Management Decision

Turning information quality into firm performance in the big data economy

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Received 12 April 2018
Revised 6 June 2018
Accepted 7 June 2018

Abstract

Purpose – Big data analytics (BDA) increasingly provide value to firms for robust decision making and solving business problems. The purpose of this paper is to explore information quality dynamics in big data environment linking business value, user satisfaction and firm performance.

Design/methodology/approach – Drawing on the appraisal-emotional response-coping framework, the authors propose a theory on information quality dynamics that helps in achieving business value, user satisfaction and firm performance with big data strategy and implementation. Information quality from BDA is conceptualized as the antecedent to the emotional response (e.g. value and satisfaction) and coping (performance). Proposed information quality dynamics are tested using data collected from 302 business analysts across various organizations in France and the USA.

Findings – The findings suggest that information quality in BDA reflects four significant dimensions: completeness, currency, format and accuracy. The overall information quality has significant, positive impact on firm performance which is mediated by business value (e.g. transactional, strategic and transformational) and user satisfaction.

Research limitations/implications – On the one hand, this paper shows how to operationalize information quality, business value, satisfaction and firm performance in BDA using PLS-SEM. On the other hand, it proposes an REBUS-PLS algorithm to automatically detect three groups of users sharing the same behaviors when determining the information quality perceptions of BDA.

Practical implications – The study offers a set of determinants for information quality and business value in BDA projects, in order to support managers in their decision to enhance user satisfaction and firm performance.

Originality/value – The paper extends big data literature by offering an appraisal-emotional response-coping framework that is well fitted for information quality modeling on firm performance. The methodological novelty lies in embracing REBUS-PLS to handle unobserved heterogeneity in the sample.

Keywords User satisfaction, Firm performance

Paper type Research paper

Introduction

Big data has emerged as a new frontier for business in either establishing competitive advantages or exploiting untapped opportunities (Frisk and Bannister, 2017; Dubey *et al.*, 2018; Prescott, 2014; Fosso Wamba *et al.*, 2017; Akter *et al.*, 2016; Hazen *et al.*, 2014; El-Kassar and Singh, 2018). In every part of the world, industries and organizations collect more data than ever before, seeking smarter business strategies to harness this big data revolution. The extant literature identifies "big data" not only as "the next management revolution" (Mcafee and Brynjolfsson, 2012), but also as "the new raw material for business" (*Economist*, 2010), or "the new science that holds the answers" (Gelsinger, 2012). As it clearly appears in both the academic and practitioner literature, the increased attention to big data, and thus to big data analytics (BDA), is eloquent proof

Management Decision
© Emerald Publishing Limited
0025-1747
DOI 10.1108/MD-04-2018-0394

that the benefits of BDA are well acknowledged in any environment: better understanding of business, markets and consumers; higher productivity linked with profitability; and improved performance measurement mechanisms (Lavalle *et al.*, 2011; Swafford *et al.*, 2008; Mcafee and Brynjolfsson 2012; Elisabeth and Frank, 2017; Michael, 2014), amongst others. And all of these are constantly reflected in Google, Amazon, Harrah's, Capital One, and Netflix's business models. Companies aiming to leapfrog competition are increasingly interested in BDA to transform their business models, notably by customizing consumers' desiderata, including when and how many they want, and what incentives will make them want more in their lifetime (Langenberg *et al.*, 2012). However, despite the widespread buzz around BDA, leveraging BDA-driven information to generate business value continues to be a challenge for many organizations. This is why consulting firms such as Gartner, IBM and McKinsey & Co. have started providing services to help firms capitalize on this opportunity. The extant literature highlights that, "[a]s big data evolves, the architecture will develop into an information ecosystem: a network of internal and external services continuously sharing information, optimizing decisions, communicating results and generating new insights for businesses" (Sun and Jeyaraj, 2013). However, there are growing concerns and confusion regarding analytics-driven information quality (IQUL), business value (BVAL), user satisfaction (USAT) and firm performance (FPER) (Goes, 2014; Sun and Jeyaraj, 2013). Clearly, despite the paucity of research in this spectrum, a better understanding of IQUL dynamics is required in order to address the research gap. Because, "[w]hile generating quality information is the primary purpose of any IS [information system], few studies have explored the variables that affect Information Quality. This is a significant gap in the IS research. Quality information is a foundation of good decision making and positive outcomes, yet we know little about the variables that lead to improved Information Quality. More research is needed in order to understand better how to influence Information Quality" (Petter *et al.*, 2013, p. 30).

In this study, we investigate ways to leverage IQUL in BDA so as to achieve enhanced firm performance, by proposing and testing a theory from the perspective of managers/users. This perspective is put in this context because firm performance ultimately depends on managers who are the most critical stakeholders, given their interest in knowing more about their businesses and therefore translating big data into better information and improved decisions (Mcafee and Brynjolfsson, 2012). The study also focuses on managers because they have the greatest curiosity about unlocking the power of big data for large-scale interventions and predictions (Davenport, 2012; Lavalle *et al.*, 2011). Furthermore, the managers' perspective is examined as they want to understand "how to fish out answers to important business questions from today's tsunami of unstructured information" (Davenport and Patil, 2012, p. 73). Despite the importance of analytics-driven IQUL and its impact on USAT, BVAL and FPER, little research on manager-side BDA has focused on such dynamics. We aim to help fill this knowledge gap, and to this effect, we propose a conceptual model which is rooted in the traditional appraisal (IQUL)–emotional response (BVAL and USAT)–coping (FPER) framework (Lazarus, 1991; Michelman, 2017). To empirically test the proposed relationships, we collected data from 307 managers who rely on BDA for their day-to-day operations and strategic directions across various industries in the USA and France. The study's findings suggest that analytics-driven IQUL has a positive impact on BVAL and USAT, which again influences FPER. Heterogeneity is likely to exist in the sample used in information systems (IS) studies (Becker *et al.*, 2013). Therefore, we decided to investigate the presence of unobserved heterogeneity in our sample, thus coming out with three groups of business analytics users characterized by different model parameters. More precisely, the study aims at answering the following research questions:

RQ1. How do IQUL perceptions of BDA determine critical business outcomes?

