Association for Information Systems
AIS Electronic Library (AISeL)

ICEB 2020 Proceedings
International Conference on Electronic Business (ICEB)

Winter 12-5-2020

Impacts of Competitive Uncertainty on Supply Chain Competence and Big Data Analytics Utilization: An Information Processing View

Wei-Hsiu Weng
National Chengchi University, Taiwan, wengvictor@gmail.com

Follow this and additional works at: https://aisel.aisnet.org/iceb2020

Recommended Citation

Weng, Wei-Hsiu, "Impacts of Competitive Uncertainty on Supply Chain Competence and Big Data Analytics Utilization: An Information Processing View" (2020). *ICEB 2020 Proceedings*. 32.
https://aisel.aisnet.org/iceb2020/32

This material is brought to you by the International Conference on Electronic Business (ICEB) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICEB 2020 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Weng, W.H. (2020). Impacts of competitive uncertainty on supply chain competence and big data analytics utilization: An information processing View. In *Proceedings of The 20th International Conference on Electronic Business* (pp. 181-190). ICEB'20, Hong Kong SAR, China, December 5-8.

Impacts of Competitive Uncertainty on Supply Chain Competence and Big Data Analytics Utilization: An Information Processing View

(Full Paper)

Wei-Hsiu Weng*, National Chengchi University, Taiwan, wengvictor@gmail.com

ABSTRACT

Research advancements in big data analytics have invoked tremendous attention from both academics and industries. Many researchers refer that the adoption and application of big data analytics could lead to performance impact to organizations, and therefore further affect organizational adoption intention of this technology. However, few studies discuss the association between business strategy and big data analytics adoption under uncertainty such as pandemics or disasters. Furthermore, the role of firms' functional activities such as supply chain operations has seldom been addressed in the adoption considerations of big data analytics under abnormal situations. In this research, empirical data from enterprises were collected and analyzed to assess the impact of competitive strategy uncertainty on big data analytics adoption and the possible effect of supply chain competence in the linkage. The results supported positive effects of strategy practices and supply chain competence on big data analytics utilization. The implications for management decisions are then elaborated.

Keywords: Big data analytics, information processing view, uncertainty, supply chain competence, competitive strategy.

*Corresponding author

INTRODUCTION

Big data is characterized by scholars and practitioners with three Vs: Volume, or the large amount of data that either consume huge storage or entail of 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 (Fosso Wamba *et al.*, 2015; Hashem *et al.*, 2015; McAfee & Brynjolfsson, 2012). Big data analytics refers to the methods, algorithms, middleware and systems to discover, retrieve, store, analyze and present big data, in order to generate the fourth V: Value for business.

The development of big data analytics is a response 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 (Weng & Lin, 2013, 2014c). Other emerging technologies, such as cloud computing and internet of things, also enhanced the needs of big data analytics (Weng & Lin, 2014a, 2014d, 2015b). 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; as a result, big data analytics and its applications are becoming ever more noticed (Agrawal, Das, & Abbadi, 2011; Hashem *et al.*, 2015).

While the influences of big data analytics on enterprise performance were explored in previous studies (Fosso Wamba *et al.*, 2015), the essential issue of whether firms will adopt big data analytics remains unresolved, and factors associated with enterprise adoption intention of big data analytics have not been comprehensively investigated. Studies of organizational information processing theory (Galbraith, 1974; Tushman & Nadler, 1978) have shown that the uncertainty that firms encounter when formulating and executing business strategy is an important factor for firms' adoption of innovative information technologies (Koo, Koh, & Nam, 2004; Porter & Millar, 1985; Smith, McKeen, & Singh, 2007). This result leads to the speculation that business strategy pursuit is associated with big data analytics adoption intention. However, so far studies of possible relationships between big data analytics adoption and firms' business level strategies are rare in the literature.

Furthermore, when facing uncertain situations such as a global pandemic or a financial turmoil, supply chain competence is particularly noticeable as a possible factor for big data analytics adoption for several reasons (Hazen *et al.*, 2014; Waller & Fawcett, 2013). First, the growing data volume in supply chain operations. This is because supply chain activities need to be collaborated with all other trading partners across corporate boundary, and supply chains need to be integrated with value chains of all participating parties (Cheung, Myers, & Mentzer, 2010; Cook, Heiser, & Sengupta, 2011). Second, the increasing data velocity in supply chain operations. Many organizations are gradually aware of that they must compete, as part of a supply chain against other supply chains, to quickly reflect customers' changing demands (Wu & Chuang, 2010). And third, the expanding data variety in supply chain operations. Supply chain management is closely integrated with more and more other functions such as production, marketing and information systems (Dong, Xu, & Zhu, 2009; Kozlenkova *et al.*, 2015). For these reasons, 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 a review of 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 and recommendations for future work.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Big Data Analytics and Information Processing View

Big data analytics is used to store, convert, transmit and analyze large quantities of dynamic, diversified data, which may be structured or unstructured data, for the purpose of business benefit (Borkar, Carey, & Li, 2012; Chen, Chiang, & Storey, 2012). Big Data processing requires tools and techniques that leverage the combination of various IT resources: processing power, memory, storage, network, and end user devices to access the processed outcomes. Efficient analytical tools are developed to process the large amounts of unstructured heterogeneous data collected continuously in various formats such as text, picture, audio, video, log file and others (Babiceanu & Seker, 2016). Current examples of such tools include the Hadoop Distributed File System (HDFS) (Shafer, Rixner, & Cox, 2010), the parallel processing system MapReduce (Glushkova, Jovanovic, & Abelló, 2017), the non-relational database system NoSQL (Stonebraker, 2010), and others. These tools provide processing functionality for big data which are beyond the application scope of traditional data mining and business analytics tools (Gupta & George, 2016).

