Impact of Business Strategy on Big Data Analytics Adoption: The Mediating Effect of Supply Chain Competence

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Abstract

Recent 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 researches study the association between business strategy and big data analytics adoption. Furthermore, the role of firms' functional activities such as supply chain operations has seldom been addressed in the adoption considerations of big data analytics. In this research, empirical data from enterprises were collected and analyzed to assess the impact of business strategy on 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: big data analytics, business strategy, supply chain competence, information processing view, technology adoption

1. 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 [1-3]. 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. Other emerging technologies, such as cloud computing and internet of things, also enhanced the needs of big data analytics. 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 [3, 4].

While the influences of big data analytics on enterprise performance were explored in previous studies [2], 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. Furthermore, possible relationships between big data adoption intention and firms' business level strategies and functional level strategies are also rare in the literature.

Studies of organizational information processing theory [5, 6] 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 [7-9]. This result leads to the speculation that business strategy pursuit is associated with big data analytics adoption intention. Furthermore, the high level concept of business strategy needs to be implemented and realized in efficient functional level activities such as human resource management, research and development, production, marketing, sales, customer services, and supply chain operations [10]. Among these functional level activities, this paper focuses on the role of supply chain operations for several reasons. First is the growing data volume in supply chain operations. Supply chain activities need to collaborate with other trading partners across corporate boundary. Supply chains link value chains of participating parties [11, 12]. The second reason is 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 [13]. The third reason is 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 [14, 15]. 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 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.

2. Hypotheses

2.1 Business Strategy and Supply Chain Competence

Porter's framework for business strategy of competition is one of the most widely accepted typology of business competition models [16, 17]. 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 [16, 18]. 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 [19]. 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 [20, 21].

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 [22, 23]. 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 [24]. Thus, the following two hypotheses are proposed:

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

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

2.2 Business Strategy and Big Data Analytics

From the information processing view [5], 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 [6]. This information can be acquired and processed by applying big data analytics.

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 [25].

Therefore, we propose the following hypotheses:

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

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

2.3 Supply Chain Competence and Big Data Analytics

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 [26]. 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 [27-29]. Thus to pursue supply chain competence, firms will intend to adopt big data analytics.

Therefore, the hypothesis of this research suggests that:

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

3. 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 adoption intention discussed previously. We operationalized the study variables by using multi-item reflective measures on a 7-point scale [30].

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 the generation of 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 [19]. Second, pursuing of cost leadership is often reflected in price competitiveness [31, 32]. The third item was the economic scale. A firm can gain a cost advantage through economies of scale or superior manufacturing processes [16, 18]. Finally, larger firms with greater access to resources are more likely to take advantage of cost leadership strategy through development of lower cost products, whereas smaller firms are often forced to compete using highly differentiated products and services in a niche market [33].

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 [16]. Differentiation prevents a business from competitive rivalry, insulating it from competitive forces that reduce margins [34]. Extending Porter's competitive strategy framework, Miller distinguished differentiation strategies based on innovation from those based on marketing [19]. These propositions form two items included in the construct. Differentiation strategies based on innovation may create a dynamic environment or a distinct business model in which it is difficult for competitors to predict and react. This unpredictability may provide the innovator a substantial advantage over its competitors [19, 32].

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 past few years. Beamon [35] proposed a framework for measuring supply chain competence. The framework included the measurement of 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 have been recognized as direct and observable measures of supply chain practice. Firms in a supply chain achieve efficiency by lowering operational costs, reducing inventory, promoting flexibility, ensuring on-time deliveries, and minimizing shortages of critical resources. These objectives relate to all parties in a buyer–supplier relationship, and therefore, can represent the efficiency of the supply chain operations [36, 37].

The big data analytics adoption intention construct 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 within one year's time. To facilitate this measurement, we followed the guidelines established by Ajzen [38] and adapted items employed by Venkatesh and Bala [39]. These items measure user intention in the context of the technology acceptance model [40].