RQ2. Do existing groups of users share the same behaviors (in terms of strength of the effects) when determining the IQUL perceptions of BDA? And if yes, how different are they?

The answers to these research questions clearly contribute to the business–technology–analytics alignment of global organizations by framing the impact of IQUL on individual and business outcomes. This paper is structured as follows: the next section focuses on the conceptual model and the development of hypotheses, which is followed by the description of the adopted method and the research findings. The last section focuses on the study's theoretical and practical contributions and provides guidelines for future research.

Research model

The proposed conceptual model on BDA illuminates IQUL as the core concept that enhances BVAL and USAT, which, in turn, influences FPER within an organization. The focus on analytics-driven IQUL to establish a linkage between BVAL, USAT and FPER is based on the fact that "[b]ig data still aims in large part to deliver the right information to the right person at the right time in the right form, but is now able to do so in a significantly more sophisticated form" (Agarwal and Dhar, 2014, p. 447). Using a coordination perspective, this study hypothesizes that IQUL enhances BVAL, which is required to increase USAT and the overall FPER. This investigation of a manager-side BDA strategy is set in analytics-driven organizations across various industries. The conceptual model draws on the IS and services marketing literature, thus enabling the interdisciplinary approach that is required to tackle the challenges and opportunities in BDA (Agarwal and Dhar, 2014; Goes, 2014). Figure 1 shows the research model while Table I defines the constructs in the model.

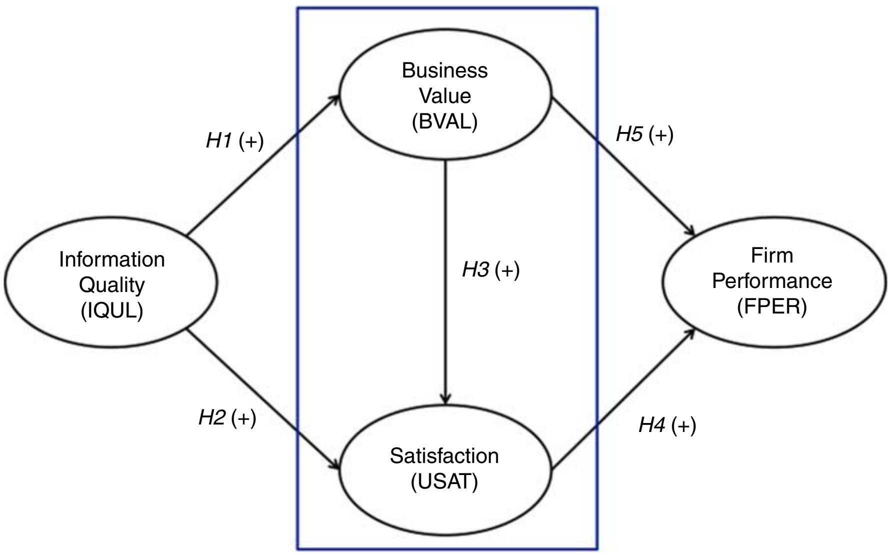


Figure 1.
Research model

Construct and definition	Source
Information quality is defined as the completeness, accuracy, format, and currency of information produced by BDA. Completeness indicates the extent to which the user perceives that BDA provide all the necessary information; accuracy focuses on the perceived correctness of information; format refers to the perception of how well the information is presented; and, finally, currency refers to the user's perception of the extent to which the information is up to date	Wixom and Todd (2005)
Business value is defined as the transactional, strategic, and transformational value of BDA. Transactional value refers to the degree to which the user perceives that BDA provide operational benefits, e.g., cost reductions: strategic value refers to the degree of perceived benefits to the organization at a strategic level, e.g., competitive advantage; and, finally, transformational value refers to the degree of perceived changes in the structure and capacity of a firm as a result of BDA, which serve as a catalyst for future benefits	Gregor *et al.* (2006)
Satisfaction refers to users' feelings about (or affect from) BDA use	Spreng *et al.* (1996)
Firm performance refers to the firm's ability to gain and retain customers; and to improve sales, profitability, and return on investment (ROI)	Miah *et al.* (2017) and Alan *et al.*

Table I.
Constructs and definitions

Defining big data analytics

Big data refers to huge quantities of data in the form of clickstreams, voices and videos, for transactions and other types of operations (Sun and Jeyaraj, 2013). In an attempt to define big data, Schroeck *et al.* (2012) identified its various dimensions, which span greater scope of information, real-time information, new kinds of data and analysis and non-traditional forms of media data, new technology-driven data, large volumes of data such as social media data, and the latest buzzwords. In their defining big data, IBM (2012), Johnson (2012), and Davenport (2013) focus more on aspects such as the variety of data sources, while other authors, such as Rouse (2011), Fisher *et al.* (2012), Havens *et al.* (2012), and Jacobs (2009), emphasize the importance of storing and analyzing "big data." IDC (2013) defines "big data" while focusing on its three main characteristics: the data itself, the analytics of the data, and the presentation of analytics results that allow business value creation in terms of new products or services. In this study, we define BDA as a holistic process that involves the collection, analysis, use and interpretation of data for various functional divisions, with a view to gaining actionable insights, creating business value, and establishing competitive advantages (Fosso Wamba *et al.*, 2015).

