Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is data quality a way to extract business value?

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Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is data quality a way to extract business value?

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Highlights

- Data quality can significantly impact directly and indirectly firm performance
- The value extracted from BDA and IoT is similar in European and American firms
- BDA tools are being used mainly on production run and inventory optimization
- IoT is being used in areas of innovation and continuous process improvement programs
- Complex business processes fed with bad data can decrease BDA and IoT capabilities

Abstract

Big data analytics (BDA) and the Internet of Things (IoT) tools are considered crucial investments for firms to distinguish themselves among competitors. Drawing on a strategic management perspective, this study proposes that BDA and IoT capabilities can create significant value in business processes if supported by a good level of data quality, which will lead to a better competitive advantage. Responses are collected from 618 European and American firms that use IoT and BDA applications. Partial least squares results reveal that better data quality is needed to unlock the value of IoT and BDA capabilities.

Keywords: big data analytics, internet of things, strategic management, knowledge-based theory, dynamics capability theory.

Leveraging IoT and BDA initiatives in European and American firms:Is data quality a way to extract business value?

1. Introduction

Past research shows that the value of having data-driven organizations take advantage of several IT capabilities to improve their performance [1]. Big Data Analytics (BDA) and the Internet of Things (IoT) are considered the most profound transitions in technology [2, 3]. Because of the increasing number of IoT services on a global scale, various industries are adopting IoT technologies to generate big data [4]. It is forecasted that by 2020, the number of connected devices in the IoT will be between 26 billion (Gartner) [5] and 75 billion (Morgan Stanley) [6]. There is a general belief that IoT will become ubiquitous in the next decade and will be able to generate vast amounts of data that can be analyzed to create value to firms. This increase will affect the growth of big data. Introducing data analytics for IoT and other big data requires enormous resources. IoT has the ability to provide several data analytics opportunities for BDA [2]. The IDC FutureScape report predicts that by 2018, investments in data analytics for IoT will deliver a 30% improvement in critical business processes [7]. BDA technologies are considered the mother lode of disruptive change in the business environment for all types of industries, as they have the ability to capture big data and extract its value by analyzing the data with powerful analytical techniques [3]. BDA and IoT capabilities can impact the different actors in a big data ecosystem where different players generate, use, or benefit from big data and their applications. The data actors need to develop BDA and IoT capabilities to extract value that can impact their business and society. This process is key to digital transformation and the creation of sustainable societies and big data ecosystems [8]. According to the Big Data Value Association, the U.S. and Europe are regions where most of the BDA initiatives take place [9]. The U.S. data market and economy in 2013-2014 were the first in value followed by Europe, which was growing almost as quickly [9]. In line with this, an IBM study stated that companies using BDA are five times more likely to make faster decisions than their competitors [10].

However, these benefits can only be attained if a certain level of data quality is ensured. In this study, we considered data quality as data that are fit for use by data consumers [11]. With the increasing availability of data lakes from different data sources and representation forms, data quality emerges as one of the most important data management issues. Recent literature has highlighted data quality management as the top issue to be able to extract value from BDA and IoT [12-14]. It is paramount to quantify the full impact of data quality to mitigate risks in the utilization of BDA and IoT technologies to ensure the effectiveness of business outcomes [13]. Data quality issues can have a considerable impact on the organizational decision-making processes, as the quality of the analysis is fully correlated with the quality of the data analyzed [15]. Additionally, bad data can impact on financial performance. According to Gartner, 25% of critical data in the world's top companies are flawed [15]. IBM's estimate of the annual cost of poor-quality data in the U.S. alone, in 2016, was $3.1 trillion. Therefore, there is no doubt that these hidden data factories are costly [16]. Analysts estimate that firms have seen 8% to 12% of their revenues doomed due to poor-quality data. New strategies, tools, and technologies should, therefore, consider this topic as a challenge to address to have the appropriate solution in place [17]. Moreover, the effect of data quality on BDA and IoT can be greater depending on the level of business process sophistication [18]. Considered as a challenge to organizations, process sophistication combines information intensive and also complex processes [19]. Consequently, firms with higher degrees of process sophistication are more likely to experience the benefits of improved data quality than those with a low degree of process sophistication. [20].

Because of the recent revolution with IoT data, which poses a colossal data quality challenge, in this paper, we clearly distinguish the two types of big data (IoT big data and the remaining big data) to holistically assess big data impact and understand the different behaviors that might arise from different levels of maturity. At the first glance, BDA and IoT may appear to be very similar. In fact, these technologies are interdependent. Both collect a considerable amount of data and analyze it to extract information. Both complement each other when firms have the ability to combine both. Although these technologies are intimately linked, they are quite different. First, from a data source perspective, IoT turns everyday “things” into smart objects. It aggregates data from a variety of sensors. This information can become big data when it is combined with information from other sources (variety) and requires high processing capacity (velocity). Second, the techniques and architectures used in big data cannot be used in IoT. While BDA tries to extract patterns from data about millions of cases to find ways to generalize results that cannot be explained, IoT analytics evaluates the individual behavior and determines the best treatment for that specific “thing” based on their unique data history, and therefore, the results are specific and can be explained. Third, these technologies have different time sequencing. BDA does not leverage the information to take real-time decisions. IoT analytics must include managing real-time streaming data and making real-time analytics and real-time decisions [2]. Companies that do not develop enough resources and capabilities to use both types of big data effectively will be challenged to develop a sustainable competitive advantage and to survive the Big Data revolution [21]. Therefore, executives and researchers need to understand how to leverage the potential of BDA tools and IoT [17] and how their use can lead to competitive advantages [22].

This study aims to understand the full effect of big data quality on BDA and IoT capabilities and their impact on firm performance to organizations. Because of the fact that most big data research is focused on technical issues, there is a lack of theoretical-driven research on how to use big data tools to achieve a competitive advantage [23]. On the BDA side, grounded in Resource-Based View (RBV) and the DeLone and McLean theories, only two studies have assessed BDA value from a data quality perspective [24, 25]. On the IoT side, there is a lack of theoretical foundation, and most earlier studies on data quality have been focused on technical topics [22]. A more holistic view to understand BDA and IoT drivers and impacts at the firm level is needed [22, 23, 26, 27]. Most BDA and IoT research is dominated by work conducted in Europe and Asia considering only one country [22, 25]. As these technologies are context specific [26, 28], recent research claims that multi-country analysis is needed [25]. No study has used an extensive multi-region survey to conduct a holistic evaluation of big data quality effect by not only considering two types of big data (BDA and IoT) but also assessing the direct and indirect effects on firm performance. Motivated by these gaps in the literature, grounded in knowledge management and dynamic capability theoretical lenses, this study seeks to propose a research model to assess the BDA and IoT value process from a data quality spectrum. The contribution of this study is threefold. First, by investigating BDA and IoT value in two different regions (data sample of 618 EU and U.S. firms), we contribute to a broader scientific knowledge that has not yet been examined in BDA and IoT data quality research. Second, by linking two types of big data (BDA and IoT), it assesses the full effect of big data quality and their direct and indirect effects on firm performance. Third, it extends the existing BDA and IoT theoretical knowledge body by proposing an integrated and strategic theoretical framework using knowledge management and dynamic capabilities. These gaps in the literature restrict the current understanding of BDA and IoT usage and impact in organizations. Our study addresses the following research questions:

(1) How does data quality impact the BDA and IoT capabilities to support key business processes in European and American firms?

(2) What is the impact of BDA and IoT capabilities on competitive advantage in European and American firms?

The structure of the remainder of the article is as follows. Section 2 includes a review of relevant literature to understand the importance of having data quality to encourage the creation of BDA and IoT capabilities toward competitive advantage. Section 3 presents the conceptual research model and the related hypotheses. The procedures used to test the hypotheses are described in Section 4. Section 5 presents the results. Finally, the discussion, implications, and conclusions are presented in the last section of the paper.

2. Theoretical background

The following subsections provide an overview of the importance of taking advantage of BDA and IoT capabilities in firms. While academics can understand the state-of-the-art of BDA and IoT use and value literature research, practitioners can understand the potential value of these tools. Hence, the rationale for our research contribution is presented next.

2.1. Big data analytics

The term big data analytics was initially coined by Chen [29] as a set of business intelligence and analytics (BI&A) technologies that are mostly concerned with data mining and statistical analysis. Although several definitions are presented in the literature [27, 30], the general idea is the same. It can be defined as "*a holistic approach to manage, process and analyze the '5 Vs' data-related dimensions (i.e., volume, variety, velocity, veracity, and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages*" [31]. Although there is a symbiotic relationship between big data and IoT, which allows them to generate massive amounts of data, only with BDA applications can companies combine and integrate all types of data, thus providing insights into all levels of the organization [17, 32]. By providing insights into several areas (e.g., customer relationships, marketing, inventory management, product and service development, and other core business areas), the use of BDA technologies provides them the opportunity to innovate and create temporary advantages [33, 34]. Together, big data, IoT big data, and BDA allow firms to increase their operational efficiency, reduce costs, and develop value-added services and ultimately profitability [17, 22]. A recent study performed by SAS revealed that 93% of businesses that have invested in big data have experienced a cost saving, while 91% of businesses that invested in the IoT were able to reduce their costs [17]. BDA and IoT have the potential to reshape our world. It is foreseen that in the next years, their contribution will be of high importance to the economy and society.

With the exception of some large companies focused on information such as LinkedIn, Facebook, and Google, which are actively adopting BDA, most large- and medium-sized firms are in an early stage of adoption, struggling to understand and decide upon their strategy regarding BDA.