Studies of organizational information processing theory (Galbraith, 1974; Tushman & Nadler, 1978) have revealed that the uncertainty that firms confront when pursuing and developing business strategy is an important factor for firms' adoption of innovative information technologies (Koo *et al.*, 2004; Porter & Millar, 1985; Smith *et al.*, 2007). Information processing theory views firms as information processing systems which help firms deal with uncertainty in business decisions and actions. Nowadays, organizations are facing even greater challenge in decision making than before, as the information to be processed is growing rapidly in volume, velocity and variety. This challenge motivated the study and utilization of big data analytics (Bharati & Chaudhury, 2018; Shirish *et al.*, 2018; Wang *et al.*, 2018).

Competitive Uncertainty and Supply Chain Competence

Porter's framework for business strategy of competition is one of the most widely accepted typology of business competition models (A. Miller & Dess, 1993; Porter, 1980). Porter's research in industrial economics suggested two fundamental types of generic business level strategies for achieving above average rates of return: cost leadership and differentiation (Porter, 1980, 1985). Porter proposed that to succeed in business, a firm must pursue one or more of these generic business strategies, and that a firm's strategic choice eventually determines its competitiveness and profitability (D. Miller, 1988). Other scholars argued that the two types of business strategies are not strictly mutual exclusive. Firms adopting cost leadership strategy may seek to deliver distinctive products or services under the main theme of low cost thinking. Firms with differentiation strategy could also attempt low cost operations as long as the uniqueness of products or services is maintained (Hill, 1988; Murray, 1988). Competitive uncertainty triggers firms to adopt contingent and hybrid strategies (Wernerfelt & Karnani, 1987). Competitive uncertainty may be caused by several different types of sources: demand structure, supply structure, competitors and externalities (Wernerfelt & Karnani, 1987). Thus both the supply chain situations of a firm and the external events such as a global pandemic may affect a firm's strategic posture and sustained competitive advantage (Dreyer & Grønhaug, 2004; K.-J. Wu, Tseng, Chiu, & Lim, 2017).

The successful implementation of the business strategies relies on making right decisions 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 (Porter, 1985). A firm's ability to acquire superior functional efficiency, including supply chain competence, will determine if its product offering is differentiated from that of 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 (Hill, 1988; Huo *et al.*, 2014).

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 (Huan, Sheoran, & Wang, 2004; Lockamy & McCormack, 2004). For differentiation strategy, the principal thinking in these operations are geared towards the design and delivery of distinctive products and services. Differentiation may also eventuate in unique methods or channels of sourcing or delivery, in innovative manufacturing processes or inventory operations in a supply chain (Wagner, Grosse-Ruyken, & Erhun, 2012). Thus, the following two hypotheses are proposed:

H1. Cost efficiency under competitive uncertainty is positively associated with supply chain competence.
H2. Differentiation proficiency under competitive uncertainty is positively associated with supply chain competence.

Competitive Uncertainty and Big Data Analytics Utilization

From the information processing view (Galbraith, 1974), an organization is an imperfect decision-making system due to incomplete knowledge. Therefore, firms seek to systematically progress to support decision-making when facing increased uncertainty. Uncertainty is associated with inadequate information related to decision-making. The competitive information extracted from big data comprises information of sales and marketing, research and development, manufacturing and production, finance and accounting, human resources, and similar data from the other competitors (Tushman & Nadler, 1978). This information can be acquired and processed by applying big data analytics. Organizing and leveraging these big data analytics from functional operations up the hierarchy and systematically using it to ascertain the competitive situation along with the formation of business strategies involve the essence of the managerial decisions on competition (Mathews, 2016). Furthermore, business strategies of most organizations are frequently a combination of their intended strategies and the emergent strategies (Mintzberg, 1985). Firm leaders need to analyze the process of emergence and to make strategy adjustment when appropriate (Mintzberg & Waters, 1985). For this purpose, big data analytics could also serve as the tool to facilitate the strategic decisions to be accurately aligned with competition changes (Akter *et al.*, 2016; Janssen, van der Voort, & Wahyudi, 2017).

