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

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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 researchers study the association between business strategy and big data analytics adoption, and empirical documents in this regard are also scant in the literature. In this study, empirical data from enterprises were collected and analyzed to assess the impact of business strategy on big data analytics adoption. The results supported our hypotheses and the implications are elaborated.

Keywords: big data analytics, business strategy, information processing view, technology adoption, differentiation, cost leadership

1. Introduction

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 [1, 2].

While the influences of big data analytics on enterprise performance were explored in previous studies [3], 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 [4, 5] 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 [6-8]. This result leads to the speculation that business strategy pursuit is associated with big data analytics adoption intention.

Therefore, this research intends to investigate the linkage between business strategy and big data analytics adoption. The paper begins with a review of the relevant literature about the relationships between business strategy and big data analytics. Then it proposes hypotheses which link these variables. Following that, the hypotheses are 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.

2. Hypotheses

A business strategy concerns the competitive positioning, market segmentation and industry environment of a company [9]. 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 [10, 11].

From the information processing view [4], 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 [5]. 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 [12].

Furthermore, business strategies of most organizations are frequently a combination of their intended strategies and the emergent strategies [13]. Firm leaders need to analyze the process of emergence and to make strategy adjustment when appropriate [14]. For this purpose, big data analytics could also serve as the tool to facilitate the strategic decisions to be accurately aligned with competition changes [15, 16].

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 [17, 18]. 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 [19, 20]. 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 [21]. Current examples of such tools include the Hadoop Distributed File System (HDFS) [22], the parallel processing system MapReduce [23], the non-relational database system NoSQL [24], and others. These tools provide processing functionality for big data which are beyond the application scope of traditional data mining and business analytics tools.

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 [9, 25]. 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 [26].

In summary, we propose the following hypotheses:

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

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

Technology is one of the most prominent factors influencing the rules of competition [9]. Through the help of technology use, a firm creates products and services that can differentiate itself from its rivals or to produce at a lower cost [8, 27]. However, while Ha and Hb both hypothesize positive effects on big data analytics adoption intention from two different business strategies, the purposes for which the two strategies utilize big data analytics are relatively different.

A firm with a differentiation strategy uses big data analytics to achieve product uniqueness through innovation or customization. Identifying distinctive innovative features and customer preferences is mainly an exploratory activity. On the other hand, a firm with a cost leadership strategy uses big data analytics for possible higher efficiency and lower cost, which is primarily exploitative [28]. Firms placing great emphasis on differentiation strategies are likely to rely more strongly on the functionality of big data analytics because of the higher information uncertainty and diversity in exploration than in exploitation.

Differentiation strategy pursuit represents an approach to product or service innovation, whether through the development of unique product features or through the enablement of business innovations which explore opportunities, it requires the support of highly effective predictive analytics which realize changing customer preferences. These business analytics are required to analyze and learn the unique customer experiences with accuracy and flexibility. To sustain in competition, the differentiators constantly need to watch for the next unique innovation. Therefore, the differentiators are more likely to require the outcomes of big data analytics. In this regard, the following is hypothesized:

Hc. The relationship between differentiation strategy pursuit and big data analytics adoption intention will be stronger than the relationship between cost leadership strategy pursuit and 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 and big data analytics adoption intention discussed previously. We operationalized the study variables by using multi-item reflective measures on a 7-point scale [29].

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 [27]. Second, pursuing of cost leadership is often reflected in price competitiveness [30, 31]. The third item was the economic scale. A firm can gain a cost advantage through economies of scale or superior manufacturing processes [9, 25]. 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 [32].

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 [9]. Differentiation prevents a business from competitive rivalry, insulating it from competitive forces that reduce margins [33]. Extending Porter's competitive strategy framework, Miller distinguished differentiation strategies based on innovation from those based on marketing [27]. 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 [27, 31].

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 [34] and adapted items employed by Venkatesh and Bala [35]. These items measure user intention in the context of the technology acceptance model [36].