Also, business executives are hesitating to invest in BDA because of their past experience with business intelligence initiatives that rendered unsatisfactory results [26]. In terms of adoption, Europe has been slow in adopting big data when compared to the U.S. According to research performed by IBM in 2014, 68% of American firms use BDA, whereas 48% of European firms have BDA initiatives [10]. Although BDA adoption is increasing, the potential value that can be extracted is still in an early stage. For example, if the U.S. health care system were using big data creatively, it would be possible to create more than $300 billion in value annually. In Europe, governments could create more than €100 billion by using big data to reduce fraud and errors and boost the collection of tax revenues [35]. Developed economies such as the UK expect that the value of BDA and IoT will reach £322 billion by 2020, which represents 2.7% of the annual expected GDP. This forecast can be explained by the plethora of undertaking and industries such as supply chain management, manufacturing, healthcare, transports, tourism, and many other spheres that already benefit from it and will continue to invest in this type of technology [36]. Another example is Cisco, which uses BDA to drive their entry into new markets with their acquisitions. They eliminated 80% of the efforts spent in manipulating the data from thousands of systems and moved their processes into analyzing the insights and actions. eBay uses BDA to analyze 500 metrics and select the best model automatically to determine true positives with 100% accuracy at 97% confidence. Through this, eBay can connect buyers with things they need and care about in real time. Amazon uses BDA to predict when a customer will make a purchase and begins shipping the product to the nearest hub before the customer submits the order online. Depending on these consumer insights, Amazon is able to recreate a distribution strategy instead of merely improving those activities [21].

Most of the BDA literature has been focused on technical topics, disregarding how these tools create value and consequent competitive advantage [37]. Although some research has been done on the antecedents and effects of BDA value [26-28, 38, 39], only two studies have assessed it from a data quality standpoint [24, 25]. Particularly, in one of these studies, as BDA is context specific [26, 28], Fosso Wamba et al [25] concluded that there is a need to extend BDA data quality research by investigating the link of data quality and firm performance in more than one country. Therefore, our study contributes to extending the knowledge on BDA data quality research by examining the direct and indirect effects (through BDA capabilities) of data quality effects on competitive advantage in a multi-region survey (European and American firms).

2.2. Internet of Things

The IoT is a paradigm in which all types of objects can have sensing, networking, and processing capabilities that allow them to communicate with other devices and services provide value-added services [36]. It allows things, people, and processes to be connected Anytime, Anyplace, with Anything and Anyone, if possible using Any path/network and Any service. Although there are several definitions of IoT [40, 41], which can depend on the type of technology used [42], it can be generally defined as a process able to integrate smart object identification, active intelligence, network capabilities, and interaction with users. In this complex network of things and people, anything can be connected and communicated with using wireless sensors and RFID (Radio-Frequency Identification) tags. Once they are connected, these "things" can send data and interact with other "things" and people on a real-time basis [32]. Considering the processes for data acquisition and transmission in IoT, its architecture usually has three layers: device (sensing), connection (network), and application [3]. A major part of IoT hardware such as RFID, Near Field Communication (NFC), and Sensor Networks [36] already exists.

IoT is an important source of big data [3]. As big data come from a variety of sources in massive amounts, and often in real time, some authors consider that IoT is essentially an extension of big data, with the ability to link smart objects to the Internet and share information [22]. The big data created by IoT has characteristics different from those of general big data. The data are characterized by heterogeneity, variety, noise, redundancy, and a lack of structure. Although IoT data are not the most prominent part of big data currently, it is foreseen by HP that in 2030, IoT data will be the most important big data [3]. As IoT technologies and applications are still in their infancy [22], the future trend is strongly driven by the pervasive diffusion and adoption of IoT [22]. The use of IoT by firms allows new ways to create business value. New data-driven strategies will help firms to improve their performance by gathering and evaluating these data [4]. Firms can use the data for customer sentiment analysis, fraud detection, risk management, and other purposes [17]. For governments, smart cities are an example of IoT big data that can be collected from industry, agriculture, traffic, transportation, public departments, etc. The knowledge extracted can be used to make strategic decisions such as the placement of traffic lights, construction of roads, and future city plans [3, 43]. For example, analytics applied to IoT allowed Kaeser Compressors to create a new business model by selling metric cubits of air instead of selling equipment, allowed Trenitalia to reduce 8% in total maintenance costs (130Mi€ per year), and allowed a supply chain to execute decisions and control the external environment. IoT-enabled factory equipment allows communicating within data parameters (i.e., machine utilization and temperature) and optimizing performance by changing equipment settings or process workflow [2].

To holistically understand and unlock the value of big data and IoT, it is necessary to understand the extent to which BDA and IoT capabilities exist in firms [17]. IoT and BDA technologies are interdependent and should be jointly promoted and developed for two principal reasons: (1) the use of IoT creates an opportunity to increase big data and empower BDA tools; (2) BDA and IoT accelerate research development and IoT business models [3, 30]. In practical and academic fields, earlier literature has focused on providing overview descriptions, concepts, architectures, algorithms, opportunities and challenges to define future research roadmaps [41, 44]. According to Riggins [22], several positioning papers have been discussing the importance of understanding IoT and BDA capabilities at an organizational level (see [22]). Concerning empirical studies, little empirical research has examined IoT and BDA capabilities at the organizational level [1, 22, 31, 45]. Because IoT is a recent development, there is a lack of studies focusing on the behavioral and managerial concerns of IoT. In this sense, companies are struggling to understand the drivers of IoT capabilities and their impact on firm performance [22, 33, 36]. It is relevant to understand the main differences in using analytics based on IoT or regular big data. A more holistic view to understand BDA and IoT capabilities drivers and impacts at the firm level is needed [22, 23, 26, 27]. Notably, most earlier studies on IoT data quality have been focused on technical topics [22]. To our knowledge, this is the first study that assesses the full effect of big data quality on firm performance, directly and indirectly, considering the two types of big data (IoT and BDA). Moreover, as most of the literature has used European and Asian data, this article improves BDA and IoT value research by examining their behavior in two different regions (Europe and the United States).

2.3. Conceptualizing the enablers of IoT and BDA capabilities and their impacts on competitive advantage

In recent decades, studies in management information systems (MIS) and management fields have examined IT business value (see review articles - [46, 47]). Although the majority of IT business value research is theoretically dominated by the use of the resource-based view (RBV) [47-51], other recent strategic theories have emerged to overcome some of the RBV limitations [52]. Drnevich (2013) argues that MIS and strategic management research should be theoretically integrated. Additionally, because of the fact that theoretical MIS research has been evolving in parallel with strategic management theories, it makes sense to join both perspectives. The research in IT business value considering strategic management theories has been scarce [27, 46, 53]. We believe that a combined strategic management framework allows researchers in both fields to understand how investments in IoT and BDA capabilities create business value for the firm. In this paper, we clearly distinguish the analytical power to explore two types of big data: IoT big data and the remaining big data. In the next sections, we explain the rationale to consider the combination of knowledge-based view and dynamic capability theories to support our conceptual model.

2.3.1. Knowledge-based view – Data quality as an enabler of BDA and IoT capabilities

Defined as a competency-based theory [46], KBV is considered an extension of RBV, in which organizational knowledge resources are regarded as unique and inimitable and that the firm's primary function is to leverage them into productive outcomes [54, 55]. These resources and capabilities may be inherited by the firm and its history or consciously built. The effective use of these resources and capabilities determines the firm's competitive advantage. This type of theory is useful to support the creation and capture of business value through digitally improving the firm's existing resources and capabilities and/or allowing the firm to create new capabilities. In the IT field, earlier literature has used KBV to theorize the antecedents of dynamic capabilities. While Sher [56] explained the impact of knowledge management in the creation of dynamic capabilities, Saraf (2007) explained the impact of IS application capabilities in the creation of relational value [56, 57]. Specifically, empirical studies have used this theory to understand the impact of knowledge resources in BDA applications (e.g., [27, 58]). In this study, we consider data quality and process sophistication as two crucial knowledge resources to explain BDA and IoT capabilities.

Regarding data quality, earlier research has demonstrated that it can significantly impact the organizational knowledge and use in IT solutions [19], and consequent data-driven decision making [45]. Specifically, grounded in Resource-Based View (RBV) and DeLone and McLean theories, only two studies have assessed BDA value from a data quality perspective [24, 25]. On the IoT side, there is a lack of theoretical foundation [22]. Moreover, Dubey, Gunasekaran [59] recently suggested the need to examine the antecedents of BDA capabilities using another theoretical lens such as KBV. In this study, we consider data quality as an organizational knowledge resource, as by having this knowledge about the level of data quality the firm can consciously leverage BDA and IoT capabilities, which ultimately improves competitive advantage. Hence, this study contributes to academia by providing a theoretical view of knowledge management appertaining to the link of big data quality and BDA and IoT capabilities in firms.

Strong, Lee [11] defined "data quality" as data that are fit for use by data consumers. Following their empirical approach for data quality, this dimension determines the characteristics they use to assess whether or not the data are fit for use in their tasks. As firms need to be able to deal with huge amounts of structured and unstructured big data and IoT, data quality is considered key for a decision-making process [12]. Grounded in the Nonaka knowledge classification framework [60], we conceptualize data quality as explicit knowledge. This type of knowledge is formal, precise, easily codified, documented, transferred, or shared. Although explicit knowledge represents only a part of the organizational intellectual landscape, it has a crucial impact on the strategy of a firm, as it is considered to be one of the most critical factors of knowledge production [61]. As this type of knowledge is expected to flow using IT tools (such as BDA and IoT tools), we consider that this can be represented through data quality. Past research emphasizes that the nature of knowledge can impact the use of IT tools in organizations. Specifically, dimensions of technology performance improvement rely on explicit knowledge. For instance, if users are told about the level of data quality that is associated with the data they use, they can use this knowledge immediately. In this sense, this type of knowledge can be easily transferred and is more predictable than others (e.g., tacit knowledge) [62]. Therefore, the possession of explicit knowledge based on data quality enables firms to renew and reconfigure their resource base, thus creating dynamic capabilities through the usage of BDA and IoT [63]. Value is generated as a result of better decision making enabled by accurate data [64]. This value creation process can generate temporary or sustainable competitive advantage [21, 65].