Big data analytics with the 3Vs (Volume + Velocity + Variety) provides a clear picture of product use, showing instantly which features customers prefer or dislike, by means of the increased volume, velocity and variety of data collected from customer responses. An example is the effects of word of mouth created by a large number of online visitors on consumer's purchase preference for manufacturers and retailers (Wien & Olsen, 2017; Xie *et al.*, 2016). By analyzing and comparing more dimensions of usage patterns, firms can do much precise customer segmentation, by industry, geography, age, income, and even more granular attributes. Decision makers can apply this deeper knowledge to tailor special offers or after-sale service packages, create features for certain segments, and develop more sophisticated pricing strategies that better match price and value at the segment or even the individual customer level (Qi *et al.*, 2016). These price and value analytics further forms the basis for decisions of differentiation and cost structure.

For companies pursuing cost leadership strategy, cost analytics of all levels is more accurately analyzed to maintain a viable leading cost structure. For firms pursuing differentiation strategy, customer preference analytics determines the need to differentiate their products against the need to keep their cost structure under control in order to offer a product at a competitive price (Xie *et al.*, 2016). In summary, we propose the following hypotheses:

H3. Cost efficiency under competitive uncertainty is positively associated with big data analytics utilization intensity.
H4. Differentiation proficiency under competitive uncertainty is positively associated with big data analytics utilization intensity.

Supply Chain Competence and Big Data Analytics Utilization

Supply chain operations generate and utilize large-scale heterogeneous data with time-varying nature (Gunasekaran, Patel, & Tirtiroglu, 2001). The timely and accurate flow of information is a necessity for successful supply chain operations (White, Daniel, & Mohdzain, 2005). The evolution of big data analytics is expected to transform enterprises' managerial paradigm, including supply chain management (Waller & Fawcett, 2013). The relationships between supply chain competence and information technology adoption have been widely studied. The findings suggest that IT advancement and IT alignment can facilitate the development of supply chain competence (DeGroote & Marx, 2013; Qrunfleh & Tarafdar, 2014; Vijayasarathy, 2010; Wu *et al.*, 2006). These results lead to the conjecture of the association between supply chain competence and big data analytics (Schoenherr & Speier-Pero, 2015; Waller & Fawcett, 2013). The possible association between supply chain competence and big data analytics adoption has thus become a crucial topic to both academics and practitioners (Hazen *et al.*, 2014).

The efficiency considerations in supply chain operations mainly centers around time efficiency, cost efficiency and flexibility (Beamon, 1999; Gunasekaran, Patel, & McGaughey, 2004). The time efficiency in supply chain includes reducing lead time, response time and delivery time of products and services. The cost efficiency consideration in supply chain comprises lowering the costs of materials, inventory, distribution and transportation, and information exchange among various sites in supply chain. The flexibility of supply chain is enhanced by instant adjustment to changes from customer requirements, supplier and distributer conditions, and any other possible events such as natural disasters (Beamon, 1999; Gunasekaran *et al.*, 2004).

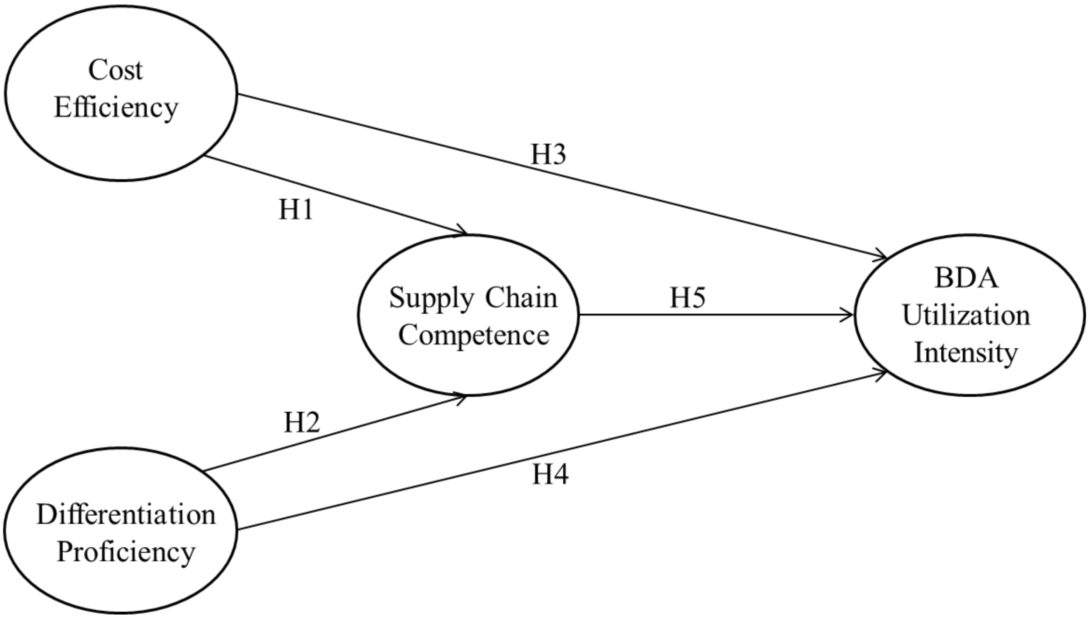
The 3Vs capability of big data is desired for efficient supply chain operations. The efficiency in supply chain operations is supported by prompt interchange of status data among parties participating in the supply chain. As the supply chain competence keep enhancing, data volume may grow from more detailed information regarding price, quantity, items sold, time of day, date, customer data, and inventory at more locations and a more dispersed level. Data velocity is also increased 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 delivering products and services become more versatile (Robak, Franczyk, & Robak, 2013). These 3Vs of big data are also amplified by joining applications of other emerging technologies such as cloud computing, RFID, and Internet of Things in the supply chain (Angeles, 2005; Atzori, Iera, & Morabito, 2010; Cegielski *et al.*, 2012). Thus, to pursue supply chain competence, firms will intend to adopt big data analytics. Therefore, the hypothesis of this research suggests that:

H5. Supply chain competence is positively associated with big data analytics utilization intensity.