Information quality

Drawing on coordination theories (Crowston, 1997; Malone and Crowston, 1990; Setia *et al.*, 2013), this study proposes that BDA uses various sources of data to provide the business information that are needed to identify and assess patterns based on diverse actors. This diversity of data was highlighted in big data literature as, "[i]ndeed, companies that learn to take advantage of big data will use real-time information from sensors, radio frequency identification and other identifying devices to understand their business environments at a more granular level, to create new products and services, and to respond to changes in usage patterns as they occur" (Sun and Jeyaraj, 2013). In other words, BDA can enable the coordination of data from a variety of fields to improve information quality and organizational performance. This study contends that complex and interdependent BDA platforms produce coordinated information for the enhancement of BVAL, USAT and FPER. The extant research assessing the organizational impacts of BDA highlights the importance of IQUL in these environments (Schläfke *et al.*, 2013; Langenberg *et al.*, 2012). The application of BDA-driven quality information, rather than gut instinct, in decision making has become a core focus of research after evidence of the success of FPER in many organizations (Lavalle *et al.*, 2011; Mcafee and Brynjolfsson, 2012). The extant literature identifies that IQUL influences various outcomes, such as satisfaction (Nelson *et al.*, 2005; Barney, 2001), loyalty (Zhou *et al.*, 2009), trust in the IT artifact (Vance *et al.*, 2008) and user and knowledge-sharing behavior (Durcikova and Gray, 2009). We propose that IQUL is a critical component of a firm's BDA success (Delone and Mclean, 1992; Wixom and Todd, 2005). The ultimate managerial challenge in the BDA environment lies in the finding of patterns in data and their translation into useful business information as mentioned in big data literature; "[b]ut to compete on that information, companies must present it in standard formats, integrate it, store it in a data warehouse, and make it easily accessible to anyone and everyone" (Langenberg *et al.*, 2012).

Information quality: the antecedent for generating business value and managers' satisfaction in a big data environment

Organizations with BDA capabilities aim to establish a robust foundation of quality information for decision making and business problem solving (Wixom *et al.*, 2013). BDA with high information quality facilitates intra-organization operational coordination, thus enhancing the effectiveness of functional managers and generating different types of business value, as reflected in Table II. The research model of this study is based on the appraisal-emotional response-coping framework (Lazarus, 1991; Michelman, 2017), which suggests that more cognitively oriented information quality and value appraisal lead to emotive satisfaction, which, in turn, drives firm performance. This study argues that the assessment of analytics-driven information and relevant business value (appraisal) results in an affective or emotional response (i.e. satisfaction), which again leads toward a coping behavior (firm performance). This situation is identified by Bagozzi as an "outcome desire fulfilment" in which a manager in a big data environment assesses information quality and business value to increase satisfaction, which, in turn, influences perceived firm performance.

This study focuses on IQUL dynamics because "quality information" is the primary purpose of any application of BDA; however, few studies have conceptualized BDA in this context. A recent review of IS success studies states that "[i]nformation is the core reason for IS, and Information Quality is particularly important to classes of IS related to business intelligence, data-driven decision making, among others. More research is needed in order to better understand how to positively influence Information Quality" (Petter *et al.*, 2013, p. 43). Therefore, the proposed model addresses this gap by modeling the effects of IQUL on BVAL, USAT and FPER in the BDA context.

Information quality and business value

Business value is at the heart of what managers pursue from a BDA perspective. The extant literature reports that the business value of analytics will be directly influenced by information quality in a big data environment (Wixom *et al.*, 2013). The importance of the relationship between IQUL and BVAL was evidenced by Lavalle *et al.*'s (2011) study ranging over 30 industries across 100 countries. This relationship is also highlighted because, "[t]he goal of big data programs should be to provide enough value to justify their continuation while exploring new capabilities and insights" (Mithas *et al.*, 2013, p. 18). Drawing on Gregor *et al.* (2006), this study defines business value as having several dimensions, namely, transactional, strategic and transformational, all of which benefit from BDA. "Transactional value" refers to the benefits added to firms as a result of IT use through its support of operation management, thus improving efficiency and cutting costs (Levich, 2015). As shown by Davenport (2012), an alignment between analytics-driven information quality and operational effectiveness results in the identification of profitable