All items for this study were assessed with a 7-point Likert scale ranging from "strongly disagree" to "strongly agree." In addition, we use firm size, IT department size and industry sector as control variables, as these factors have been noted in several studies to affect intention to adopt information technologies [41, 42]. 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 pursuit
CLS1: We provide low cost products or services based on operational efficiency.
CLS2: We deliver products or services with lower price than competitors.
CLS3: We provide products or services with economy of scale.
CLS4: We develop our products or services with lower cost than our competitors.
DFS: Differentiation strategy pursuit
DFS1: We deliver products or services with 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 delivery products or services on time.
SCC2: Reducing lead time is crucial to us in our supply chain operations.
SCC3: We respond promptly to changes of 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 important to us.

BDA: Big data analytics adoption intention
BDA1: If we have the ability to adopt any big data analytics for our company, we will do so.
BDA2: If we have access to any big data analytics, we would want to use it.
BDA3: My company plans to adopt big data analytics within one year.
Control Variables (rescaled)
Firm Size: Total number of employees.
IT Size: Total number of IT staffs.
Industry: Industry sectors of firms. 1 for service firms and 0 for manufacturing firms.

3.2 Sample and Data Collection

A Taiwanese 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.

Table 2 shows the profile of the final sample list.

Table 2 Profile of the final sampling firms

	Count	% of sample
Number of employees		
Under 100	33	16%
100~1,000	64	32%
1,000~5,000	59	29%
5,000~10,000	35	17%
Above 10,000	10	5%
Total	201	100%

Number of IT Staffs		
Under 5	66	33%
6~10	31	15%
11~20	49	24%
21~50	34	17%
Above 50	21	10%
Total	201	100%
Industry sectors		
Manufacturing	93	46%
Services	108	54%
Total	201	100%

4. Results

Our goal was to investigate the impact of business strategy pursuit on big data analytics adoption intention, mediated by a firm's supply chain competence. The empirical results were expected to demonstrate that pursuing business strategy, such as cost leadership strategy and differentiation strategy, influences the adoption intention of big data analytics. The results were also expected to verify the mediating role of supply chain competence on the link between business strategy pursuit and big data analytics adoption intention. Finally, the results were used to test the relationship between business strategy pursuit and supply chain competence.

4.1 Reliability and Validity

The reliability of the survey instrument was tested by using Cronbach's alpha [43] to assess the internal consistency of the CLS, DFS, SCC and BDA constructs listed in Table 1. Cronbach's alpha tests the interrelationship among the items composing a construct to determine if the items measure a single construct. Nunnally and Bernstein [44] recommended a threshold alpha value of .7. Cicchetti, et al. [45] suggested the following reliability guidelines for determining significance: $\alpha < .70$ (unacceptable), $.70 \leq \alpha < .80$ (fair), $.80 \leq \alpha < .90$ (good), and $\alpha > .90$ (excellent).

Content validity [46] refers to the extent to which the instrument measures what it is designed to measure. Most of the measures used in the study were adopted from relevant studies. Although basing the study on the established literature provided a considerable level of validity, the study's validity was further improved by pre-testing the instrument on a panel of experts comprising 15 business executives and supply chain managers.

To assess convergent and discriminant validity, the items that were used to measure the CLS, DFS, SCC and BDA constructs were subjected to principal components analysis with varimax rotation. The Bartlett test of sphericity and the Kaiser–Meyer–Olkin measure of sampling adequacy were conducted to ensure that the sample was satisfactory and confirm the appropriateness of proceeding with further data analysis.

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 [44, 45]. In addition, 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 constructs loaded on to single factors with all loadings greater than 0.8. These results confirm that each of the construct in our hypothesized model is unidimensional and factorially distinct, and that all items used to operationalize a construct is loaded onto a single factor.