METHOD

Research Framework

Based on our proposed hypotheses, the research framework is illustrated in Figure 1. The main constructs for competitive strategy contingency are cost efficiency and differentiation proficiency. Supply chain competence is the construct for functional operations under uncertainty. Big data utilization intensity is the construct for complex information processing to cope with uncertainty. In addition to the main constructs, control variables of firm size, IT department size, and industry sector are included as these variables may affect firms' intention to adopt information technologies.



Source: This study.

Figure 1: Research framework.

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 intensity discussed previously. We operationalized the study variables by using multi-item reflective measures on a 7-point scale (1 – strongly disagree; 7 – strongly agree) (Jarvis, MacKenzie, & Podsakoff, 2003). Table 1 presents the construct and item description.

Table 1: Constructs and items used in the survey.

CEF: Cost efficiency under competitive uncertainty
The construct of cost efficiency under competitive uncertainty (CEF) was measured using four items that reflect the extent to which a firm practices cost efficiency. Cost efficiency refers to the generation of higher margins than those of competitors by achieving lower operation costs. CEF1: Operational efficiency CEF2: Economy of scale CEF3: Learning curve of productivity CEF4: Agility and leanness
DFP: Differentiation proficiency under competitive uncertainty
The differentiation proficiency under competitive uncertainty construct (DFP) was measured using four items that reflect the extent to which a firm conduct differentiation. Differentiation entails being unique or distinct from competitors, for example, by providing superior quality, information, prices, distribution channels, and prestige to the customer. DFP1: Quality DFP2: Innovation DFP3: Customization DFP4: Marketing intelligence
SCC: Supply chain competence

The construct of supply chain competence (SCC) was measured using six items. Respondents rated their strength of supply chain operations. The rating included the measurement of resources, output, and flexibility as the strategic goals of supply chain operations. SCC1: Lead time SCC2: Response time SCC3: Inventory control SCC4: Flexibility SCC5: Supply side relationship SCC6: Demand side relationship
BDA: Big data analytics utilization intensity
The big data analytics utilization intensity construct (BDA) served as the dependent variable and was measured using three items by the subjects' responses to whether, if given the opportunity, they would adopt big data analytics for their respective firm to cope with uncertainty. BDA1: Big data analytics utilization for data volume BDA2: Big data analytics utilization for data velocity BDA3: Big data analytics utilization for data variety
Control Variables
Firm size, IT department size, and industry sector are employed as control variables, as these factors have been noted in several studies to affect the intention to adopt information technologies.

Source: This study.

Sample and Data Collection

Empirical data for testing the hypothesized relationships were obtained by conducting a survey of large Taiwanese companies. A questionnaire developed in accordance with Table 1 was implemented as the survey instrument. It was pretested in an iterative manner among a sample of 15 executives and managers. The questionnaire items were revised on the basis of the results of the expert interviews and refined through pretesting to establish content validity. The pretesting focused on instrument clarity, question wording, and validity. During the pretesting, members of the testing sample were invited to comment on the questions and wording of the questionnaire. The comments of these respondents then provided a basis for revisions to the construct measures.

A marketing research organization publishes comprehensive data of the 1,000 largest corporations in Taiwan. Most of these companies are public 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, 201 valid questionnaires were obtained, with a valid response rate of 20.1%. 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.

RESULTS

Reliability and Validity

To test the hypothesized research model, partial least square - path modeling (PLS-PM) was applied (Ringle, Wende, & Will, 2005). Table 2 reports the quality indicators of the PLS-PM model.

Table 2: Constructs reliability and validity.