Table II.
Business value of big data analytics

Study	Organizational functions	Description	Firm(s)
Davenport (2006)	Customer selection, loyalty, and service	Identify customers with the greatest profit potential, loyalty, and service. Increase likelihood that they will want the product or service offering, retain their loyalty	Harrah's, Capital One, Barclays
	Pricing	Identify the price that will maximize yield or profit	Progressive, Marriott
	Product or service quality	Detect quality problems early and minimize them	Honda, Intel
	Promotion	Fine-tuning of global promotions for every medium in every region	Dell (DDB matrix)
	Sales, consumer research, and marketing	Analysts from functions such as operations, supply chain, sales, consumer research, and marketing to improve total business performance by analyzing interrelationships among functional areas	Procter & Gamble (P&G)
	Customer defection	Customer intelligence group examines usage patterns and complaints data to accurately predict customer defections	United Parcel Service (UPS)
Sun and Jeyaraj (2013)	Pricing	Optimize pricing of 73 million items in just over one hour	Macys.com
Schroeck *et al.* (2012)	Pricing	Scheduling price reductions to sell perishable products before they spoil	Automercados Plaza's
DalleMule and Davenport (2017)	Pricing	Deriving the most accurate pricing of products and services with precise calculation of customer profitability	Royal Bank of Canada
	Customer choice preferences and product offerings	Analyze customer choice and customer feedback from over one billion reviews	Netflix
Kiron *et al.*	Service innovation	Use personal profile and psychology-based analytics to help people connect and fall into a loving relationship	Match.com
	New product development	Each new PayPal initiative across finance, operations, and products is examined with quantified impact and leveraging analytics	PayPal
LaValle *et al.* (2011)	Data-driven customer insights	Collected 80–90% of possibly needed information about customers to generate analytics-driven customer insights	Best Buy
Manyika *et al.* (2011)	Market share analysis	Uses big data to capture market share from its local competitors	Tesco
	Direct marketing through recommendation, relationship marketing	Recommendation engine to generate "you might also want" prompts to generate sales	Amazon.com
	Customer behavior, customer segmentation, customer profitability	Developed behavioral segmentation and a multi-tier membership reward program by analyzing customer profile, real-time changes in customer behavior, and customer profitability	Neiman Marcus

(*continued*)

Study	Organizational functions	Description	Firm(s)
	Email marketing	Integrated customer databases with information on some 60m households to improve response rate of e-mail marketing	Williams-Sonoma
	Customize service offerings, customer loyalty	Compiled holistic customer profiles in detail, and conduct experiments and segment their customers systematically and effectively to personalize product offers and increase customer loyalty	Harrah's, Progressive Insurance, Capital One
Chandrasekaran *et al.* (2013)	Customer segmentation, customer loyalty	Systematically integrates analytics and consumer insights using data from its Clubcard loyalty program to better segment and target customer occasions	Tesco
	New product acceptance rate	Simulate new products placed on shelves in order to test design effects internally and with consumers to enhance product acceptability after launching	Procter & Gamble (P&G)
Davenport and Patil (2012)	(a) Core search (b) Advertisements	Google uses data scientists to refine its core search and ad-serving algorithms	Google
	Product, feature (e.g. "People you may know") and value-adding service	To generate ideas for products, features, and value-adding services. By using "People you may know," they generated millions of new page views which resulted in LinkedIn's growth trajectory shifting significantly upward	LinkedIn
Liebowitz (2013)	Product management	Macy's analyze data at stock-keeping unit (SKU) level to make sure of the ready availability of product assortments	Macys.com

Table II.

customers for Harrah's, Capital One, and Barclays, and in yield maximization for Progressive and Marriott. In a similar spirit, Wixom *et al.* (2013) indicate that GUESS INC., a fashion retailer, has been able to use less paper, save time, reduce the number of meetings, and increase cycle time and convenience by embracing BDA.

"Strategic value" takes place when firms change either their strategy (the ways in which they operate) or their products through the use of BDA, with a view to gaining competitive advantages together with offering better products and services to customers than their competitors. As reported by Manyika *et al.* (2011), Amazon.com has been hugely successful in generating strategic business value by implementing BDA for direct marketing, using recommendations such as "you might also want" prompts. These authors also report that Neiman Marcus establishes competitive advantages in customer segmentation and targeting by analyzing their customer profile and real-time changes in customer behavior. Similar strategies have been applied by Harrah's, Progressive Insurance, and Capital One, to personalize product offers and increase customer loyalty in a systematic and effective manner. The extant literature focuses on the strategic benefits of BDA, because "[o]ne important benefit is that users develop a deeper understanding of the business […] this understanding led to better purchasing and distribution decisions, and, ultimately, more sales of higher profitability items" (Wixom *et al.*, 2013, p. 118).

Finally, "transformational value" refers to the benefits which flow into organizations in many forms, such as offering firms a simplification of their business process by restructuring internal organizational processes and activities or by performing tasks in an innovative way (Madden, 2015; Steenbruggen *et al.*, 2014; Kirac *et al.*, 2015; Lue *et al.*, 2014). BDA-driven information quality ensures "transformational value" by establishing a management culture based on factual and real-time decisions, a single version of truth, more collaboration, and the discovery of business patterns (Wixom *et al.*, 2013). Although analytics-driven information quality plays a critical role in generating business value, there is a paucity of empirical studies which confirm this relationship in a big data environment (Wixom *et al.*, 2013; Lavalle *et al.*, 2011; Goes, 2014). Therefore, the study hypothesizes that:

H1. Perceived IQUL has a significant positive impact on perceived BVAL in BDA.

Information quality, business value and satisfaction

The extant literature in marketing (Kane, 2017; Bowers *et al.*, 2017) and IS (Nelson *et al.*, 2005; Wixom and Todd, 2005; Delone, 2003) identifies information quality as both a cognitive and attitudinal construct. In a big data environment, scholars (Langenberg *et al.*, 2012; Mcafee and Brynjolfsson, 2012) have demonstrated that user satisfaction has a significant impact on BDA use; that is, a higher level of satisfaction creates greater user dependence on BDA. An evaluation of managers' (or users') satisfaction can help to track areas for improvement in order to strengthen BDA systems. Thus, we postulate that:

H2. Perceived IQUL has a significant positive impact on perceived USAT in BDA.

H3. Perceived BVAL has a significant positive impact on perceived USAT in BDA.