In addition, process sophistication was considered in our study for many reasons. First, in a conceptual perspective of KBV, following Karimi, Somers [66], process sophistication can be considered a knowledge resource, as know-how about business processes can provide a better way to implement these BDA and IoT systems (e.g., accurate elicitation of system requirements, integrating data and processes across value-chain activities, etc.) and consequently promote their usage. Second, business processes provide a perspective by which to analyze IT business value [67] and a vehicle to build and materialize BDA and IoT capabilities [68]. IT investment occurs at the operational level by process efficiency and effectiveness. By improving operational efficiency, effectiveness, and flexibility, business processes will boost profitability and competitiveness. Third, data quality is likely to be even more influential for decision-making effectiveness associated with IoT, and BDA capabilities with more sophisticated processes. Hence, higher data quality becomes even more important for BDA and IoT capabilities, as it facilitates the quick execution of complex or information-intensive business activities [19].

2.3.2. Dynamic capabilities theory – BDA and IoT capabilities as dynamic capabilities

Considered to be one of the most important theoretical views in the strategic management field, in the last decade, the dynamic capabilities (DC) approach has attracted the interest of business and IT management researchers [69-71]. Although several definitions have been proposed over the years, the central concept was coined by Teece as "*the ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments*" [72]. In other terms, DC can be defined as strategic organizational processes that firms possess [72].

As a flexibility-based theory [46], it can be considered as an extension of RBV and it can serve as a complementary view of the KBV in a dynamic market context [73], while KBV (as a competence theory) allows us to identify and evaluate the capabilities for BDA management as a source of competitive advantage. This theory provides us with an opportunity to see the flexible effect of information in the firm's strategy [46]. As DC literature recognizes knowledge resources as a strategic resource for sustainable competitive advantage [55], we combine both theories.

The DC theory emphasizes the firm's ability to rapidly respond to change in a way that either enhances its efficiency (e.g., minimizes the costs of adapting to a new situation) or effectiveness (e.g., enabling the company to discover new opportunities by creating new products or services) [46]. In this sense, the value creation does not come from the possession of the resources but their use, and how much value is created would depend on how these resources are combined within the firm [65]. According to Teece (1997), DC can be classified by three main processes: (a) coordination/integration (a static concept), (b) learning (a dynamic concept), and (c) reconfiguration (a transformational concept) [72]. In this study, we consider that BDA and IoT capabilities can be seen as dynamic capabilities. First, by performing a concept analysis of DC, grounded in some of the most known authors in DC literature, we can establish a link with BDA and IoT capabilities. Hence, based on the Eisenhardt and Martin [74] concept, BDA and IoT capabilities can be seen as the capacity to use organizational routines that allow companies to readjust their resources to support decision making. This consequently will allow matching or creating market change. Further, grounded in the Ambrosini and Bowman [65] concept, BDA and IoT capabilities represent the ability of companies to improve their resource base toward better competitive advantage.

Overall, these definitions reflect the fact that dynamic capabilities are organizational processes and that their role is to change the firm's resource base. According to Ambrosini and Bowman [65], a dynamic capability is not an *ad hoc* problem-solving event or a spontaneous reaction. It must contain some patterned element, i.e., it must be repeatable. IoT and BDA capabilities have these characteristics. Moreover, earlier empirical studies highlight that business intelligence capabilities can be considered as IT process-oriented dynamic capabilities. Kim (2011) states that DC can be considered "*a firm's competence to change existing business processes better than its competitors do in terms of coordination/integration, cost reduction, and business intelligence/learning.*" Specifically, a recent empirical study conceptualized and empirically confirmed that BDA capability is a DC [26]. Therefore, based on the concept analysis and empirical studies, we follow the same approach and use Chen's construct for BDA capabilities. The same rationale to consider IoT capabilities as a DC is used.

Consequently, following the same approach as Chen (2015), the constructs' items represent highly complex and information-intensive processes categorized according to Teece's classification [72]. The business processes supported by BDA capabilities are operationalized based on several types of Teece's classification: learning (sourcing analysis, purchasing spend analytics, CRM analysis, and forecasting/demand management), reconfiguration (network design/optimization, production optimization, inventory optimization), and coordination/integration (warehouse operations improvements, process/equipment monitoring, and logistics improvements). Along the same line, IoT capabilities also cover the same type of routines: learning (problem analysis and stakeholders' awareness and added value to customer services), reconfiguration (continuous process improvement, innovation, and reduced risks and costs), and coordination/integration (improve operational effectiveness, firm agility, corporate strategy, and planning).

A recent systematic literature review highlighted there is a lack of theoretical-driven research on how to use big data tools to achieve competitive advantage [23]. While in IoT there is no theoretical framework used to examine business value [22], most of the limited research on BDA value is grounded in RBV [39] combined with other theories such as Sociomaterialism [28, 38], DeLone and McLean [24, 25] and DC [23]. Moreover, some BDA value empirical literature is supported by the DC theory [26] in combination with other theories such as KBV [27] and Contingency Theory [59]. Particularly, the only assessment of BDA value through a data quality perspective has been explained using RBV and DeLone and McLean frameworks [24, 25]. This article extends the existing BDA and IoT theoretical knowledge body by proposing a new strategic theoretical framework (KBV and DC) to assess the link between big data quality and firm performance.

3. Research model

Figure 1 depicts the conceptual model of our study. Grounded in the value creation process logic of Soh and Markus [48], in which assets are leveraged by the use of IT toward a better firm performance, this model represents the business value chain provided by BDA and IoT. It is based on the premise that data quality is able to impact core business processes supported by IoT and BDA capabilities. This effect is moderated by firms' process sophistication. Finally, both capabilities will positively impact the creation of competitive advantages.

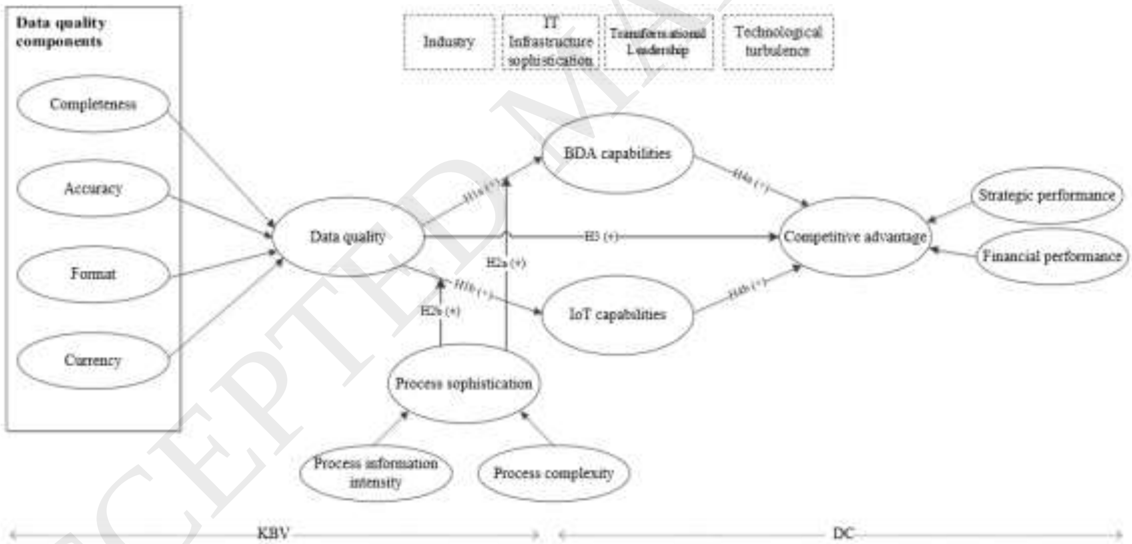

Figure 1 – Research model

Data quality role on BDA and IoT capabilities

According to Zollo [75], dynamic capabilities emerge from the development of tacit experience accumulation processes with knowledge articulation [65]. Although big data is considered to be a valuable organizational knowledge asset [76], companies can extract competitive value from BDA and IoT applications only if data have a certain level of quality [3, 31]. By using BDA and IoT tools with a good level of data quality, the decision-making process will improve the confidence in the outputs. Additionally, it will allow the users to be more productive, and focus on their core business instead of spending time validating and fixing data errors.

Moreover, when considering data needed to be compliant with regulatory requirements, ensuring good data quality in BDA and IoT tools can be the difference between being compliant or paying millions in fines. Finally, these tools can also be used to support marketing processes. This process can only be valuable if supported by good-quality data. The positive impacts of using BDA and IoT tools can be compromised by data quality [31].

