# Impact of Competitive Strategy on Big Data Analytics Adoption: The Construction of a Research Framework

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March 9, 2020

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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' core competences such as supply chain competence has seldom been addressed in the adoption considerations of big data analytics. In this research, a research framework was developed for assessing the impact of business strategy on big data analytics adoption and the effect of supply chain competence in the linkage. Possible applications and extensions of the research framework are then discussed.

*Keywords:* business strategy, big data analytics, supply chain competence, technology adoption, information processing view, core competence

# 1. Introduction

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 [1, 2]. 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 [3, 4]. 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 [5]. Current examples of such tools include the Hadoop Distributed File System (HDFS) [6], the parallel processing system MapReduce [7], the non-relational database system NoSQL [8], and others. These tools provide processing functionality for big data which are beyond the application scope of traditional data mining and business analytics tools.

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 [9-11]. 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 [11, 12].

While the influences of big data analytics on enterprise performance were explored in previous studies [10], 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 [13, 14] 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 [15-17]. 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 [18]. Among these functional level activities, supply chain management is particularly noticeable as a possible factor for big data analytics adoption for several reasons [19, 20]. First, the growing data volume in supply chain operations. This is because supply chain activities need to be collaborated with all other trading partners across corporate boundary, and supply chains need to be integrated with value chains of all participating parties [21, 22]. Second, the increasing data velocity in supply chain operations. Many organizations are gradually aware of that they must compete, as part of a supply chain against other supply chains, to quickly reflect customers' changing demands [23]. And third, the expanding data variety in supply chain operations. Supply chain management is closely integrated with more and more other functions such as production, marketing and information systems [24, 25]. For these reasons, this research intends to investigate the linkage between business strategy and big data analytics adoption, and the effect of supply chain competence in this linkage.

The paper begins with a review of the relevant literature about the relationships between business strategy, supply chain competence and big data analytics. Then it proposes a model which links these variables. Following that, the model is presented as a research framework. Finally, possible applications and extensions of the framework are discussed with recommendations for future work.

## 2. Method

A bottom-up approach is employed in the development of the research framework. First, key phrases in the problem domain are identified. These include business strategy, supply chain competence and big data analytics. Next, literature review is conducted to discover possible linkages between pairs of the key phrases. These linkages are then hypothesized. Finally, the hypotheses are integrated into a model and depicted as a research framework. Details of the construction process are as follows.

### 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 [26, 27]. 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 [26, 28]. 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 [29]. 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 [30, 31].

The successful implementation of the business strategies relies on making right decisions on core functions of a firm, such as human resource management, production, marketing, research and development, sales, information systems, and supply chain management. These functions form a value chain and all have a role in lowering the cost structure and increasing the value of products through differentiation [28]. A firm's ability to acquire superior functional efficiency, including supply chain competence, will determine if its product offering is differentiated from that of its competitors, and if it has a low cost structure simultaneously. Firms that increase the utility consumers get from their offerings through differentiation, while at the same time lowering their cost structure, can create more value than their rivals, and will acquire a competitive advantage, superior profitability, and profit growth [30, 32].

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 [33, 34]. 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 [35]. 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.

Although H1a and H1b both hypothesize positive effects on supply chain competence from two different business strategies, the means through which the two strategies are linked to supply chain competence are quite different. Differentiation strategy pursuit is linked to supply chain competence through effectiveness in product innovation and customization, whereas cost leadership strategy pursuit is linked to supply chain competence through efficiency in operations [36]. Even though both strategies have a positive impact on supply chain competence, differentiation strategy pursuit is considered to have a stronger relationship with supply chain competence than cost leadership strategy pursuit will have. Because 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 efficient supply chain operations which are responsive to changing customer preferences. These supply chain operations need to react to unique customer experiences with speed and flexibility. To sustain in competition, the differentiators will always need to be a step ahead, looking for the next uniqueness enhancing innovation. The differentiators are therefore more likely to require promptness and flexibility in supply chain operations. Furthermore, the impact that the introduction of a radical product or business innovation has on the supply chain activities of a firm is likely to exceed that of the implementation of a cost efficient solution that is more common in an industry regardless of the efficiency that it brings [37]. Thus the following is hypothesized:

H1c. The relationship between differentiation strategy pursuit and supply chain competence will be stronger than the relationship between cost leadership strategy pursuit and supply chain competence.

## 2.2 Business Strategy and Big Data Analytics

A business strategy concerns the competitive positioning, market segmentation and industry environment of a company [26]. 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 [9, 38].

From the information processing view [13], 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 [14]. 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 [39]. Furthermore, business strategies of most organizations are frequently a combination of their intended strategies and the emergent strategies [40]. Firm leaders need to analyze the process of emergence and to make strategy adjustment when appropriate [41]. For this purpose, big data analytics could also serve as the tool to facilitate the strategic decisions to be accurately aligned with competition changes [42, 43].

Big data analytics with the 3Vs (Volume + Velocity + Variety) provides a clear picture of product use, showing instantly which features customers prefer or dislike, by means of the increased volume, velocity and variety of data collected from customer responses. An example is the effects of word of mouth created by a large number of online visitors on consumer's purchase preference for manufacturers and retailers [44, 45]. 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 [46]. These price and value analytics further forms the basis for decisions of differentiation and cost structure.

For companies pursuing cost leadership strategy, cost analytics of all levels is more accurately analyzed to maintain a viable leading cost structure. For firms pursuing differentiation strategy, customer preference analytics determines the need to differentiate their products against the need to keep their cost structure under control in order to offer a product at a competitive price [44].

In summary, 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.

