J. J. L. Li, “Achieving superior financial performance in China: Differentiation, cost leadership, or both?,” *Journal of International Marketing,* vol. 16, no. 3, pp. 1-22, 2008.

[80] W. H. Weng, and W. T. Lin, “Development assessment and strategy planning in mobile computing industry,” in 2014 IEEE International

Conference on Management of Innovation and Technology, Singapore, 2014, pp. 453-457.