A data quality assessment constitutes an opportunity to improve BDA and IoT applications, optimizing decision-making processes at operational, tactical, and strategic levels, which might significantly impact firm performance [45]. Firms should treat data as an asset and manage it to maintain quality to derive effective insights that can lead to competitive advantage. Earlier studies have demonstrated that the level of data management can influence the creation of dynamic capabilities [34, 56]. In addition, the IT Business strategic thinking can positively enable dynamic capabilities [34]. Specifically, Setia [19] suggests a link between data quality and the creation of customer service dynamic capabilities. Data quality can influence the use of BDA and IoT capabilities [3, 45]. The use of highly sophisticated analytical tools is meaningless if poor-quality data are being used [30]. High-quality data represent a precondition for using BDA and IoT and for guaranteeing the value of the data. The effective use of big data and IoT must be based on accurate and high-quality data, which is a necessary condition for generating value [14]. In this sense, data quality can be defined as a combination of completeness, accuracy, format, and currency of the information produced by BDA and IoT applications. Completeness refers to "the degree to which the system provides all the necessary information"; accuracy is "the user's perception that the information is correct"; format refers to "the user's perception of how well the information is presented"; and currency is "the user's perception of the degree to which the information is up to date" [19]. As higher quality data may facilitate and reorient the routines and activities of BDA and IoT applications, we propose that information quality is an enabler of BDA and IoT capabilities. Hence, we put forward the following hypotheses:

H1a: Strong data quality can positively impact BDA capabilities.

H1b: Strong data quality can positively impact IoT capabilities.

The moderating role of process sophistication

Dynamic capabilities can be moderated by several endogenous variables such as managerial behaviors and the presence of complementary assets and resources [65]. Recently, Wamba [38] considered that the organizational culture should be studied as a moderator of BDA and IoT capabilities. In this sense, the level of business process sophistication can be seen because of managerial behaviors and an indicator of organizational culture. Process sophistication is defined as "the complexity and information intensity of a process." Process complexity refers to "the non-routineness, difficulty, uncertainty, and interdependence within a process." Process information intensity can be defined as "the amount of information processing required to effectively manage the activities of the business process" [19]. The strategic benefit that firms can derive from information systems is related to their process sophistication [20]. If we consider that the firm has several complex or information-intensive processes, the benefit that will be taken from the use of BDA and IoT capabilities is expected to be greater, as these tools are typically used to support these types of processes [19]. Considering that the level of data quality is high, the value extracted from using BDA and IoT will be higher, depending on the level of process sophistication. Thus, we hypothesize

H2a: Process sophistication positively moderates the impact of data quality on BDA capabilities.

H2b: Process sophistication positively moderates the impact of data quality on IoT capabilities.

Data Quality and competitive advantage

Previously, we posited that data quality could affect the use of BDA and IoT capabilities that ultimately impact competitive advantage. However, past empirical research on IT literature supports a direct and positive relationship between data quality and organizational performance [77-79]. Specifically, Xiang (2013) concluded that by improving the level of data quality management maturity, firm performance can be increased by 33.7% in sales, 64.4% in operating profit, and 26.2% in value added [78]. Another study argues that when better information is provided (not only through BDA and IoT applications), firms increase their efficiency in several ways, namely, their operational, tactical and strategic performance (e.g., increased profit margin and reducing labor costs) [79]. Improving data quality impacts firm performance directly by optimizing time. For instance, analytics teams can spend up to 90% of their time manipulating and cleaning data in preparation for analysis and modeling [12]. Improving data quality will increase the time available for modeling [12], which will allow firms to create business value through BDA and IoT applications. By improving access to relevant, accurate information, decision-making processes will likely improve, which can contribute to competitive advantage. [79]. In this sense, we posit:

H3: Data quality positively impacts firms' competitive advantage.

BDA and IoT capabilities on competitive advantage

As previously conceptualized in Section 2.3.2, in this study, we assess the combined effect of two dynamic capabilities: BDA and IoT capabilities. BDA capabilities are seen as dynamic capabilities leveraged by data quality. First, BDA capabilities represent organizational information processing capability that allows knowledge creation [26] based on the exploitation of big data. They can be defined as the extent to which BDA has been used to provide business insights into primary activities (e.g., production, distribution, and customer service). It is expected that BDA use will allow organizations to plan and make better decisions for the future, optimizing resources [26]. In this sense, BDA capabilities represent an innovative IT capability that can increase competitive advantage [45]. Second, IoT capabilities can also be considered as dynamic capabilities. Although it is widely recognized that information has a crucial role in firms' performance, the information has little impact if not used to support decisions [80]. Recognized as one of the most important measures for IS value, IoT capabilities can refer to the ability to apply acquired and transmitted IoT data to support organizational decision-making. Firms can use IoT to reconfigure their business processes (e.g., continuous process improvement) and optimize them to adapt to environmental changes rapidly. These knowledge-based routines are critical particularly when the environmental dynamism is high [74]. Considering the current business environment exposed to rapid market changes, the dynamic capabilities framework highlights the organizational and strategic management competences that allow firms to achieve sustainable competitive advantage [72]. Most scholars have considered the impact of DC on firm performance [46, 72]. Several studies show that DC can have a positive effect on firm competitive advantage [69, 81, 82]. Although these capabilities may not be sufficient to ensure better performance, they are needed [56]. In this sense, when supported by knowledge management activities such as data quality, BDA and IoT capabilities can improve firm performance. As BDA and IoT tools supported by quality data can help operational efficiency, cost reduction and developing value-added services ultimately contribute to profitability [17, 22], we hypothesize

H4a: As a dynamic capability, BDA capabilities positively impact firms' competitive advantage.

H4b: As a dynamic capability, IoT capabilities positively impact firms' competitive advantage.

The mediating role of BDA and IoT capabilities on the relationship between data quality and performance

IT literature demonstrates that dynamic capabilities can establish a link between knowledge assets and firm performance [27]. As we consider BDA and IoT capabilities to be dynamic capabilities, they can be seen as mediators. The impact of data quality can be seen through the use of these tools [14] or simply by the use of reliable data to make decisions that do not imply their use. In this sense, we hypothesize:

H5a: *BDA capability positively mediates the relationship between data quality and competitive advantage.*
H5b: *IoT capability positively mediates the relationship between data quality and competitive advantage.*

Competitive advantage

Competitive advantage occurs when a firm is having greater success than its current or potential competitors [83]. One of the most common indicators of competitive advantage is superior firm performance [69]. Grounded on Schilke's construct [69] (used under the DC framework), we operationalize competitive advantage as a composite formative reflective type [84], composed of two first-order dimensions: (1) strategic performance (qualitative dimension) and (2) financial performance (quantitative dimension). On the basis of a number of studies that provide competitive advantage constructs [85-87], this construct was considered to be generic and more comprehensive, as most of the studies consider only one dimension of firm performance. In addition, the construct was used and considered valid to assess BDA tools in a previous study [27].

Control variables

Control variables are essential to consider the impact of factors other than the theoretical constructs that can explain the variance in the dependent variables. As our study assesses two different regions (North America and Northern Europe), where firms might have different systems that influence their competitive advantage, we used four control variables in this study. The *type of industries* was used to control for the possible effect of the extent of diversification. According to Winter [75], the industry can be considered a contingency factor when a firm is making a decision to develop and implement dynamic capabilities [65]. As BDA and IoT applications can be accelerated by the implementation of a strong IT infrastructure [42, 88], *IT Infrastructure sophistication* was included as a control. Firms also need *transformation leadership* to ensure data effectively oriented culture toward the usage of BDA and IoT in business processes to improve their performance [65, 89]. Nowadays, organizational leaders often lack the understanding of the value of big data and how to extract this value from the use of systems. Many firms do not structure their processes in ways that optimize the use of big data to make better decisions [30]. Finally, following the approach of Menguc and Auh [90] and Drnevich and Kriauciunas [91], the study includes *turbulent technological environment* as a control. Due to the innovative nature of BDA and IoT, this type of volatility can influence not only the type of usage of these technologies but also their effect on competitive advantage (e.g., in-memory computing technologies) [92].

4. Methodology

4.1. Measurement instrument

A multi-region survey of European and American firms from several industries was performed to test the model (Figure 1) and the hypotheses. Following the recommendations of Moore and Benbasat [93], the instrument was developed based on a number of valid constructs that were adapted on literature research and interviews with IT executives in some countries (Portugal and Germany). Regarding the content validity of the items, the initial survey was reviewed by four academic researchers involved in the IoT and BDA fields to ensure the proper wording, content, and understandability. Next, a pretest was conducted with a sample of 30 SAP customers who provided feedback on readability, clarity, and ease of completing the survey. The feedback was included to improve the final survey. Finally, a web-based survey using SAP data collection software was performed. Considering that IoT technology is not currently widespread, the study considers all types of IoT technologies. Appendix A includes the survey instrument and measurement items.

4.2. Data

The data for this study were collected through a web survey sponsored by SAP. This survey was carried out over two months in 2017. The sample was defined based on an SAP customer database that implemented technologies from the SAP Hana and SAP Leonardo portfolios (analytical and IoT platforms commercialized by SAP). Both regions were selected to allow assessing the difference between European and American firms. The respondents were instructed to respond to the questionnaire based on their most recent experience with IoT and BDA technologies. A total of 1200 survey invitations were sent to SAP customers in the selected countries (600 American and 600 European firms) that have used these technologies for more than one year. A total of 618 complete responses were received, thus resulting in a response rate of 51.5%. Nonresponse bias was assessed comparing early and late respondents (first and second months, respectively) based on the Kolmogorov–Smirnov test to test the quality of the results [94]. The test indicated the absence of nonresponse bias. Table 1 presents the respondent profile. Regarding the respondents' position, while in Europe, the most representative functions are other IT executives, the United States sample comprises business managers. As it is clear that a high proportion of businesses across all industries are using big data [17], we decided to perform the study with firms from all types of sectors. In terms of industry distribution, both regions have a substantial percentage of manufacturing (13.9% in both samples) and retail trade firms (12.8% and 14.3%). The sampling was stratified by firm size (more than 250 employees), and by industry to allow generalizing the survey results [95].