Technology is one of the most prominent factors influencing the rules of competition [26]. 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 [17, 29]. However, while H2a and H2b 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 [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. In this regard, the following is hypothesized:

H2c. 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.

**2.3 Supply Chain Competence and Big Data Analytics**

Supply chain operations generate and utilize large-scale heterogeneous data with time-varying nature [48]. The timely and accurate flow of information is a necessity for successful supply chain operations [49]. The evolution of big data analytics is expected to transform enterprises' managerial paradigm, including supply chain management [20]. 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 [50-53]. These results lead to the conjecture of the association between supply chain competence and big data analytics [20, 54]. The possible association between supply chain competence and big data analytics adoption has thus become a crucial topic to both academics and practitioners [19]. 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 [55]. The 3Vs capability of big data analytics is well aligned for responding to the requirement of supply chain operations [9, 20]. Therefore, big data analytics adoption in a firm is expected to produce significant results concerning enhancement of supply chain competence.

The efficiency considerations in supply chain operations mainly centers around time efficiency, cost efficiency and flexibility [56, 57]. 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 [56, 57].

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 [58]. 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 [59-61]. 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. Results

The development process results in the following hypotheses.

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

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

H1c. The relationship between differentiation strategy pursuit and supply chain competence will be stronger than the relationship between cost leadership strategy pursuit and supply chain competence.

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.

H2c. 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.

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

Based on our proposed hypotheses, the research framework is illustrated in Figure 1.

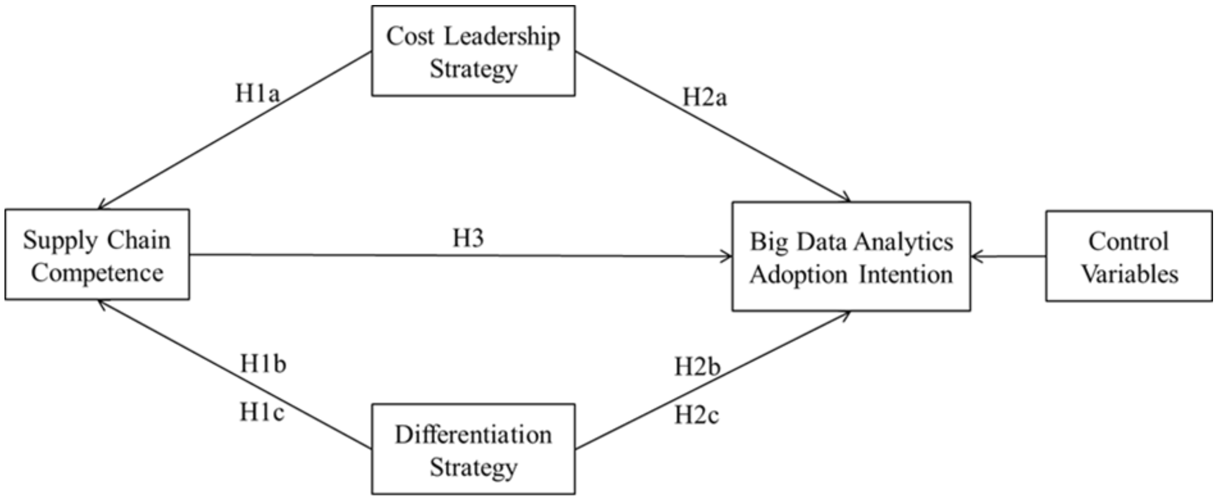


Figure 1 Research framework

Note that in Figure 1 we have included possible control variables such as firm size, IT department size and industry sector, which have been noted in several studies to affect deployment of information technologies [62, 63].

# 4. Discussion

### 4.1 Applicability and Extensibility of the research framework

This paper provides a research framework for business strategy, supply chain competence and big data analytics adoption. The effectiveness of this framework is based on theories of organizational information processing, core competence and competitive strategy. The framework is generic and is applicable to manufacturing, service sector or public organizations.

The research framework presented in Figure 1 could be viewed as a kernel framework and extended in several directions.

For research aiming at innovative technology adoption, in addition to the adoption intention, other constructs such as perceived usefulness or perceived ease of use of the technology could be included.

For research emphasizing technology based resource and capability, big data analytics capability construct can be included as a high level construct and decomposed into formative or reflective sub-constructs.

For research focusing on supply chain management, the supply chain competence construct could be linked to lower level supply chain capabilities such as supply chain efficiency and supply chain flexibility. Supply chain management strategy such as agile supply chain strategy or lean supply chain strategy could also be included in the framework.

For research toward competitive strategy, formative or reflective secondary constructs of differentiation and cost leadership could be extended. Other strategy typology could also be employed.

Furthermore, the output of the big data analytics adoption construct could be linked to competitive advantage, business performance, value creation or profitability.

Also noticed is the possible mediating role of supply chain competence in the framework. Other mediators or moderators could be included in the framework. For example, technology innovation capability, customer service competence and marketing intelligence capability [64] are some of the candidates for consideration.

### 4.2 Suggestions for Further Research

Empirical studies are suggested to test the kernel framework in Figure 1 or its extensions. Both of quantitative data or qualitative data from enterprises of various sizes are recommended. Research which focus on accumulating more empirical evidence for assessing and validating the research framework or its derivatives are recommended to overcome the scope of the present study.

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 other emerging big data technologies relate to business strategies and functional operations. For example, mobile big data analytics [65] or big data analytics in mobile computing [66, 67] have received inadequate attention from strategic considerations and technology adoption theories.

Further research could also investigate the relative importance of the factors affecting each stage of the strategy shaping process. These efforts should 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 business level strategies, functional level strategies, and innovative technology adoption intention.

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