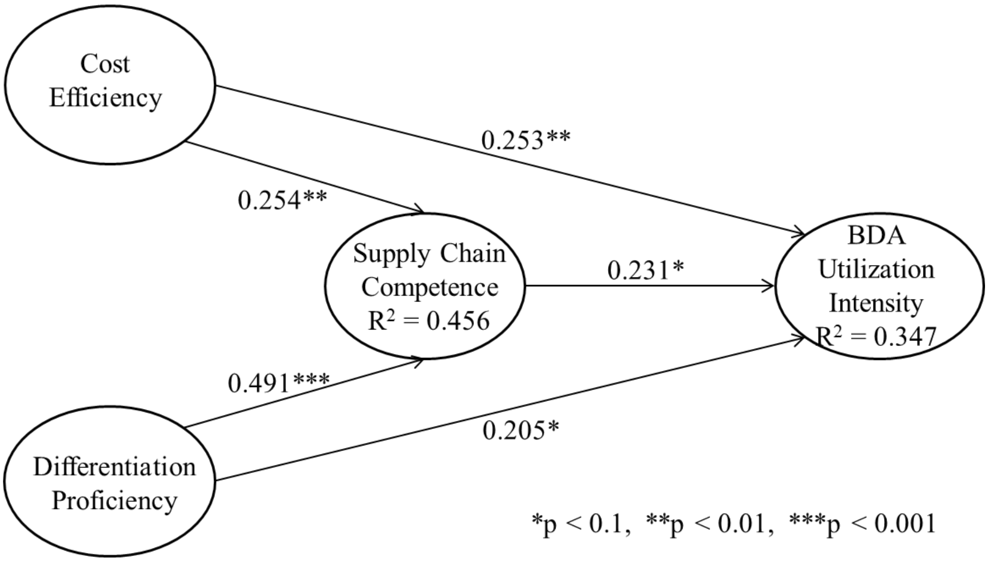
	AVE	CR	CA	VIF	R^2	Latent variable correlations			
						BDA	CEF	DFP	SCC
BDA	0.734	0.892	0.819		0.347	(0.857)			
CEF	0.714	0.909	0.867	1.697		0.504	(0.845)		
DFP	0.727	0.914	0.875	2.022		0.507	0.606	(0.853)	
SCC	0.683	0.928	0.907	1.838	0.456	0.502	0.551	0.644	(0.826)
AVE = average variance extracted, CR = composite reliability, CA = Cronbach's alpha, VIF = variance inflation factor, (···) = square root of AVE									

Source: This study.

Composite reliability scores for all indicators are greater than 0.70 and AVE for all scales exceed 0.50. Thus, the test of convergent validity is acceptable (Nunnally & Bernstein, 1994). The Cronbach's alpha was the assessment of the reliability which was scored as > 0.7. This value indicates that there is a positive internal consistency among latent variables and manifest variables. The VIF values of exogenous latent variables are all less than 5.0, indicating low collinearity among the variables. Successively R2 has been estimated to verify the quantity of variance of endogenous variables in relation to exogenous variables. The value of R2 results as moderate for all endogenous variables.

Tests of Hypotheses

Test results are shown in Figure 2. All of the hypotheses in the research model are tested significant, providing sufficient support to the hypotheses.



Source: This study.

Figure 2: Results of research model.

Table 3 shows the significance test results of the partial effects in the PLS model using bootstrapping. The VAF (variance accounted for) value for the indirect effect DFP → SCC → BDA is between 0.2 and 0.8, which indicate the partial mediation effect of SCC in the link (Hair *et al.*, 2016; Preacher & Hayes, 2008).

Table 3: Significance tests of effects.

Path	Effect type	Effect	t value	p value	* level	VAF
CEF → BDA	Total effect	0.312	4.396	0.000	***	
DFP → BDA	Total effect	0.318	4.206	0.000	***	
CEF → BDA	Effect without SCC	0.319	4.692	0.001	**	
DFP → BDA	Effect without SCC	0.325	4.348	0.000	***	
CEF → SCC → BDA	Indirect effect	0.059	1.800	0.073	*	0.188
DFP → SCC → BDA	Indirect effect	0.113	2.267	0.024	*	0.356

VAF = variance accounted for
*p < 0.1, **p < 0.01, ***p < 0.001

Source: This study.

The effects of paths in the research model are summarized in Table 4.

Table 4: Significance tests of effects.

Hypothesis	path	Effect from test results
H1	CEF → SCC	Direct effect supported
H2	DFP → SCC	Direct effect supported
H3	CEF → BDA	Direct effect supported Partial mediation of SCC not supported
H4	DFP → BDA	Direct effect supported

		Partial mediation of SCC supported
H5	SCC → BDA	Direct effect supported

DISCUSSION AND CONCLUSIONS

This study investigated the impact of a firm's competitive strategy practices on big data analytics adoption, and tested the possible mediating role of supply chain competence. The results validated our hypotheses that both cost efficiency and differentiation proficiency are positively associated with supply chain competence. Competitive strategy practices concern the competitive positioning, market segmentation and industry environment of a company (Porter, 1980). To survive, grow and sustain, a firm needs to constantly monitor its internal and external status for possible changes. Thus the formulation and execution of a business strategy rely heavily on the collection, extraction, analyze, interpretation and prediction on internal and external status data of a company, in order to make accurate managerial decisions (Claver-Cortés, Pertusa-Ortega, & Molina-Azorín, 2012; McAfee & Brynjolfsson, 2012). Since the supply chain unit of a firm is the operation unit which interact with internal and external partners, its role is critical for competitive strategy practices.