Table 1 Sample profile

Sample characteristics	**Europe (n = 373)**		**United States (n = 245)**	
(n=618)	Obs.	(%)	Obs.	(%)
Respondent position				
IT executive				
Chief Information Officer (CIO)	14	3.7%	40	16.3%
IT Director	59	15.8%	36	14.7%
IT Manager	25	6.7%	13	5.3%
Other IT executive	103	27.6%	33	13.5%
Business executive				
Chief Financial Officer (CFO)	35	9.4%	31	12.7%
Business Manager - Strategic Planning	72	19.3%	59	24.1%
Chief Operations Officer (COO)	29	7.7%	17	6.9%
Other Business executive	36	9.6%	16	6.5%
Industry				
Manufacturing	52	13.9%	34	13.9%
Mining and construction	32	8.5%	17	6.9%
Electricity, gas, and water supply activities	40	10.7%	21	8.6%
Wholesale and retail trade	48	12.8%	35	14.3%
Hotels and restaurants	38	10.1%	28	11.4%
Transport and telecommunications	36	9.6%	34	13.9%
Financial intermediation	33	8.8%	20	8.2%
Real estate, renting, and business Activities	27	7.2%	18	7.3%
Public administration and defense	25	6.7%	13	5.3%
Health and leisure	31	8.3%	18	7.3%
Other	11	2.9%	7	2.9%

Notes:

(1) The firm size is presented in accordance with European enterprises size class [96]

(2) The industries of activity are presented in accordance with NACE (European standard classification of productive economic activities)

5. Results

This study uses PLS-SEM (partial least squares – structural equation modeling) with SmartPLS 3.0 to test the research hypotheses of the proposed model [97]. Owing to the fact that this technique is better suited for theory development and does not require stringent sample distribution assumptions [85], it was chosen to be applied in our study.

5.1. Measurement model

The measurement model for the full model was assessed based on indicator reliability, construct reliability, convergent validity, and discriminant validity. The results of the measurement model are summarized in Tables 2 and 3. To examine indicator reliability, we opted to consider the loadings above 0.7. Thus, three items (COMP3, USE3, and SP2) were removed. As seen in Table 2, the instruments show good indicator reliability, as all the loadings are higher than 0.7. Considering that indicators have different loadings [97, 98], construct reliability was assessed using the composite reliability coefficient. All constructs present composite reliability above 0.7, which indicates that the constructs are reliable (see Table 3). Regarding convergent validity, average variance extracted (AVE) should be above 0.5, i.e., more than half of the variance of its indicators is explained by the latent variable [98, 99]. Table 3 reports that all constructs meet this criterion. To assess discriminant validity, we used Fornell-Larcker, in which the square root of AVE of each construct should be larger than the inter-construct correlations. As shown in Table 3, the square roots of AVE of the constructs meet these guidelines. Further, by examining the cross-loadings in Table 2, the loading of each indicator is higher than all-cross loadings [100]. Moreover, finally, the heterotrait-to-monotrait ratio of correlations (HTMT) values are below 0.9 [101] (results available upon request). Therefore, we conclude that all constructs present a good level of discrimination. In general, based on these figures, we conclude that the model has good indicator reliability, construct reliability, convergent validity, and discriminant validity. The reflective constructs can, therefore, be considered to test the structural model.

Table 2. Loadings and cross-loadings for the measurement model

Constructs	**Item**	**COMP**	**ACC**	**CUR**	**PII**	**PC**	**UI**	**USE**	**FP**	**SP**
Data quality (2^{nd} order) DQ	COMP1	**0.986**	0.774	0.842	0.216	0.341	-0.418	0.524	0.464	0.578
	COMP2	**0.985**	0.722	0.789	0.285	0.349	-0.354	0.433	0.419	0.523
	ACC1	0.735	**0.933**	0.804	0.434	0.466	-0.660	0.248	0.607	0.646
	ACC2	0.720	**0.972**	0.717	0.489	0.523	-0.564	0.275	0.527	0.643
	ACC3	0.672	**0.958**	0.656	0.511	0.491	-0.544	0.226	0.515	0.627
	CUR1	0.646	0.711	**0.922**	0.304	0.457	-0.439	0.307	0.566	0.502
	CUR2	0.859	0.744	**0.936**	0.358	0.505	-0.422	0.366	0.530	0.512
	CUR3	0.813	0.687	**0.952**	0.162	0.264	-0.490	0.507	0.567	0.540
Process sophistication (2^{nd} order)	PII1	0.388	0.425	0.260	**0.888**	0.623	-0.013	0.037	0.193	0.253
	PII2	0.122	0.386	0.290	**0.876**	0.714	-0.032	-0.192	0.264	0.155
	PII3	0.253	0.541	0.315	**0.897**	0.594	-0.136	0.014	0.348	0.381
	PII4	0.163	0.460	0.200	**0.948**	0.653	-0.007	-0.103	0.243	0.265
	PC1	0.501	0.541	0.389	0.696	**0.797**	-0.187	0.182	0.258	0.370
	PC2	0.270	0.318	0.240	0.457	**0.805**	0.024	0.023	0.126	0.171
	PC3	0.017	0.245	0.300	0.286	**0.777**	-0,086	-0.138	0.126	0.025
	PC4	0.235	0.470	0.429	0.716	**0.881**	-0.121	-0.046	0.283	0.197
IoT capabilities	UI1	-0.270	-0.486	-0.377	0.030	0.070	**0.908**	-0.112	-0.400	-0.387
	UI2	-0.401	-0.597	-0.502	-0.019	-0.119	**0.959**	-0.187	-0.452	-0.482
	UI3	-0.363	-0.579	-0.480	-0.028	-0.143	**0.970**	-0.113	-0.391	-0.417
	UI4	-0.266	-0.551	-0.481	-0.039	-0.168	**0.925**	-0.100	-0.417	-0.413
	UI5	-0.241	-0.614	-0.409	-0.211	-0.196	**0.868**	-0.017	-0.423	-0.424
	UI6	-0.247	0.552	-0.430	-0.085	-0.170	**0.893**	-0.071	-0.351	-0.372
	UI7	-0.488	-0.580	-0.436	-0.033	-0.151	**0.835**	-0.261	-0.311	-0.461
	UI8	-0.425	-0.520	-0.355	-0.006	-0.050	**0.846**	-0.240	-0.300	-0.456
	UI9	-0.467	-0.517	-0.392	-0.026	-0.076	**0.853**	-0.224	-0.316	-0.444
BDA capabilities	USE1	0.335	0.148	0.394	-0.104	0.037	-0,046	**0.886**	0.166	0.214
	USE2	0.480	0.158	0.329	-0.110	-0.029	-0.062	**0.898**	0.190	0.304
	USE4	0.291	0.308	0.441	-0.008	0.155	-0.333	**0.746**	0.329	0.357

	USE5	0.480	0.278	0.308	-0.077	-0.075	-0.223	**0.818**	0.214	0.399
	USE6	0.452	0.168	0.227	0.019	0.039	0.028	**0.839**	0.081	0.235
	USE7	0.556	0.300	0.360	-0.074	-0.039	-0.207	**0.903**	0.224	0.422
	USE8	0.424	0.245	0.438	-0.020	0.095	-0.118	**0.917**	0.219	0.297
	USE9	0.208	0.172	0.384	-0.010	0.072	-0.090	**0.737**	0.181	0.202
	USE10	0.414	0.229	0.428	-0.115	0.009	-0.198	**0.939**	0.273	0.357
Competitive Advantage (2nd order)	FP1	0.460	0.558	0.594	0.192	0.216	-0.423	0.272	**0.937**	0.803
	FP2	0.456	0.549	0.616	0.236	0.308	-0.401	0.289	**0.797**	0.808
	FP3	0.286	0.453	0.375	0.372	0.184	-0.303	0.079	**0.821**	0.683
	SP1	0.592	0.610	0.562	0.716	0.227	-0.418	0.362	0.819	**0.910**
	SP3	0.406	0.596	0.428	0.319	0.245	-0,444	0.299	0.703	**0.890**

COMP – Completeness, ACC – Accuracy, CUR – Currency, PII – Process Information Intensity, PC – Process Complexity, UI – IoT capabilities, USE – BDA capabilities, FP – Financial Performance, SP – Strategic Performance.

Table 3. Correlation matrix, composite reliability (CR), and the square root of AVEs

	CR	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Completeness (1)	0.970	**0.971**								
Accuracy (2)	0.951	0.744	**0.911**							
Currency (3)	0.930	0.828	0.762	**0.878**						
Process Information Intensity (4)	0.926	0.254	0.500	0.293	**0.818**					
Process Complexity (5)	0.806	0.350	0.517	0.436	0.715	**0.630**				
IoT capabilities (6)	0.969	-0.392	-0.619	-0.480	-0.051	-0.124	**0.804**			
BDA capabilities (7)	0.954	0.486	0.262	0.421	-0.070	0.024	-0.164	**0.734**		
Firm performance (8)	0.886	0.448	0.577	0.591	0.289	0.264	-0.419	0.243	**0.818**	
Strategic performance (9)	0.766	0.559	0.670	0.553	0.290	0.264	-0.478	0.369	0.848	**0.810**

Notes:

(1) First column is CR (composite reliability)

(2) Diagonal elements are the square root of average variance extracted (AVE)

(3) Off-diagonal elements are correlations

We modeled the data quality as a second-order construct, composite formative-reflective type [84], with competence, accuracy, format, and currency that are reflective in themselves. These constructs are formative measures of the data quality.