Satisfaction and firm performance

In BDA, information quality is widely acknowledged as being vital for increasing business and firm performance (Wixom *et al.*, 2013). The extant literature provides evidence of a relationship between satisfaction and firm performance in terms of return on investment (Anderson *et al.*, 1994, 1997; Zeithaml, 2000); operating margin (Bolton, 1998; Rust *et al.*, 1994, 1995); and profitability (Fornell *et al.*, 2006, 2009; Mithas *et al.*, 2013; Kane *et al.*, 2017; Ransbotham and Kiron, 2017). In the context of healthcare, Srinivasan and Arunasalam (2013) show that the application of BDA in the form of predictive analytics and text mining can benefit firms by reducing cost (i.e. reduced amount of waste and fraud) and improving the quality of care (i.e. safety and efficacy of treatment). Wixom *et al.* (2013) have demonstrated that BDA can improve firm performance by improving productivity in terms of tangible (i.e. less paper reporting) and intangible (company reputation) benefits. Thus, a firm that creates superior user satisfaction should be able to maximize firm performance by facilitating pervasive use and speed via insights from BDA. Following this reasoning, we put forward the following hypothesis:

H4. Perceived USAT has a significant positive impact on perceived FPER in BDA.

Business value and firm performance

According to the extant literature on BDA, the relationship between business value and firm performance appears as one of the key issues for potential investigation (Wixom *et al.*, 2013; Mithas *et al.*, 2013; Sharma *et al.*, 2014; Agarwal and Dhar, 2014). The early research on IT business value focused on impact on organizational performance, which includes cost reduction, increased profitability, higher productivity, and competitive advantages (Devaraj and Kohli, 2000; Hitt and Brynjolfsson, 1996; Mukhopadhyay *et al.*, 1995; Kiron, 2017). This study adopts the "proxy view of IT" in defining the business value of BDA, with indication of the individual perceptions of its usefulness or value through firm performance in financial units (Orlikowski and Iacono, 2001; Burns, 2014):

H5. Perceived BVAL has a significant positive impact on perceived FPER in BDA.

Measurement development

In this study, the US survey measurement items was developed using an approach similar to the one used by Wixom and Todd (2005) and proposed by Moore and Benbasat (1991). More precisely, all constructs as well as their items were drawn from prior literature and were then adapted to fit the business analytics context (Table III). Afterward, eight experienced IS academics went through the survey to ensure the content validity. The next step was a pilot testing of the questionnaire with a total of 52 respondents recruited from various business analytics groups on LinkedIn, following the same process that was used for the subsequent main survey (Newbert, 2007). A seven-point Likert scale was used for all our items.

Once the US version of the survey in English was validated, a process similar to the one used by Setia *et al.* (2013) was followed to translate the English version of the survey into French. This consisted of a professional translator translating the survey into French and then back into English to ensure the reliability of the translation. A bilingual member of the research team went through the two versions of the survey to validate the translation. A pre-test of the final French questionnaire with nine respondents was then realized to confirm the construct validity. Subsequently, the combined 61 respondents were used to assess the robustness of our proposed model.

Survey administration

The main survey for this study was administrated by a leading market research firm, and sampling and data collection were then achieved in France and the USA. The data collection for the two samples was conducted from April 4, 2014-April 17, 2014. For the French sample, an invitation to participate in the study was sent on April 4, 2014 to a random sample of 500 members of the French panel of business analysts, business analytics and IT professionals. In all, 337 panel members agreed to participate in the study. A reminder was sent to participants on April 10, 2014, and the survey was closed on April 17, 2014. After a careful analysis of all

Table III.
Measurement of constructs

2nd-order constructs	Type	1st-order constructs	Type	Item labels	Items
Information quality (Wixom and Todd, 2005)	Molecular	Completeness	Reflective	INFQ1	The business analytics used ____ provide a complete set of information
			Reflective	INFQ2	____ produce comprehensive information
			Reflective	INFQ3	____ provide all the information needed
		Currency	Reflective	INFQ4	____ provide the most recent information
			Reflective	INFQ5	____ produce the most current information
			Reflective	INFQ6	____ always provide up-to-date information
		Format	Reflective	INFQ7	The information provided by the analytics is ____ well formatted
			Reflective	INFQ8	The information provided by the analytics is ____ well laid out
			Reflective	INFQ9	The information provided by the analytics is ____ clearly presented on the screen
		Accuracy	Reflective	INFQ10	The business analytics used ____ produce correct information
			Reflective	INFQ11	____ provide few errors in the information
			Reflective	INFQ12	____ provide accurate information
Business value (Gregor *et al.*, 2006)	Molecular	Transactional	Reflective	BVTN1	Savings in supply chain management
			Reflective	BVTN2	Reducing operating costs
			Reflective	BVTN3	Reducing communication costs
			Reflective	BVTN4	Avoiding the need to increase the workforce
			Reflective	BVTN5	Increasing return on financial assets
			Reflective	BVTN6	Enhancing employee productivity
		Strategic	Reflective	BVST1	Creating competitive advantage
			Reflective	BVST2	Aligning analytics with business strategy
			Reflective	BVST3	Establishing useful links with other organizations
			Reflective	BVST4	Enabling quicker response to change
			Reflective	BVST5	Improving customer relations
			Reflective	BVST6	Providing better products or services to customers
		Transformational	Reflective	BVTR1	An improved skill level for employees
			Reflective	BVTR2	Developing new business plans
			Reflective	BVTR3	Expanding organizational capabilities
			Reflective	BVTR4	Improving business models
			Reflective	BVTR5	Improving organizational structure/processes

(*continued*)

2nd-order constructs	Type	1st-order constructs	Type	Item labels	Items
na	na	Satisfaction (Spreng *et al.*, 1996)	Reflective	SABA1	Overall, I am ____ satisfied with business analytics
			Reflective	SABA2	____ contented with business analytics
			Reflective	SABA3	____ pleased with business analytics
			Reflective	SABA4	____ delighted with business analytics
na	na	Firm performance (Miah *et al.*, 2017)	Reflective	FPBA1	Using analytics improved ____ during the last 2 years relative to competitors ____Customer retention
			Reflective	FPBA2	____ Sales growth
			Reflective	FPBA3	____ Profitability

Table III.

responses, 150 valid questionnaires were considered correctly filled out and appropriate for further analysis. Thus, for the French sample, we had a response rate of 44.51 percent.