The results also indicate that both cost efficiency and differentiation proficiency are positively associated with big data analytics utilization. For enterprises, big data analytics adoption may facilitate and enhance information processing and exchange. Big data analytics can undertake real-time and high-complexity analytics of vast amounts of operational data, to help enterprises perform strategic decision-making within critical timeframe (Bryant, Katz, & Lazowska, 2008). The 3Vs capability of big data analytics is well aligned for responding to the changes of competitive environment (McAfee & Brynjolfsson, 2012; Waller & Fawcett, 2013). Therefore, big data analytics adoption in a firm is expected to produce significant results concerning competitive strategy practices.

The next critical observation is that the direct effect of supply chain competence on big data analytics adoption intention was positive and significant. This suggests that supply chain competence has direct impacts on big data utilization. From the information processing view (Galbraith, 1974; Tushman & Nadler, 1978), this finding indicates that the perceived complexity and uncertainty for supply chain operations are significant for firms (Waller & Fawcett, 2013), and 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 participation and collaboration with the other organizations in the supply chain. Therefore, a supply chain operation unit in a firm becomes critical for a firm to make its strategic decisions fit with its surroundings, including technology adoption decisions. This is particularly critical for uncertain situations such as a disastrous pandemic. As the data volume, data velocity, and data variety in supply chain operations continue advancing under uncertainty, the intensity of big data analytics utilization may also keep growing. The supply chain competence is therefore a significant predictor for big data analytics utilization.

Moreover, our empirical results indicate that the link between a firm's differentiation practice and its big data analytics use was partially mediated by the supply chain competence of the firm. This result is not observed for cost efficiency practice. In other words, the link between differentiation and big data analytics adoption is not only direct, but also indirect. This finding suggests that the supply chain management department of a firm may play a key role in the use of big data analytics for differentiation practices. This result provides a valuable reference for firms making management decision on adopting innovative information technologies. This also demonstrates that the complexity of a multi-faceted differentiation practice is more complicated for firms to perform than a cost efficiency practice, and thus required stronger supports of supply chain operations with big data analytics capability.

Further research efforts which focus on collecting more empirical evidences for assessing and validating firm data are recommended to extend the present study. Such research is suggested to address how other emerging technologies relate to business strategies and functional operations. For example, emerging technologies such as internet of things (IoT) (Weng & Lin, 2015a) and augmented reality (AR) (Weng & Lin, 2014d) have received inadequate attention from strategic considerations and technology adoption theories (Weng & Lin, 2014b, 2014d, 2015b). In addition, special attention could be focused on data collected in various sub-industries or specific contexts over an extended period of time. The analysis of such data may enable conclusions to be drawn about more generalized relationships among business level strategies, functional level strategies, and innovative technology adoption.

REFERENCES

[1] Agrawal, D., Das, S., & Abbadi, A. E. (2011). Big data and cloud computing: Current state and future opportunities. Paper presented at the ACM EDBT, Uppsala, Sweden.

[2] Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113-131. doi: 10.1016/j.ijpe.2016.08.018

[3] Angeles, R. (2005). Rfid Technologies: Supply-chain applications and implementation issues. Information Systems Management, 22(1), 51-65. doi: 10.1201/1078/44912.22.1.20051201/85739.7