For the formative constructs, a measurement model was performed to assess the multicollinearity and the significance and sign of weights. We performed the variance inflation factor (VIF) statistic to assess the multicollinearity. Because of multicollinearity issues (VIF>5), we opted to remove format. The remaining first-order constructs of data quality are below the threshold of 5, thus indicating the absence of multicollinearity among the constructs [102]. Regarding significance and sign, all three are statistically significant ($p<0.01$) and with a positive sign (see Figure 2). Finally, competitive was modeled as a composite formative-reflective type. No multicollinearity issues were found. The first-order constructs have a positive sign and are statistically significant. Consequently, the constructs (data quality and competitive advantage) can be used to test the structural model.

5.2. Structural model

The structural model is assessed by examining the variance inflation factor (VIF), path coefficients, t-value, and variance explained (R^2) to empirically validate the hypotheses postulated in Section 3. The VIF ranges from 1.01 to 2.40, lower than the threshold of 5 [102]. Consequently, there is no multicollinearity among variables. To determine the path significances, bootstrapping with 5000 resamples [97, 98] was used. Table 4 summarizes the hypothesis results, which shows that all hypothesized causal paths in the research model were significant, but not all of the hypotheses were supported (H1b, H2a, H2b, and H4b). The results are quite similar among the samples, and the same hypotheses are verified. A multigroup analysis was performed, suggesting that there are no statistically significant differences for any of drivers among US and EU firms (results available upon request).

Concerning R^2, as seen in Figure 2, the results of the PLS structural model shows that 42.1% of BDA use capabilities variation is explained by the research model proposed. Additionally, 55.7% of the variation in IoT use capabilities is explained by the research model. Finally, 46.3% of competitive advantage is explained by the research model.

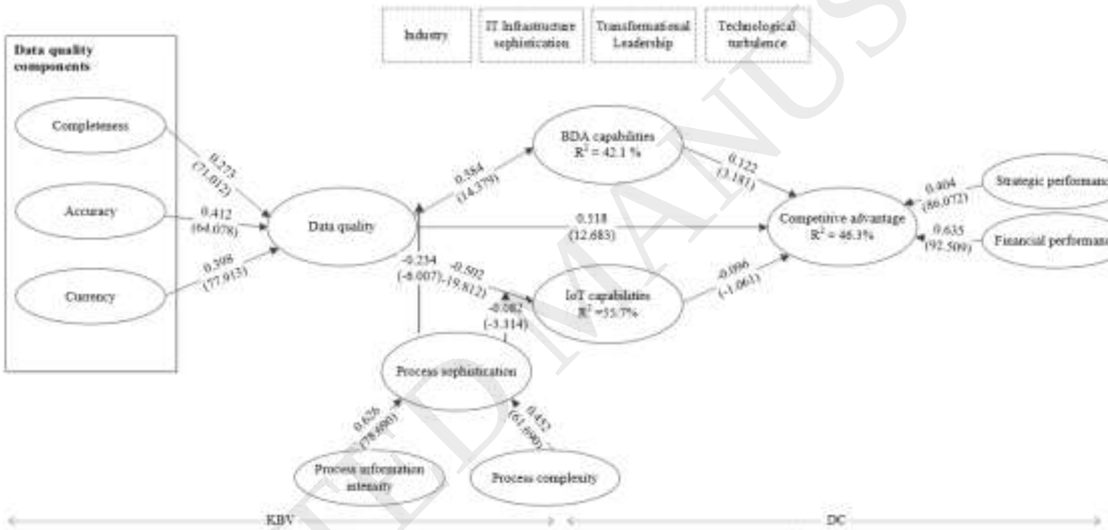

Figure 2 – Estimated model

Table 4. Results of hypotheses testing

Hypotheses	Relationship	Path coefficient	t-Value	P Value	Validation
Full sample					
H1a	DQ → USE	0.584	14.379	<0.01	Supported
H1b	DQ → UI	-0.502	-19.812	<0.01	Not supported (Significant but negative effect is observed)
H2a	PS moderates DQ → USE	-0.234	-6.007	<0.01	Not supported (Significant but negative effect is observed
H2b	PS moderates DQ → UI	-0.082	-3.314	<0.01	Not supported (Significant but negative effect is observed)
H3	DQ → CA	0.518	12.683	<0.01	Supported
H4a	USE → CA	0.122	3.181	<0.01	Supported
H4b	UI → CA	- 0.096	-1.061	>0.10	Not supported
US sample					
H1a	DQ → USE	0.591	8.488	<0.01	Supported
H1b	DQ → UI	-0.527	-12.069	<0.01	Not supported (Significant

					but negative effect is observed)
H2a	PS moderates DQ → USE	-0.223	-3.282	<0.01	Not supported (Significant but negative effect is observed)
H2b	PS moderates DQ → UI	-0.077	-1.938	<0.10	Not supported (Significant but negative effect is observed)
H3	DQ → CA	0.433	5.836	<0.01	Supported
H4a	USE → CA	0.128	1.811	<0.10	Supported
H4b	UI → CA	-0.101	-1.274	>0.10	Not supported
EU Sample					
H1a	DQ → USE	0.561	11.018	<0.01	Supported
H1b	DQ → UI	-0.484	-15.341	<0.01	Not supported (Significant but negative effect is observed)
H2a	PS moderates DQ → USE	-0.244	-4.860	<0.01	Significant Not supported (But negative effect is observed)
H2b	PS moderates DQ → UI	-0.085	-2.617	<0.01	Not supported (Significant but negative effect is observed)
H3	DQ → CA	0.553	11.866	<0.01	Supported
H4a	USE → CA	0.101	2.285	<0.05	Supported
H4b	UI → CA	-0.088	-1.504	>0.10	Not supported

Note: DQ – Data Quality; USE –BDA capabilities; UI –IoT capabilities; PS – Process Sophistication; CA – Competitive Advantage.

As an additional analysis of our model, based on interaction variables, two moderating effects (H2a and H2b) were analyzed. The results showed that the interaction terms were statistically significant (p<0.01 for both), but the moderation effects of H2a and H2b are negative, with a path coefficient of -0.234 and -0.082, respectively (see Table 4). Following the guidelines of Aiken and West [103], we plotted the interactions to better understand the behavior of the moderation by process sophistication (Figure 3a and 3b). Figure 3a shows that data quality has a more significant impact on BDA capabilities when process sophistication is low. For more complex processes, firms with higher data quality can also increase their BDA capabilities, but it is more challenging to do so. Regarding Figure 3b, when data quality is higher, firms tend to use less IoT capabilities to business processes. The importance of data quality for IoT is greater when processes are more sophisticated.

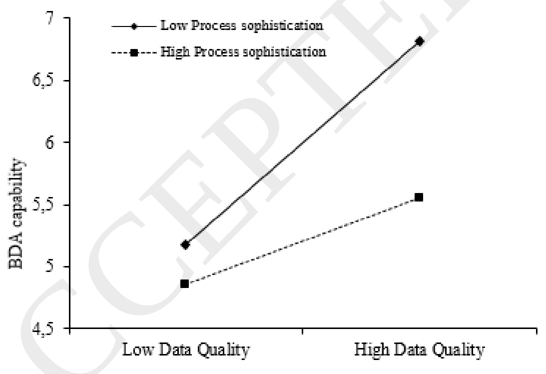

Figure 3a – Interaction plot of Data Quality and Process Sophistication on BDA capabilities

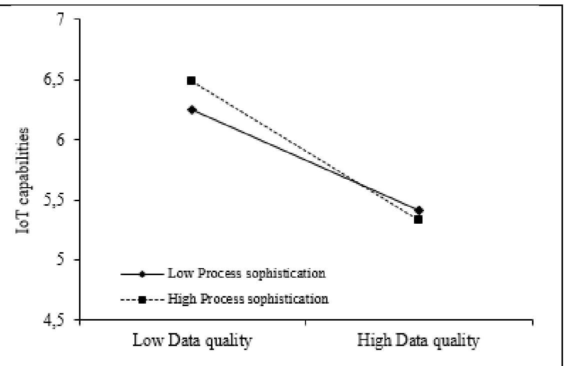

Figure 3b – Interaction plot of Data Quality and Process Sophistication on IoT capabilities

5.2.1. Mediating role of BDA and IoT capabilities

The results suggest evidence for several potential mediating effects. To establish a full nomological validity to our model, we performed a mediation analysis. A mediation effect (indirect effect or mediation) is determined by a third variable that plays an intermediary role in the relationship between an independent and a dependent variable [98]. Following the procedures proposed by Hair Jr, Hult [104], we evaluated the significance of the mediating effect of BDA and IoT capabilities. Table 5 presents the results, which fulfill the necessary conditions to perform the mediator assessment. The results show that BDA and IoT capabilities can partially mediate the relationship between data quality and competitive advantage. Thus, H5a and H5b are supported.

Table 5. Mediation analysis

	Beta	SD	t-Test	p-value
H5a				
(P1) Data Quality –> BDA capability	0.584	0.041	14.383	<0.01
(P3) Data Quality -> Competitive advantage	0.515	0.041	12.606	<0.01
(P2) BDA capability -> Competitive advantage	0.121	0.038	3.152	<0.01
(P1*P2) Data Quality –> BDA capability -> Competitive advantage	0.071	0.023	3.086	<0.01
(P1*P2*P3)	0.036	0.011	3.207	<0.01
H5b				
(P1) Data Quality –> IoT capability	-0.502	0.025	-19.823	<0.01
(P3) Data Quality -> Competitive advantage	0.515	0.041	12.606	<0.01
(P2) IoT capability -> Competitive advantage	-0.098	0.046	-2.124	<0.05
(P1*P2) Data Quality –> IoT capability -> Competitive advantage	0,049	0.023	2.133	<0.05
(P1*P2*P3)	0.025	0.011	2.222	<0.05

6. Discussion

This study develops and validates a conceptual model that explains the importance of data quality to create BDA and IoT capabilities toward sustained competitive advantage.