A similar process was used to collect data in the USA. More precisely, an invitation to participate in the study was sent on April 7, 2014 to a random sample of 826 members of the US panel of business analysts, business analytics and IT professionals. A total of 668 panel members agreed to participate in the study. A reminder was sent to participants on April 12, 2014, and the web-based questionnaire was closed on April 17, 2014. After a careful analysis of all responses, 152 valid questionnaires were considered correctly filled out and appropriate for further analysis. Therefore, for this study, we had a response rate of 22.75 percent, thus giving a final sample of 302 useful responses.

Data analysis

The proposed theoretical model includes two second-order latent constructs: IQUL measured by four first-order latent constructs, and BVAL measured by three first-order latent constructs. Overall, the model includes 11 latent constructs. The complexity of the proposed model, along with the hypothesis that model parameters may be affected by unobserved heterogeneity, renders the use of the partial least squares (PLS) path modeling (Wang *et al.*, 2016) more appropriate to estimate the theoretical model (Peng and Lai, 2012). We applied the PLS path modeling (Wang *et al.*, 2016) to estimate the theoretical model. According to Becker *et al.* (2013), unobserved heterogeneity may arise in an IS sample. This is particularly true in BDA, where it is unrealistic that a unique model may fits all the units.

We used the REBUS-PLS algorithm (Esposito Vinzi *et al.*, 2008) to investigate the presence of unobserved heterogeneity in our sample. Recently, Becker *et al.* (2013) presented a modification of the original REBUS-PLS algorithm, that is, the PLS-POS algorithm. Both of these methods allow unobserved heterogeneity to be accounted for in the whole model (i.e. the measurement as well as the structural part). In comparison to the REBUS-PLS algorithm, the PLS-POS algorithm applies to both formative and reflective indicators. However, the PLS-POS algorithm requires the number of unobserved groups to be defined in the first place. When no prior information can be used to predefine the number of groups to detect, the analysis has to be run several times with a different number of groups. The solution that best fits the data is retained. However, in REBUS-PLS, the algorithm automatically detects the number of unobserved groups. This is a key advance when there is no information about the existence (and the number) of groups. Since our model only involves a reflective measurement model and no prior information was available on the number of groups to be used, we decided to apply the REBUS-PLS algorithm. The REBUS-PLS algorithm provides, at the same time, group membership for each respondent and group-specific model parameters.

Results and discussion

The REBUS-PLS algorithm is available in XLSTAT-PLS, version 2013.6.04. According to Aloysius *et al.* (2016), all item loading values higher than 0.70 are considered adequate. Moreover, composite reliability (CR) values higher than 0.70 are considered acceptable. For average variance extracted (AVE), a value that is higher than 0.50 is considered to be an acceptable measure justifying the use of a construct (Sun and Zhang, 2008).

Execution of the REBUS-PLS algorithm and measurement validation

The REBUS-PLS algorithm automatically detected three groups with similar size (G1, G2 and G3). More precisely, 98 respondents were included in the first group, G1 (i.e. 34 percent of the sample), 108 in the second group, G2 (i.e. 36 percent of the sample), and the remaining 96 respondents (i.e. 32 percent of the sample) in the third group (G3).

In addition, the CR was verified for all the constructs in both the global model and the local models (see Table IV) (Aloysius *et al.*, 2016). All items, with the exception of the one associated with BVTR1 in the local model estimated for G2, were strongly loaded on the corresponding construct. Since the standardized loading associated with BVTR1 was higher than 0.8 in the other two groups and in the global model, we decided to retain it in the analysis. The AVE indexes were higher than 0.60 for all the constructs in the global and local models, thereby exceeding the threshold of 0.5 defined by Fornell and Larcker (1981). Discriminant validity, verified at the global model level as the square root of each AVE value (see Table IV), exceeded the inter-construct correlations in all the models (see Tables V–VIII) (Fornell and Larcker, 1981; Hillol and Viswanath, 2017; Daniel *et al.*, 2017). However, the correlation between IQUL and BVAL exceeded the square root of the AVE associated with BVAL in the local models estimated for the groups 1 and 2 (see Tables VI and VII). Multicollinearity among the constructs was tested. Variance inflation factors (VIF) indexes were reported along with the structural model results in Table IX. All the VIF values were smaller than 10, thus indicating that no serious multicollinearity affected the structural models whether at the global or the local levels (Roden *et al.*, 2017; Rashid *et al.*, 2017; Sharma *et al.*, 2009). The only VIF value exceeding the threshold of 5 (Noor *et al.*, 2015) was the one measuring the multicollinearity between IQUL and BVAL for the prediction of USAT in G1 (Table IX). This was consistent with the discriminant validity results, indicating that IQUL and BVAL were more highly correlated for respondents in G1 than for all the other respondents.