Table 3 Descriptive statistics and reliability and validity test

Construct	Item	Mean	SD	Cronbach's alpha	Cronbach's alpha if item deleted	Factor loading on single factor
CLS	CLS1	3.716	1.521	0.952	0.956	0.912
	CLS2	3.597	1.460		0.978	0.855
	CLS3	3.657	1.320		0.905	0.909
	CLS4	3.677	1.351		0.908	0.993
DFS	DFS1	4.552	1.371	0.905	0.893	0.854
	DFS2	4.393	1.375		0.857	0.921
	DFS3	4.308	1.579		0.889	0.866
	DFS4	4.214	1.456		0.870	0.895
SCC	SCP1	4.507	1.460	0.920	0.911	0.815
	SCP2	4.935	1.338		0.901	0.870
	SCP3	4.612	1.330		0.901	0.869
	SCP4	4.552	1.330		0.905	0.847
	SCP5	4.423	1.465		0.909	0.827
	SCP6	4.547	1.396		0.904	0.849

BDA	BDA1	4.451	1.619	0.892	0.768	0.952
	BDA2	4.506	1.652		0.760	0.956
	BDA3	3.998	1.478		0.972	0.806

Table 4 presents the results of factor analysis. A four-factor structure emerged with all predefined indicators loading on to their respective constructs, which thereby affirmed convergent validity and unidimensionality of the constructs. The model explained 79.830% of the variance.

Table 4 Factor analysis

Construct	Item	Factor1	Factor2	Factor3	Factor4
CLS	CLS1	**.847**	.337	.160	-.019
	CLS2	**.789**	.105	.291	.239
	CLS3	**.924**	.252	.253	.121
	CLS4	**.920**	.291	.225	.072
DFS	DFS1	.255	**.747**	.288	.109
	DFS2	.245	**.834**	.282	.133
	DFS3	.217	**.787**	.267	.146
	DFS4	.296	**.745**	.388	.082
SCC	SCP1	.230	.205	**.756**	.084
	SCP2	.114	.311	**.803**	.099
	SCP3	.131	.227	**.837**	.069
	SCP4	.249	.144	**.816**	.036
	SCP5	.236	.235	**.723**	.217
	SCP6	.164	.271	**.754**	.217
BDA	BDA1	.096	.093	.156	**.927**
	BDA2	.102	.046	.121	**.939**
	BDA3	.073	.179	.107	**.880**

We also assessed discriminant validity on the basis of the construct correlation. Table 5 summarizes the correlations among different factors. The tests indicated acceptable results with respect to discriminant validity.

Table 5 Construct correlation

Construct	1	2	3	4	5	6	7
1. CLS	1						
2. DFS	0.625**	1					
3. SCC	0.556**	0.642**	1				
4. BDA	0.272**	0.306**	0.324**	1			
5. Firm Size	-0.031	-0.048	-0.035	0.208**	1		
6. IT Size	0.185**	0.085	0.048	0.111	0.357**	1	
7. Industry	-0.024	-0.026	-0.061	0.101	-0.027	-0.144*	1

*p < 0.05, **p < 0.01

4.2 Tests of Hypotheses

Multiple linear regression analysis was performed using SPSS version 21 to test our hypotheses for significance. Table 6 summarizes the test results regarding the parameter estimates and p-values of the hypotheses. We also included firm size, IT department size and industry sector as control variables in the analysis.

Table 6 Tests results of the hypothesized model

Explanatory variable	Dependent variable					
	SCC		BDA model without SCC		BDA model with SCC	
	Estimate	P-value	Estimate	P-value	Estimate	P-value
CLS	0.237	0.000***	0.154	0.018*	0.091	0.367
DFS	0.444	0.000***	0.266	0.005**	0.154	0.144
SCC					0.255	0.019*
Firm size			0.079	0.102	0.073	0.112
IT size			0.008	0.979	0.055	0.856
Industry			0.117	0.080	0.127	0.064
R^2	0.451		0.168		0.191	

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

The results in Table 6 supported the hypotheses H1a, H1b and H3, that is, the direct effects of CLS on SCC, DFS on SCC and SCC on BDA. In the links of CLS on BDA of hypothesis H2a and DFS on BDA of hypothesis H2b, the direct effects were not found, instead, complete mediation effects of SCC in the links were found. This indicates that business strategy pursuit is positively related to big data analytics adoption intention through mediation effect rather than direct effect. The test procedure concerning mediation follows the suggestion of Baron and Kenny [47].