[4] Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. Computer Networks, 54(15), 2787-2805. doi: 10.1016/j.comnet.2010.05.010
[5] Babiceanu, R. F., & Seker, R. (2016). Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. Computers in Industry, 81, 128-137. doi: 10.1016/j.compind.2016.02.004
[6] Beamon, B. M. (1999). Measuring supply chain performance. International Journal of Operations & Production Management, 19(3), 275-292. doi: 10.1108/01443579910249714
[7] Bharati, P., & Chaudhury, A. (2018). Assimilation of big data innovation: Investigating the roles of IT, social media, and relational capital. Information Systems Frontiers, 1-12. doi: 10.1007/s10796-018-9839-6
[8] Borkar, V., Carey, M., & Li, C. (2012). Inside "big data management": Ogres, onions, or parfaits? Paper presented at the ACM EDBT/ICDT Joint Conference, Berlin, Germany.
[9] Bryant, R. E., Katz, R. H., & Lazowska, E. D. (2008). Big-data computing: Creating revolutionary breakthroughs in commerce, science, and society. Paper presented at the Computing Research Initiatives for the 21st Century.
[10] Cegielski, C. G., Allison Jones-Farmer, L., Wu, Y., & Hazen, B. T. (2012). Adoption of cloud computing technologies in supply chains: An organizational information processing theory approach. The International Journal of Logistics Management, 23(2), 184-211. doi: 10.1108/09574091211265350
[11] Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165-1188.
[12] Cheung, M.-S., Myers, M. B., & Mentzer, J. T. (2010). Does relationship learning lead to relationship value? A cross-national supply chain investigation. Journal of Operations Management, 28(6), 472-487. doi: 10.1016/j.jom.2010.01.003
[13] Claver-Cortés, E., Pertusa-Ortega, E. M., & Molina-Azorín, J. F. (2012). Characteristics of organizational structure relating to hybrid competitive strategy: Implications for performance. Journal of Business Research, 65(7), 993-1002. doi: 10.1016/j.jbusres.2011.04.012
[14] Cook, L. S., Heiser, D. R., & Sengupta, K. (2011). The moderating effect of supply chain role on the relationship between supply chain practices and performance. International Journal of Physical Distribution & Logistics Management, 41(2), 104-134. doi: 10.1108/09600031111118521
[15] DeGroote, S. E., & Marx, T. G. (2013). The impact of IT on supply chain agility and firm performance: An empirical investigation. International Journal of Information Management, 33(6), 909-916. doi: 10.1016/j.ijinfomgt.2013.09.001
[16] Dong, S., Xu, S. X., & Zhu, K. X. (2009). Research note—information technology in supply chains: the value of IT-enabled resources under competition. Information Systems Research, 20(1), 18-32. doi: 10.1287/isre.1080.0195
[17] Dreyer, B., & Grønhaug, K. (2004). Uncertainty, flexibility, and sustained competitive advantage. Journal of Business Research, 57(5), 484-494.
[18] Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics. doi: 10.1016/j.ijpe.2014.12.031
[19] Galbraith, J. R. (1974). Organization design: an information processing view. Interfaces, 4(3), 28-36.
[20] Glushkova, D., Jovanovic, P., & Abelló, A. (2017). Mapreduce performance model for Hadoop 2.x. Information Systems. doi: 10.1016/j.is.2017.11.006
[21] Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. International Journal of Production Economics, 87(3), 333-347. doi: 10.1016/j.ijpe.2003.08.003
[22] Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. International Journal of Operations & Production Management, 21(1/2), 71-87. doi: 10.1108/01443570110358468
[23] Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049-1064. doi: 10.1016/j.im.2016.07.004
[24] Hair, Jr., J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM): Sage publications.
[25] Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Ullah Khan, S. (2015). The rise of "big data" on cloud computing: Review and open research issues. Information Systems, 47, 98-115. doi: 10.1016/j.is.2014.07.006
[26] Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). 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, 154, 72-80. doi: 10.1016/j.ijpe.2014.04.018
[27] Hill, C. V. L. (1988). Difierentiation versus low cost or differentiation and low cost: A contingency framework. Academy of Management Review, 13(3), 401-412.
[28] Huan, S. H., Sheoran, S. K., & Wang, G. (2004). A review and analysis of supply chain operations reference (SCOR) model. Supply Chain Management: An International Journal, 9(1), 23-29. doi: 10.1108/13598540410517557
[29] Huo, B., Qi, Y., Wang, Z., & Zhao, X. (2014). The impact of supply chain integration on firm performance. Supply Chain Management: An International Journal, 19(4), 369-384. doi: 10.1108/scm-03-2013-0096
[30] Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. Journal of Business Research, 70, 338-345. doi: 10.1016/j.jbusres.2016.08.007
[31] Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research, 30(2), 199-218.
[32] Koo, C. M., Koh, C. E., & Nam, K. (2004). An examination of Porter's competitive strategies in electronic virtual markets: A comparison of two on-line business models. International Journal of Electronic Commerce, 9(1), 163-180.