The estimated local models differed based on the relationships in the structural model and on some of the mean values of the second-order constructs. Two-tailed *t*-tests with a Bonferroni correction were run to compare item and construct means across groups. In Table X, we report the mean values of all items at the aggregate and group levels. The results of the two-tailed Bonferroni tests for pairwise comparisons are presented in Table XI. According to the results reported in Tables X and XI, respondents in G2 showed higher item mean values than respondents in G1 and G3. This was particularly true for all items related to strategic and transformational aspects of BVAL and for those related to FPER.

Respondents in G3 had lower values for all items with the exception of the one related to the currency, format and accuracy aspects of IQUL. In particular, they had significant lower values for all the items associated with FPER. The main construct means are reported in Table XII. The results of pairwise comparisons among the construct means are reported in Table XIII. The mean values of all the constructs except for IQUL are significantly different across groups. In particular, G2 was characterized by significant, higher mean values for FPER and BVAL, while respondents in G1 were characterized by a significant, higher mean value for USAT. In accordance with the item mean values, G3 was characterized by the lowest mean values for all constructs. This was particularly true for FPER: respondents in G3 showed a mean value superior to one point (on a seven-point scale), but smaller than the other two groups (Table XII).

Moreover, *post hoc* analyses were run to characterize the REBUS-PLS-detected groups according to manager demographic characteristics, years of experience and firm size. For a given demographic variable, we computed the percentage of respondents showing a specific category (relative frequency per category (percent) in Table XV). We tested the difference between the relative frequencies among the groups by applying χ^2 tests for proportion. Manager proportions among the groups were not significantly different with respect to the country of origin of respondents and the size of the firm where they were employed.

However, G3 was characterized by a significantly (at a level of significance of 0.05) higher percentage of female respondents than all other groups. Moreover, no respondent in this group had a primary qualification. As for G1, its proportion of young respondents (younger than 33 years old) was not significantly high, resulting in a group with less

Table IV. Measurement model results, composite reliability and average variance extracted

2nd-order LVs	1st-order LVs	Items	Standardized loadings Global	G1	G2	G3	Composite reliability and AVE Global	G1	G2	G3
IQUL	Completeness	INFQ1	0.932	0.975	0.901	0.927	CR: 0.939	CR: 0.960	CR: 0.916	CR: 0.935
		INFQ2	0.942	0.966	0.928	0.933	AVE: 0.838	AVE: 0.925	AVE: 0.784	AVE: 0.827
		INFQ3	0.871	0.945	0.824	0.866				
	Currency	INFQ4	0.915	0.970	0.889	0.903	CR: 0.934	CR: 0.973	CR: 0.886	CR: 0.930
		INFQ5	0.870	0.977	0.744	0.873	AVE: 0.825	AVE: 0.949	AVE: 0.723	AVE: 0.816
		INFQ6	0.940	0.976	0.908	0.932				
	Format	INFQ7	0.953	0.979	0.941	0.947	CR: 0.969	CR: 0.977	CR: 0.965	CR: 0.962
		INFQ8	0.966	0.979	0.957	0.966	AVE: 0.913	AVE: 0.956	AVE: 0.902	AVE: 0.894
		INFQ9	0.948	0.975	0.950	0.924				
	Accuracy	INFQ10	0.947	0.980	0.931	0.935	CR: 0.957	CR: 0.974	CR: 0.940	CR: 0.950
		INFQ11	0.937	0.978	0.904	0.932	AVE: 0.881	AVE: 0.950	AVE: 0.842	AVE: 0.863
		INFQ12	0.931	0.966	0.917	0.919				
BVAL	Transactional	BVTN1	0.833	0.928	0.712	0.773	CR: 0.941	CR: 0.970	CR: 0.902	CR: 0.919
		BVTN2	0.893	0.937	0.826	0.872	AVE: 0.727	AVE: 0.870	AVE: 0.605	AVE: 0.656
		BVTN3	0.865	0.948	0.814	0.826				
		BVTN4	0.821	0.906	0.731	0.843				
		BVTN5	0.858	0.940	0.809	0.771				
		BVTN6	0.843	0.936	0.768	0.767				
	Strategic	BVST1	0.863	0.960	0.807	0.766	CR: 0.950	CR: 0.975	CR: 0.918	CR: 0.922
		BVST2	0.891	0.944	0.821	0.860	AVE: 0.760	AVE: 0.888	AVE: 0.652	AVE: 0.665
		BVST3	0.817	0.942	0.724	0.723				
		BVST4	0.886	0.945	0.830	0.859				
		BVST5	0.894	0.950	0.866	0.823				
		BVST6	0.879	0.912	0.787	0.851				
	Transformational	BVTR1	0.830	0.966	0.593	0.801	CR: 0.949	CR: 0.979	CR: 0.889	CR: 0.930
		BVTR2	0.884	0.953	0.789	0.826	AVE: 0.788	AVE: 0.924	AVE: 0.620	AVE: 0.728
		BVTR3	0.905	0.951	0.838	0.874				
		BVTR4	0.918	0.969	0.863	0.900				
		BVTR5	0.899	0.967	0.825	0.861				
	Satisfaction	SABA1	0.911	0.957	0.898	0.894	CR: 0.950	CR: 0.971	CR: 0.944	CR: 0.913
		SABA2	0.913	0.966	0.908	0.863	AVE: 0.825	AVE: 0.921	AVE: 807	AVE: 0.752
		SABA3	0.918	0.965	0.907	0.852				
		SABA4	0.890	0.951	0.881	0.793				
	Firm performance	FPBA1	0.896	0.957	0.826	0.808	CR: 0.945	CR: 0.973	CR: 0.914	CR: 0.881
		FPBA2	0.899	0.953	0.872	0.780	AVE: 0.812	AVE: 0.924	AVE: 0.728	AVE: 0.640
		FPBA3	0.910	0.963	0.853	0.824				
		FPBA4	0.901	0.972	0.859	0.809				

Notes: CR, composite reliability; AVE, average variance extracted experienced managers as compared to the other two groups. Regarding G2, it replicated a sample composition with all the demographic characteristics. However, it did not include managers lacking formal education.