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 [37, 38]. 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.

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

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 Taiwanese marketing research organization publishes comprehensive data of the 1,000 largest corporations in Taiwan with global operations. 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. 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.

4.1 Reliability and Validity

The reliability of the survey instrument was tested by using Cronbach's alpha [39] to assess the internal consistency of the CLS, DFS 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 [40] recommended a threshold alpha value of .7. Cicchetti, et al. [41] suggested the following reliability guidelines for determining significance: α < .70 (unacceptable), .70 ≤ α < .80 (fair), .80 ≤ α < .90 (good), and α > .90 (excellent).

Content validity [42] 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 information system 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 [40, 41]. In addition, factor analysis was performed to confirm the construct validity. 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
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	6
1. CLS	1					
2. DFS	0.625**	1				
3. BDA	0.272**	0.306**	1			
4. Firm Size	-0.031	-0.048	0.208**	1		
5. IT Size	0.185**	0.085	0.111	0.357**	1	
6. Industry	-0.024	-0.026	0.101	-0.027	-0.144*	1

*p < 0.05, **p < 0.01

4.2 Tests of Hypotheses Ha and Hb

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 hypotheses. We also included firm size, IT department size and industry sector as control variables in the analysis.

Table 5 Tests results of the hypotheses Ha and Hb

Explanatory variable	Dependent variable BDA	
	Estimate	P-value
CLS	0.154	0.018*
DFS	0.266	0.005**
Firm size	0.079	0.102
IT size	0.008	0.979
Industry	0.117	0.080
R^2	0.168	

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

The results in Table 5 supported the hypotheses Ha and Hb.

4.3 Tests of Hypothesis Hc

For hypothesis Hc, we used hierarchical linear regression to test the differences in the effects of differentiation strategy pursuit and cost leadership strategy pursuit on big data analytics adoption intention.

Hc stated that the relationship between differentiation strategy pursuit (DFS) and big data analytics adoption intention (BDA) will be stronger than the relationship between cost leadership strategy pursuit (CLS) and big data analytics adoption intention (BDA). The test results indicated that the standardized beta is 0.134 for the cost leadership strategy's relationship with big data analytics adoption intention and 0.236 for the differentiation strategy. The analysis showed a change in R^2 of 0.034 (F change = 7.940, p = 0.005) when the differentiation strategy was added to the model with the cost leadership strategy (original R^2 of 0.134). This signifies that the differentiation strategy explains above and beyond what the cost leadership strategy can explain for big data analytics adoption intention, thereby supporting Hc.

5. Discussion

5.1 Research Implications

This study investigated the impact of a firm's business strategy pursuit on big data analytics adoption intention. 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 significant. This finding provides empirical evidence for information processing theory.

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 adoption of big data analytics [43-45].

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 [19]. 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 [26, 46]. 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 [47]. These price and value analytics further forms the basis for decisions of differentiation and cost structure.

Furthermore, while both cost leadership strategy and differentiation strategy are related to big data analytics adoption intention, our results showed that differentiation strategy pursuit is more strongly related to big data adoption intention than is cost leadership strategy pursuit, as hypothesized in Hc. This demonstrates that the complexity of a multi-faceted differentiation strategy is more difficult for firms to pursuit than the efficiency-based cost leadership strategy, and thus required higher support of business analytics capabilities. Therefore, a differentiation strategy can offer multiple and complex dimensions such as innovation and customization through which a firm can create competitive advantage, and is more difficult for competitors to imitate than a cost leadership strategy.

5.2 Suggestions for Further Research

Further research efforts which focus on collecting more empirical evidences for assessing and validating firm data are recommended. Such research is suggested to address how other emerging technologies relate to business level strategies and functional level strategies. For example, emerging technologies such as internet of things [48, 49] and augmented reality [50, 51] have received inadequate attention from strategic considerations and technology adoption theories.

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 intention.

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