We compared the proposed mediation model with an alternative direct effect model without SCC variable. The test results show that positive relationships exist between CLS and SCC ($\beta = 0.237$, $p < 0.001$), between DFS and SCC ($\beta = 0.444$, $p < 0.001$), and between SCC and BDA ($\beta = 0.255$, $p < 0.05$). Furthermore, the significant relationships between CLS and BDA ($\beta = 0.154$, $p < 0.05$) and between DFS and BDA ($\beta = 0.266$, $p < 0.01$) in the direct effect model is not significant in the model with mediation. Taking into account these results as a whole, we thus conclude that the effect of business strategy pursuit on big data analytics adoption intention is completely mediated by supply chain competence [47]. The effects of paths are summarized in Table 7.

Table 7 Effects of paths in the hypothesized model

Hypothesis	path	Effect from test results
H1a	CLS → SCC	Direct effect supported
H1b	DFS → SCC	Direct effect supported
H2a	CLS → BDA	Direct effect not supported Complete mediation of SCC supported
H2b	DFS → BDA	Direct effect not supported Complete mediation of SCC supported
H3	SCC → BDA	Direct effect supported

5. Discussion

This study investigated the impact of a firm's business strategy pursuit on big data analytics adoption intention, and tested the possible mediating 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 pursuit and its intention of big data analytics adoption was completely mediated by the supply chain competence of the firm. This result is observed for both cost leadership strategy and differentiation strategy. In other words, the link between business strategy pursuit and big data analytics adoption intention is not direct, but indirect instead. By adopting a mediating framework in this study, we isolated the specific effects by which business strategy pursuit are linked to big data analytics adoption intention. This finding suggests that pursuing business level strategy alone does not directly link to innovative technology adoption intention. Functional level efficiency of firms may play a key role in the link. This result provides valuable evaluation reference for firms making management decision in adopting innovative information technologies.

The second 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 more of direct impact on big data adoption intention than business strategy pursuit. From the information processing view [5, 6], this finding indicates that the perceived complexity and uncertainty for supply chain operations are significant for firms [48], 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. As the data volume, data velocity and data variety in supply chain operations continue advancing, the demand for big data analytics may also keep evolving. The intensity of supply chain competence is therefore a significant predictor for big data analytics utilization.

Our findings also provide evidence that for both cost leadership strategy and differentiation strategy, there is a positive relation between business strategy pursuit and supply chain competence. This result supports the theoretical literature on the relationship of business level strategies and functional level strategies [49-51]. Our results also indicate that supply chain competence influences big data analytics adoption intention significantly regardless of which business strategy a firm chooses to pursue. Both cost leadership strategy pursuit and differentiation strategy pursuit influence big data adoption intention through supply chain competence. This finding is consistent with the results of some previous studies that compare the associations of the two types of business strategy with functional level efficiency, and the mediating role of functional level efficiency in strategic links [52-54]. A managerial interpretation is that a firm's business strategy pursuit leads its functional level operations with an extensive efficiency objective, clear motivation, and planned strategic goal [55, 56]. This goal could be cost structure oriented or differentiation oriented, or a combination of them [20, 21, 57]. To this goal, functional level operations pursue required efficiency through acquiring and applying decision-support tools, such as big data analytics. Therefore, although there is no significant direct association between business strategy pursuit and big data analytics adoption intention, the analysis of the possible mediating effect shows that the pursuit of business strategy has an indirect effect on big data adoption intention, through its direct impact on supply chain competence which, in turn, could lead to higher big data analytics adoption intention.

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