[33] Kozlenkova, I. V., Hult, G. T. M., Lund, D. J., Mena, J. A., & Kekec, P. (2015). The role of marketing channels in supply chain management. Journal of Retailing, 91(4), 586-609. doi: 10.1016/j.jretai.2015.03.003
[34] Lockamy, A., & McCormack, K. (2004). Linking SCOR planning practices to supply chain performance. International Journal of Operations & Production Management, 24(12), 1192-1218. doi: 10.1108/01443570410569010
[35] Mathews, J. (2016). An information processing view of competition analysis. IUP Journal of Business Strategy, 13(1), 7-25.
[36] McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: the management revolution. Harvard business review, 90(10), 60-68.
[37] Miller, A., & Dess, G. G. (1993). Assessing Porter’s (1980) model in terms of generalizability, accuracy, and simplicity. Journal of Management Studies, 30(4), 553-585.
[38] Miller, D. (1988). Relating porter’s business strategies to environment and structure: analysis and performance implications. Academy of Management Journal, 31(2), 280-308.
[39] Mintzberg, H. (1985). Strategy formation in an adhocracy. Administrative Science Quarterly, 30(2), 160-197.
[40] Mintzberg, H., & Waters, J. A. (1985). Of strategies, deliberate and emergent. Strategic Management Journal, 6(3), 257-272.
[41] Murray, A. I. (1988). A contingency view of Porter's "generic strategies". Academy of Management Review, 13(3), 390-400.
[42] Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3 ed.). New York: McGraw-Hill.
[43] Porter, M. E. (1980). Competitive strategy. New York: Free Press.
[44] Porter, M. E. (1985). Competitive advantage. New York: Free Press.
[45] Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. Harvard Business Review, 63(4), 61-78.
[46] Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior research methods, 40(3), 879-891.
[47] Qi, J., Zhang, Z., Jeon, S., & Zhou, Y. (2016). Mining customer requirements from online reviews: A product improvement perspective. Information & Management, 53(8), 951-963. doi: 10.1016/j.im.2016.06.002
[48] Qrunfleh, S., & Tarafdar, M. (2014). Supply chain information systems strategy: Impacts on supply chain performance and firm performance. International Journal of Production Economics, 147, 340-350. doi: 10.1016/j.ijpe.2012.09.018
[49] Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS 2.0. M3. Hamburg: SmartPLS.
[50] Robak, S., Franczyk, B., & Robak, M. (2013). Applying big data and linked data concepts in supply chains management. Paper presented at the Proceedings of the 2013 Federated Conference on Computer Science and Information Systems, Krakow, Porland.
[51] Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. Journal of Business Logistics, 36(1), 120-132. doi: 10.1111/jbl.12082
[52] Shafer, J., Rixner, S., & Cox, A. L. (2010). The hadoop distributed filesystem: Balancing portability and performance. Paper presented at the Performance Analysis of Systems & Software (ISPASS), 2010 IEEE International Symposium on.
[53] Shirish, J., Rameshwar, D., J., C. S., Thanos, P., David, R., & Anand, P. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. The International Journal of Logistics Management, 29(2), 513-538. doi: doi: 10.1108/IJLM-05-2017-0134
[54] Smith, H. A., McKeen, J. D., & Singh, S. (2007). Developing information technology strategy for business value. Journal of Information Technology Management, 18(1), 49-58.
[55] Stonebraker, M. (2010). SQL databases vs NoSQL databases. Communications of the ACM, 53(4), 10-11. doi: 10.1145/1721654.1721659
[56] Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. Academy of Management Review, 3(3), 613-624.
[57] Vijayasarathy, L. R. (2010). An investigation of moderators of the link between technology use in the supply chain and supply chain performance. Information & Management, 47(7-8), 364-371. doi: 10.1016/j.im.2010.08.004
[58] Wagner, S. M., Grosse-Ruyken, P. T., & Erhun, F. (2012). The link between supply chain fit and financial performance of the firm. Journal of Operations Management, 30(4), 340-353. doi: 10.1016/j.jom.2012.01.001
[59] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics, 34(2), 77-84.
[60] Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. Information & Management, 55(1), 64-79. doi: https://doi.org/10.1016/j.im.2017.04.001
[61] Weng, W. H., & Lin, W. T. (2013). A Big Data technology foresight study with scenario planning approach. International Journal of Innovation in Management, 1(2), 41-52.
[62] Weng, W. H., & Lin, W. T. (2014a). Development assessment and strategy planning in cloud computing industry. International Journal of Electronic Commerce Studies, 5(2), 257-266. doi: 10.7903/ijecs.1158
[63] Weng, W. H., & Lin, W. T. (2014b). Development assessment and strategy planning in mobile computing industry. Paper presented at the 2014 IEEE International Conference on Management of Innovation and Technology, Singapore.
[64] Weng, W. H., & Lin, W. T. (2014c). Development trends and strategy planning in big data industry. Contemporary Management Research, 10(3), 203-214. doi: 10.7903/cmr.12288

[65] Weng, W. H., & Lin, W. T. (2014d). A scenario analysis of wearable interface technology foresight. Paper presented at The International Conference on Electronic Business (ICEB), Taipei.

[66] Weng, W. H., & Lin, W. T. (2015a). A mobile computing technology foresight study with scenario planning approach. International Journal of Electronic Commerce Studies, 6(2), 223-232. doi: 10.7903/ijecs.1242

[67] Weng, W. H., & Lin, W. T. (2015b). The impact of internet of things technologies on supply chain performance: The mediating role of competitive strategy. Paper presented at the The International Conference on Electronic Business (ICEB), Hong Kong.

[68] Wernerfelt, B., & Karnani, A. (1987). Competitive strategy under uncertainty. Strategic Management Journal, 8(2), 187-194.

[69] White, A., Daniel, E. M., & Mohdzain, M. (2005). The role of emergent information technologies and systems in enabling supply chain agility. International Journal of Information Management, 25(5), 396-410. doi: 10.1016/j.ijinfomgt.2005.06.009

[70] Wien, A. H., & Olsen, S. O. (2017). Producing word of mouth – a matter of self-confidence? Investigating a dual effect of consumer self-confidence on WOM. Australasian Marketing Journal (AMJ), 25(1), 38-45. doi: 10.1016/j.ausmj.2017.01.005

[71] Wu, F., Yeniyurt, S., Kim, D., & Cavusgil, S. T. (2006). The impact of information technology on supply chain capabilities and firm performance: A resource-based view. Industrial Marketing Management, 35(4), 493-504. doi: 10.1016/j.indmarman.2005.05.003

[72] Wu, I.-L., & Chuang, C.-H. (2010). Examining the diffusion of electronic supply chain management with external antecedents and firm performance: A multi-stage analysis. Decision Support Systems, 50(1), 103-115. doi: 10.1016/j.dss.2010.07.006

[73] Wu, K.-J., Tseng, M.-L., Chiu, A. S., & Lim, M. K. (2017). Achieving competitive advantage through supply chain agility under uncertainty: A novel multi-criteria decision-making structure. International Journal of Production Economics, 190, 96-107.

[74] Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. Information & Management, 53(8), 1034-1048. doi: 10.1016/j.im.2016.06.003