The findings show that data quality can impact BDA and IoT capabilities. Data quality impacts can be noticed through the usage of BDA and IoT tools and directly on firm performance. The higher efficiency of data quality is seen on BDA capabilities (H1a), which is consistent with a recent BDA study [24]. On the contrary, if the level of data quality is higher, IoT capabilities are expected to decrease (H1b). This result is unexpected. The outcome can be related to the fact that a certain level of data quality is difficult to achieve with the specificities of IoT big data, thus reducing the ability to analyze data. This appraisal is aligned with earlier studies finding that there is a need to improve IoT data quality to take advantage of more data generated by IoT devices [36, 76, 105]. Informatica (2017), a software provider, stated that *"trust is the necessary glue that will make IoT work."* They found that it is possible to increase the use of IoT by improving timeliness, detail, accuracy, and reliability of data [106]. Several challenges need to be overcome to extract value from IoT data. The diversity of data sources (e.g., social media data, sensor data, open data, etc.) brings abundant data types and complex data structures and increases the difficulty of data integration. In addition, data volume is huge, which makes the judgment on data quality within a reasonable amount of time difficult [14]. Moreover, as the maturity of IoT tools is in an early stage in firms [2], data quality can play a fundamental role in enabling the widespread diffusion of IoT [14, 76]. In this sense, by improving the data quality, it will be possible to improve the use of BDA and IoT capabilities [19]. For instance, in the health care industry, by aggregating and analyzing health data from different sources (clinical, financial, and administrative), the results of treatments and the respective resource allocation can be monitored.

Consequently, this will improve operational efficiency [107]. In general, in terms of data quality, there are no significant differences between U.S. and EU firms. The results demonstrate that accuracy is the most valued topic to address in data quality for BDA applications. Our results show that data quality can have a direct effect on firm performance, which demonstrates that the effect of data quality goes beyond BDA and IoT capabilities. This result is inconsistent with a prior empirical data quality study in BDA that demonstrated that the link between BDA data quality and firm performance is not significant [24]. Nevertheless, due to the fact that BDA is context specific, the same author in a recent study claimed that this link requires further investigation, particularly by using a sample with more than one country [25]. Further, prior IT literature showed that this direct link could be significant [108, 109], which leads us to believe that this result might be explained by the limited data context to Chinese firms. On the other side, the effect of data quality can be seen as a result of the use of BDA and IoT tools. In European and American firms, BDA tools are being used mainly in production run optimization, inventory optimization, logistics improvement, and purchasing analytics. IoT is being used to feed business processes in areas of innovation, continuous process improvement programs and to reduce uncertainty in decision making. This result demonstrates that BDA and IoT capabilities are not merely operational capabilities, as they are more focused on changing and optimizing operational routines [110]. Specifically, Erevelles, Fukawa [21] stated that DC stimulates innovation and enables firm to create value. With big data, firms create business value through innovation. For instance, Google is able to determine whether an ad displayed on a user's smartphone during a Google search actually resulted in a store visit. The act of understanding customer behavior improves the effectiveness of existing marketing activities and potentially leads to innovation. Moreover, when data quality is moderated by the existence of sophisticated business processes (H2a and H2b), it is observed that BDA and IoT capabilities to support business processes can decrease. The negative impact of sophisticated business processes might be explained by several organizational factors that constitute barriers to extracting value. First, with more sophisticated processes, there is always a certain level of uncertainty if the tools are in fact delivering the correct data to make decisions. In addition, BDA and IoT technologies are in an early stage of adoption [17, 26], which means that not all the conditions are being met to take full advantage of their capabilities. A recent report from the European Big Data Value Association concludes that the main issue is how to use data [9]. There is still a cultural barrier to be overcome before these tools can be diffused properly [111]. According to a report produced by the European Commission, the disruptive effect of BDA in the decision-making process requires time to be accepted. The existence of analytical systems in firms that will be obsolete after the full implementation of BDA tools is another factor contributing to the reluctance of firms to use them effectively. There is also a lack of analytical skills to leverage the use of BDA and IoT. In this sense, *Harvard Business Review* points out that in addition to the cultural obstacles, methodological issues can explain a low usage of BDA applications. For example, a data science team created an overly complex model to predict whether a car would be a total or a partial loss after the first accident report. The model was too complex for the IT department to reproduce, which led to performing this process outside the BDA tool. In the end, the IT department discovered that a simple logistic regression was almost as effective [111]. Our results show that most firms assumed that the majority of their core business processes are quite complex, and information is considered a large component of their products/services to customers. Thus, we believe that the combination of the right skills, structure, and problem-solving approach can unlock the value of BDA and IoT to improve decision-making processes [111].

At the same time, BDA and IoT capabilities can impact competitive advantage differently. Our overall results show that while BDA usage leads to the achievement of competitive advantages, which is consistent with the earlier literature (e.g., [21, 26, 28]), as of today, the use of IoT capabilities in business processes can harm a firm's profitability. The low level of maturity of IoT reduces the potential business value and can even be harmful to firms. In light of the "IT productive paradox," earlier studies have argued that IS investments do not necessarily improve firm performance (e.g., [112]). This negative link may be explained by several factors including the quality of data; the time lags between an investment and the generation of business value, and the lack of assessment of intangible benefits of IT (e.g., [1, 42]). Moreover, the DC literature demonstrates that some DC can decrease firm performance, especially when extensive management is needed and their usage is complex [113]. The resulting difficulties in using them and associated costs might lead to this decrease in performance. The greater the change the firm attempts to implement with these IoT capabilities, the greater the risk of failure [91].

In summary, the model demonstrates the emergent need for firms to have an effective data quality to be able to extract proper value from BDA and IoT.

6.1. Academic implications

From a strategic management perspective, this study contributes to the growing body of knowledge by extending IoT and BDA capability literature with a new:

1) Theoretical framework – The limited empirical research on BDA data quality has been using RBV to assess BDA value theoretically. Combinations between RBV and Delone and McLean [24, 25] and also with the DC theory [23] have been proposed. In IoT research, there is a lack of theoretical foundations to understand its use and impacts at firm level [22]. In this paper, we contribute to the academic body by considering strategic management theories such as KBV and DC to assess IoT and BDA impact on organizations.
2) Data quality perspective – Because of data quality issues [8, 12, 13], BDA still represents a challenging mission. Quantifying the adverse effects of data quality is essential to mitigate the risks in the big data era [13]. With the emerging importance of BDA and IoT tools, recent research has concluded that more attention is needed on data quality practices and their effect on business value and firm performance [14, 24]. Specifically, Fosso Wamba, Akter [25] claims that there is little empirical evidence in what concerns BDA quality dynamics and its holistic impact on performance. Our study extends BDA an IoT capability literature by empirically examining the link between data quality, BDA, and IoT capabilities and the impact on firm performance for European and American companies. Particularly, contrary to the recent literature, it demonstrates that a direct link between data quality and firm performance can exist. Although IoT is considered a strategic asset for organizations, our study shows that its use can be harmful to firm performance if certain data quality standards are not met. As recent BDA literature suggests focusing on organizational culture moderators of BDA capabilities [38], a moderating effect of business process sophistication on BDA and IoT capabilities was analyzed. This study extends BDA and IoT empirical literature, by being the first study that considers the moderation role of business processes between the effect of data quality on BDA and IoT capabilities.

3) Big data perspective – A holistic view to understand BDA and IoT drivers and impacts is needed [22, 27]. Specifically, empirical research linking IoT and BDA is scarce and requires further investigation [22, 31, 45]. Because of the fact these technologies have emerged in different time periods to assess big data holistically, we need to distinguish two types of big data (big data and IoT). To the best of our knowledge, this is the first study that proposes a research model that jointly assesses the effect of big data through BDA and IoT in firm performance.

4) Data scope – Because of their different cultures, the recent BDA value literature has highlighted the need to extend empirical studies to more than one country and industry [25, 27]. Most BDA and IoT research is dominated by work done in Europe and Asia considering only one country [22, 27]. This study extends BDA and IoT research by assessing not only European but also American firms' perceptions.

6.2. Practical implications

In addition to its theoretical contributions, this article provides valuable business implications for companies to maintain a competitive advantage by efficiently adopting IoT and BDA applications together. The paper presents insights for them to assess the potential impact of data quality on BDA and IoT capabilities and consequently achieve better performance.

Managers can use our research model as a baseline model for performance assessment during the implementation and postadoption of BDA and IoT applications. The findings provide guidance to executives and consulting firms seeking to leverage and implement BDA and IoT initiatives at a firm level. The empirical findings of this study have implications regarding the strategic use of adaptation mechanisms by BDA and IoT developers and vendors concerning a robust data quality layer and the areas in which the applications of these tools is greater. A good data quality level can leverage the efficiency of BDA and IoT capabilities and lead to a full extraction of business value. If matured and aligned to organizational needs, BDA and IoT capabilities can increase competitive advantage. Otherwise, they could harm the organizational performance. We suggest that firms

1. **Justify their investments in IoT and BDA** – Despite the rapid progress of IoT and BDA technologies, there is also high uncertainty in implementing them. Several firms appear to be at an early stage of understanding the value of big data, BDA and IoT applications, the potential risks, and how they can present a good business case to support this type of investment [17, 26]. Only the potential value created and captured through the use of these applications can motivate firms to make significant investments [1]. This study provides findings that pinpoint the potential value of BDA and IoT that executives can use to justify investments in these tools.

