On the Adoption of Big Data Analytics: The 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, the literature is less clear about the association between organizational core competence and big data analytics adoption. Furthermore, the role of firms' functional activities such as supply chain operations has seldom been addressed in adoption considerations of big data analytics. In this research, empirical data from enterprises were collected and analyzed to assess the effect of supply chain competence on big data analytics adoption. The results supported the effect and the implications for business management are elaborated.

Keywords: big data analytics, core competence, supply chain, 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.

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 [4, 5]. 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 [6, 7]. 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 [8]. Current examples of such tools include the Hadoop Distributed File System (HDFS) [9], the parallel processing system MapReduce [10], the non-relational database system NoSQL [11], and others. These tools provide processing functionality for big data which are beyond the application scope of traditional data mining and business analytics tools.

Studies of organizational information processing theory [12, 13] 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 [14-16]. This result leads to the speculation that business strategy pursuit is associated with big data analytics adoption intention. However, 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 [17]. Among these functional level activities, this paper focuses on the role of supply chain operations for several reasons. The first reason is the growing data volume in supply chain operations. Supply chain activities need to collaborate with other trading partners across corporate boundary. Thus supply chains have to link value chains of participating parties [18, 19]. 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 [20]. The third reason is the expanding data variety in supply chain operations. This requires supply chain operations closely integrated with more and more other functions such as production, marketing and information systems [21, 22].

Therefore, this research intends to investigate the linkage between supply chain competence and big data analytics adoption. The paper begins with a review of the relevant literature about the relationships between supply chain competence and big data analytics. Then it proposes a hypothesis which links these variables. Following that, the hypothesis 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

Recent development of the extensive globalization, the meticulousness of enterprise internationalization and business integration, and the rapid development of information technology have caused business environments to change rapidly and tremendously. For enterprises, customers require an increasingly rapid response and fulfillment. To respond promptly to changing internal situations and external environments, enterprises must interact efficiently with vendors of upper, middle, and lower streams to form a highly efficient supply chain network. Supply chain competence thus becomes a critical core competence pursued by enterprises [23-26].

Supply chain operations generate and utilize large-scale heterogeneous data with time-varying nature [27]. The timely and accurate flow of information is a necessity for successful supply chain operations [28]. The evolution of big data analytics is expected to transform enterprises' managerial paradigm, including supply chain management [29]. 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 [30-33]. These results lead to the conjecture of the association between supply chain competence and big data analytics [29, 34]. The possible association between supply chain competence and big data analytics adoption has thus become a crucial topic to both academics and practitioners [35].

The efficiency considerations in supply chain operations mainly centers around time efficiency, cost efficiency and flexibility [36, 37]. 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 [36, 37].

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 [38]. 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 [39-41]. Thus to pursue supply chain competence, firms will intend to adopt big data analytics.

Therefore, the hypothesis of this research is proposed.

Hypothesis: 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 supply chain competence and big data analytics adoption intention discussed previously. We operationalized the study variables by using multi-item reflective measures on a 7-point scale [42].

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 [36] 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 core competence of the supply chain operations [27, 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 [43] and adapted items employed by Venkatesh and Bala [44]. These items measure user intention in the context of the technology acceptance model [45].

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 [46, 47]. 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)
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 market research organization publishes comprehensive data of the 1,000 largest corporations based 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

4.1 Reliability and Validity

The reliability of the survey instrument was tested by using Cronbach's alpha [48] to assess the internal consistency of the 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 [49] recommended a threshold alpha value of .7. Cicchetti, et al. [50] suggested the following reliability guidelines for determining significance: $\alpha < .70$ (unacceptable), $.70 \le \alpha < .80$ (fair), $.80 \le \alpha < .90$ (good), and $\alpha > .90$ (excellent).

Content validity [51] 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.

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 [49, 50]. 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
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

We also assessed discriminant validity on the basis of the construct correlation. Table 4 summarizes the correlations among different factors. The tests indicated acceptable results with respect to discriminant validity.

Table 4 Construct correlation

Construct	1	2	3	4	5
1. SCC	1				
2. BDA	0.324**	1			
3. Firm Size	-0.035	0.208**	1		
4. IT Size	0.048	0.111	0.357**	1	
5. Industry	-0.061	0.101	-0.027	-0.144*	1

*p < 0.05, **p < 0.01

4.2 Tests of the Hypothesis

Multiple linear regression analysis was performed using SPSS version 21 to test our hypotheses for significance. Table 5 summarizes the test results regarding the parameter estimates and p-values of the hypothesis. We also included firm size, IT department size and industry sector as control variables in the analysis.

Table 5 Tests results of the hypothesis

Explanatory variable	Dependent variable BDA	
	Estimate	P-value
SCC	0.414	0.000***
Firm size	0.194	0.093
IT size	0.161	0.485
Industry	0.127	0.504
R^2	0.191	

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

The results in Table 5 supported the hypothesis, that is, the direct effects of SCC on BDA.

5. Discussion

5.1 Research Implications

The key result 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 impact on big data adoption intention. From the information processing view [12, 13], this finding indicates that the perceived complexity and uncertainty for supply chain operations are significant for firms [29], 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.

A further 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 [52, 53]. To this goal, functional level operations such as supply chain operations will pursue required core competences through acquiring and applying decision-support tools, such as big data analytics.

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 decision-making within critical timeframe [54]. The 3Vs capability of big data analytics is well aligned for responding to the requirement of supply chain operations [1, 29]. Thus, big data analytics adoption in a firm is expected to produce significant results concerning enhancement of supply chain competence. Therefore, the analysis of the possible effect shows that the higher intensity of supply chain competence could lead to higher big data analytics adoption intention.

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 on the basis of a single study. In our study, empirical data used for tests were collected from large firms based in Taiwan with global 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 evidences for assessing and validating firm data are recommended to overcome the limitations of the present study. Such research is suggested to address how organizational distinctive competences and functional level strategies relate to other emerging technologies. For example, emerging technologies such as internet of things [55] and augmented reality [56] have received inadequate attention from strategic considerations and technology adoption theories. These efforts could involve studies identifying the organizational core competences which affect business operations, information processing, and decision support. 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 core competence, functional level strategies, and innovative technology adoption intention.

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