On the Adoption of Big Data Analytics: A Business Strategy Typology 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 influences of various types of business strategies on big data analytics adoption, and empirical documents in this regard are also scant in the literature. In this study, business strategies were classified into four different types. Empirical data from enterprises were collected and analyzed to assess the impact of strategic typology on big data analytics adoption. The results and the implications are then elaborated.

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

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 association 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. Business strategies are classified into four different types. Then it proposes hypotheses which compare big data analytics adoption with respect to different strategy types. 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.

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.

Furthermore, business strategies of most organizations are frequently a combination of their intended strategies and the emergent strategies [12]. Firm leaders need to analyze the process of emergence and to make strategy adjustment when appropriate [13]. For this purpose, big data analytics could also serve as the tool to facilitate the strategic decisions to be accurately aligned with competition changes [14, 15].

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 [16, 17]. 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 [18, 19]. 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 [20]. Current examples of such tools include the Hadoop Distributed File System (HDFS) [21], the parallel processing system MapReduce [22], the non-relational database system NoSQL [23], 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 framework for business strategy of competition is one of the most widely accepted typology of business competition models [9, 24]. 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]. 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 [26]. 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 [27, 28].

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 [29].

Thus using cost leadership and differentiation as two major strategic orientations, this study classified firms into four strategic types, as depicted in Table 1.

Table 1 Classification of firms by strategy types

Firm type	Criteria	
	Intensity of differentiation strategy pursuit	Intensity of cost leadership strategy pursuit
Hybrid	high	high
Differentiator	high	low
Cost leader	low	high
Obscurer	low	low

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, 26]. Pursuing cost leadership strategy and differentiation strategy concurrently, firms are facing greater uncertainties than pursuing a pure strategy. This is because firms in this case need to deal with uncertainties in both differentiation and low cost. Therefore, firms with a hybrid strategy are expected to have higher intensity in big data analytics adoption intention. Firms with low intention in strategy pursuit are expected to exhibit lower intensity in big data analytics adoption intention.

In summary, the following is hypothesized:

Hypothesis: There are significant differences in the intensity of big data analytics adoption intention with respect to different business strategy types.

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 [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 [26]. 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 [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 [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 [9]. 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 [26]. 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 [26, 32].

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 [35] and adapted items employed by Venkatesh and Bala [36]. These items measure user intention in the context of the technology acceptance model [37].

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 [38, 39]. Table 2 presents the items used to measure each of the independent and dependent construct variables.

Table 2 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 3 shows the profile of the final sample list.

Table 3 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 [40] 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 [41] recommended a threshold alpha value of .7. Cicchetti, et al. [42] 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 [43] 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 4 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 [41, 42]. 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 4 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 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
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

We compared firms with different strategic orientations using ANOVA test with Scheffé's method. The firms were classified as hybrid, differentiator, cost leader and obscurer firms. Firms were classified as hybrid if their ratings for both the differentiation strategy pursuit (DFS) and cost leadership strategy pursuit (CLS) were, on average, above the sample means for differentiation and cost leadership, respectively. Otherwise, they were classified as either differentiator or cost leader depending on the strategy on which they rated higher than average. The rest of firms were classified as obscurer. Table 6 summarized the classification of firms with their average ratings on big data analytics adoption intention (BDA).

Table 6 Big data analytics adoption intention of firms by strategy types

Firm type	Criteria		Count	% of sample	BDA	
	DFS	CLS			Mean	SD
hybrid	high	high	71	35.3%	4.903	1.073
Differentiator	high	low	27	13.4%	4.425	1.598
Cost leader	low	high	46	22.9%	3.946	1.642
Obscurer	low	low	57	28.4%	3.840	1.343
Total			201	100.0%	4.318	1.438

To determine whether the differences in the means of BDA for each group of firm strategies were statistically significant, we used an ANOVA test with Scheffé's method. The Scheffé method is used for post hoc multiple comparisons and is suitable whether sample sizes are equal or unequal. Table 7 summarizes the results of the comparison.

Table 7 Comparison of big data analytics adoption intention by strategy types

Firm type A	Firm type B	BDA		
		Mean (A – B)	SE	P-value
Hybrid	Differentiator	0.479	0.310	0.497
	Cost leader	0.957	0.259	0.004**
	Obscurer	1.064	0.244	0.000***
Differentiator	Cost leader	0.478	0.332	0.558
	Obscurer	0.585	0.320	0.344
Cost leader	Obscurer	0.107	0.271	0.985

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

Results from this analysis revealed that the mean BDA difference between hybrid and differentiators was not statistically significant, but that the difference between hybrid and cost leaders was statistically significant, as was the difference between hybrid and obscurer firms.

5. Discussion

This study investigated the impact of a firm's business strategy pursuit on big data analytics adoption intention from a strategy typology perspective. The first critical insight we obtained from our empirical results is that a hybrid strategy is actually a common practice among enterprises, and it relates to higher adoption intention than pure cost leadership strategy and obscure strategy.

The ANOVA results revealed that when firms that are both differentiators and cost leaders are considered hybrids, they compose a large proportion of the sample (35.3%) and, on average, tend to have higher ratings in big data analytics adoption intention than firms that implement any other strategy in the typology. An explanation for this result is that firms with a hybrid strategy tend to be more salient in strategy management and have more prominent business intent than the others, and thus are able to conduct higher investment for technologies. On the other hand, firms with low intent in both differentiation and cost leadership (28.4% of the sample) tend to be strategically irresolute and stuck-in-the-middle, and without a clear motivation for pursuing operational efficiency or investment for technologies.

Moreover, comparing the percentage of hybrids (35.3% of the sample) with that of the firms with a dominant pure business strategy, differentiators (13.4% of the sample) and cost leaders (22.9% of the sample), we see that hybrid strategy is actually a relatively common practice among enterprises. Thus our findings support the literature that pure strategies may only be theoretical in principle, and a combination of business strategies is what is practiced by firms in reality [44-46].

However, while a hybrid strategy may achieve competitive advantage, it requires agile deployment and coordination of various firm resources to avoid or resolve possible conflict of interests between the two pure strategies, and will increase the complexity of business operations, thus demand the support of more advanced business analytics capability, which motivate the management decision of big data analytics adoption. The results of our study provide empirical support for this implication.

Furthermore, the results indicate that BDA difference between hybrid and differentiators was not statistically significant, but that the difference between hybrid and cost leaders was statistically significant, as was the difference between hybrid and obscurer firms. An explanation for this is that the purposes for which differentiators and cost leaders 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 [47]. 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.

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