2. **Invest in strong data quality and leverage the usage of BDA and IoT –**

In both European and American firms, data quality has a significant impact on BDA and IoT capabilities, but their effect can only be positive if a proper organizational environment is created (e.g., data management strategy, organizational structure, skills, and methodological approach to improve business processes). A good level of data quality can unlock considerable value by making information more transparent through data quality (completeness, accuracy, format, and currency). Consequently, it can be used to improve business processes (e.g., it can be used to develop the next generation of products and services). The benefits of improving data quality can promote operational efficiency and also reduce costs. Only reliable data can allow an effective value from BDA and IoT to correctly support decisions. By understanding the status of data quality, managers can allocate resources to develop a data quality management program. Data quality needs to be improved at the business and technical levels. On the business side, managers can create teams to focus on data quality issues and use cases. Yet, by applying our research model, IT and business managers can measure the business value of improved data quality by focusing on business processes and firm performance. On the technical side, companies can seek to (1) understand the content, relationships, patterns, anomalies, and redundancies in data through data profiling tools supported by machine learning algorithms; (2) make sure their data are normalized; (3) create a semantic metadata management process to ensure the uniformization of concepts and terms; and (4) create a data quality firewall to keep data-error free and nonredundant [114, 115].

3. **Develop and promote BDA and IoT capabilities to achieve competitive advantage –** Our study demonstrates that 46.3% of competitive advantage can be explained by the existence of BDA and IoT capabilities leveraged by data quality. Companies are embracing new information-driven models to outperform their peers. To be more competitive, forward-thinking leaders should invest in the development of these capabilities by assuring a proper environment in which to use BDA and IoT (e.g., organizational structure, skills, a methodological approach for process optimization). Nevertheless, executives should bear in mind that the maintenance of DC can be expensive and involve long-term commitments. DC involves significant cognitive, managerial, and operational costs and managers should be committed to spending time deploying them. Misperception of the firm's situation might trigger inappropriate DC. Therefore, although DCs are developed to create strategic advantages, their development may not ensure firm performance [65]. Our study demonstrates this with regard to the use of IoT in business processes. For firms that are reluctant to invest in BDA and IoT because of their lack of knowledge, our study provides some "proof of concept" that the focus on BDA and IoT capabilities can actually be profitable for European and American firms, thus assuring proper data management and organizational environment.

6.3. Limitations and future research

The limitations of this study will become the focus of future studies. Our study has some limitations such as

1. Data collection – this study assesses the variables based on managers' perceptions, which implies a certain level of subjectivity. Nevertheless, the sample includes this type of respondent profile because executives have more comprehensive knowledge about the strategic variables of this study. The data collected in our study are based on key

respondents representing each company, in a sample of SAP customers. This approach could potentially create a common method bias issue. Common method bias tests were performed, thus concluding that there is no risk of bias. Future research can consider including more than one respondent per firm to mitigate this risk and to have samples from two different software providers.

2. Scope – Our paper examines IoT and BDA capabilities at the firm level. Although some specific initiatives will occur at the process, unit, and departmental level, we believe our instrument is a reliable representation of the enablers and impacts of BDA and IoT capabilities. The respondents were selected from the top management, which suggests that the study results are valid regarding the firms' use of BDA and IoT. Additionally, this study was performed in Europe and the United States for all industries. Future studies might focus on specific industries (e.g., banking and health care).
3. Research strategy – Our study follows a quantitative research strategy to assess the drivers and impacts of IoT and BDA capabilities. The results demonstrate that organizational factors might diminish the creation of BDA and IoT capabilities. Future research could use qualitative methods such as Delphi studies to identify additional organizational factors that positively influence IoT and BDA capabilities and their impacts on firm performance. Researchers are encouraged to combine quantitative with qualitative techniques. Moreover, the interactions of process complexity and process intensity (part of process sophistication construct) can be analyzed in more detail in future research.
4. Instrument measurement – Subjective measures were used to examine firm performance. Although the earlier literature has concluded that subjective measures of firms' performance are highly correlated with objective measures (e.g., [34]), there are likely gaps between these two types of measures. In this study, firm performance was assessed based on qualitative measures. However, the ideal scenario would have been to use only objective metrics. Future works should use secondary data to measure this variable.

7. Conclusions

The emergence of big data has made data quality management more challenging than ever, but the idea that it could be an opportunity for firms remains unclear. Hence, is data quality a way to extract business value? Yes. Our study is the first that empirically assesses that data quality must be part of a BDA & IoT strategy to create business value for organizations. This study contributes to academia by providing a BDA and IoT business value model. It examines the influence of data quality on the creation of BDA and IoT capabilities moderated by business process sophistication, and it assesses the impact of these capabilities in competitive advantage. The findings provide a theory-based understanding of BDA and IoT business value in light of effective data quality. It provides guidance to managers of what they should expect by using these technologies. In summary, our findings show that BDA and IoT diffusion can increase if a proper data quality framework is in place. Finally, European and American firms were considered to be behaving similarly regarding data quality and how competitive value is created.

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Appendix A. Survey questionnaire

Constructs	Items	Source
Data Quality (2nd order) (Composite formative-reflective)	Please rate the quality of information provided by BDA systems used in core business processes (1 = strongly disagree . . . 7 = strongly agree). **Completeness** COMP1. BDA systems used provide a complete set of information. COMP2. BDA systems used produce comprehensive information. COMP3. BDA systems used provide all the information needed.** **Accuracy** ACC1. BDA systems used produce correct information. ACC2. There are few errors in the information obtained from BDA systems. ACC3. The information provided by BDA systems is accurate. **Format***** FMT1. The information provided by BDA systems is well formatted. FMT2. The information provided by BDA systems is well laid out FMT3. The information provided by BDA systems is clearly presented on the screen. **Currency** CUR1. BDA systems provide the most recent information. CUR2. BDA systems produce the most current information. CUR3. The information from the BDA systems is always up-to-date.	[19, 116]
Process sophistication (2nd order) (Composite formative-reflective)	Please rate the extent of information processing and complexity involved in your firm's core business processes (1 = strongly disagree . . . 7 = strongly agree). **Process information intensity** PII1. Our core business processes require a significant amount of information processing. PII2. There are many steps in our core business processes that require frequent use of information. PII3. Information used in the core business processes needs frequent updating. PII4. Information constitutes a large component of our products/services to customers. **Process complexity** PC1. Our core business processes often cut across multiple functional areas. PC2. We frequently deal with *ad hoc*, non-routine business processes.** PC3. We generally have a high degree of uncertainty in our core business processes.** PC4. A majority of our core business processes are quite complex.	[19, 66]
IoT capabilities (Reflective)	The available IoT data within our organization's business processes … (1 = strongly disagree . . . 7 = strongly agree) UI1. … exposes the problematic aspects of current business processes and makes stakeholders aware of them. UI2. … provides valuable input for assessing business processes against standards, for continuous process improvement programs, and for business process change projects. UI3. … stimulates innovation in internal business processes and external service delivery. UI4. The IoT data reduce uncertainty in the decision-making process, enhance confidence and improve operational effectiveness. UI5. The IoT data enable us to rapidly react to business events and perform proactive business planning. UI6. We are using the information provided to make changes to corporate strategies and plans, modify existing KPIs, and analyze newer KPIs. Through managing the organization's IoT data, we are …	[80]

	UI7. … adding value to the services delivered to customers. UI8. … reducing risks in the business. UI9. … reducing the costs of business processes and service delivery.	
BDA capabilities (Reflective)	To what extent has your organization implemented Big Data Analytics in each area? (1 = little or no usage . . . 7 = heavy usage) USE1. Sourcing analysis USE2. Purchasing analytics USE3. CRM/customer/patient analysis** USE4. Network design/optimization USE5. Warehouse operations improvements USE6. Process/equipment monitoring USE7. Production run optimization USE8. Logistics improvements USE9. Forecasting/demand management – S&OP USE10. Inventory optimization	[26]
Competitive advantage (2nd order) (Composite formative-reflective)	Please indicate the degree to which you agree with the following statements. *Strategic Performance* SP1. We have gained strategic advantages over our competitors SP2. We have a large market share.** SP3. Overall, we are more successful than our major competitors. *Financial performance* FP1. Our EBIT (earnings before interest and taxes) is continuously above the industry average. FP2. Our ROI (return on investment) is continuously above the industry average. FP3. Our ROS (return on sales) is continuously above the industry average.	[69]
Control Variables		
IT Infrastructure sophistication	Please indicate the degree to which you agree with the following statements (1 = strongly disagree . . . 7 = strongly agree). NET1. The technology infrastructure needed to electronically link our business units is presented and in place today. NET2. The technology infrastructure needed to electronically link our firm with external business partners is presented and in place today. NET3. The technology infrastructure needed for current business operations is present and in place today. NET4. The capacity of our network infrastructure adequacy meets our current business needs.	[117]
Transformational leadership	Please indicate the degree to which you agree with the following statements (1 = strongly disagree . . . 7 = strongly agree) TL1. To what extent does your firm's leadership team talk about the most important values and beliefs? TL2. To what extent does your firm's leadership team talk enthusiastically about what needs to be accomplished? TL3. To what extent does your firm's leadership team treat workers as individuals rather than just as members of a group? TL4. To what extent does your firm's leadership team seek differing perspectives when solving problems?	[118]
Industry	Type of industry (Manufacturing or Services)	n.a
Technological turbulence	Please indicate the degree to which you agree with the following statements. TT1. Extent of technological turbulence in the environment TT2. Leadership in product/process innovation TT3. Impact of new technology on operations	[90]

Notes: (1) Items were measured using a 7-point numerical scale (1 is Strongly Disagree, and 7 is Strongly Agree). (2) ** items eliminated due to low loading. (3) *** construct removed due to multicollinearity issues (VIF>5).