The structural model

The results of the structural model testing are presented in Figure 2, and in Tables IX, XIV, XVI–XVIII. In Figure 2, we present the estimated structural path models at both the global model and group levels. The arrow thickness on the path depends on the associated significance at each path coefficient. As for the structural models, the three groups show different patterns of relationships among the second-order latent constructs: USAT and FPER (see Figure 2 and Tables IX and XIV). In general, the R^2 values of G1 are higher than those of other groups; it is also the group where the correlations among the latent constructs are higher (see Tables V–VIII). As our sample was of relatively small size (especially at local

	IQUL	BVAL	USAT	FPER
IQUL	*0.818*			
BVAL	0.779	*0.815*		
USAT	0.744	0.757	*0.908*	
FPER	0.652	0.809	0.666	*0.901*

Note: The square roots of the average variance extracted (AVE) are shown on the diagonal (in italic)

Table V. Correlation matrix among latent constructs in the global model

	IQUL	BVAL	USAT	FPER
IQUL	*0.948*			
BVAL	0.947	*0.924*		
USAT	0.929	0.889	*0.960*	
FPER	0.922	0.931	0.860	*0.961*

Note: The square roots of the average variance extracted (AVE) are shown on the diagonal (in italic)

Table VI. Correlation matrix among latent constructs in the local model for G1

	IQUL	BVAL	USAT	FPER
IQUL	*0.770*			
BVAL	0.734	*0.713*		
USAT	0.721	0.861	*0.898*	
FPER	0.676	0.813	0.796	*0.853*

Note: The square roots of the average variance extracted (AVE) are shown on the diagonal (in italic)

Table VII. Correlation matrix among latent constructs in the local model for G2

	IUQL	BVAL	USAT	FPER
IQUL	*0.765*			
BVAL	0.717	*0.736*		
USAT	0.582	0.740	*0.851*	
FPER	0.494	0.566	0.581	*0.806*

Note: The square roots of the average variance extracted (AVE) are shown on the diagonal (in italic)

Table VIII. Correlation matrix among latent constructs in the local model for G3

Table IX. Structural model results

		Standardized path coefficients				R^2 value				Contribution to R^2 (%) and R^2 value				VIF value			
Dependent constructs	Structural paths	Global	G1	G2	G3	Global	G1	G2	G3	Global	G1	G2	G3	Global	G1	G2	G3
BVAL	IQUL→BVAL	0.779***	0.947***	0.734***	0.717***	0.61	0.90	0.55	0.51	na				na			
USAT	IQUL→USAT	0.393***	0.843***	0.191***	0.106ns	0.63	0.86	0.76	0.55	*46.19%*	*90.64%*	18.19%	11.21%	2.520	*9.73*	3.915	2.04
	BVAL→USAT	0.451***	0.009ns	0.721***	0.663***					*53.81%*	9.36%	*81.82%*	*88.79%*				
FPER	BVAL→FPERF	0.716***	0.795***	0.496***	0.299*	0.66	0.87	0.70	0.38	*87.51%*	*84.94%*	*57.88%*	44.58%	2.337	4.78	2.206	2.22
	USAT→FPER	0.124*	0.153**	0.369***	0.361**					12.49%	15.06%	42.12%	*55.42%*				

Notes: *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001

2nd-order LVs	1st-order LVs	Items	Overall Mean	Overall SD	G1 Mean	G1 SD	G2 Mean	G2 SD	G3 Mean	G3 SD
IQUL	Completeness	INFQ1	4.84	1.25	5.04	1.09	4.97	1.23	4.48	1.35
		INFQ2	4.85	1.21	5.07	1.12	4.93	1.25	4.55	1.22
		INFQ3	4.62	1.39	5.05	1.09	4.66	1.49	4.15	1.39
	Currency	INFQ4	5.04	1.08	4.94	1.10	5.16	1.00	5.01	1.14
		INFQ5	4.91	1.21	5.02	1.12	4.93	1.18	4.77	1.33
		INFQ6	5.04	1.16	5.01	1.19	5.18	1.03	4.93	1.24
	Format	INFQ7	5.08	1.13	4.97	1.02	5.19	1.24	5.08	1.09
		INFQ8	5.11	1.15	4.95	1.03	5.23	1.22	5.14	1.15
		INFQ9	5.03	1.26	4.95	1.09	5.13	1.35	4.99	1.29
	Accuracy	INFQ10	5.17	1.06	4.97	1.07	5.31	1.02	5.21	1.07
		INFQ11	5.09	1.17	4.97	1.12	5.20	1.20	5.08	1.18
		INFQ12	4.99	1.22	4.90	1.14	5.12	1.31	4.95	1.18
BVAL	Transactional	BVTN1	4.70	1.15	4.83	1.08	5.10	1.04	4.11	1.11
		BVTN2	4.90	1.17	5.01	1.09	5.31	0.99	4.32	1.21
		BVTN3	4.78	1.18	4.93	1.15	4.99	1.11	4.40	1.19
		BVTN4	4.71	1.24	4.86	1.06	4.96	1.37	4.27	1.12
		BVTN5	4.95	1.17	4.93	1.15	5.43	0.97	4.45	1.18
		BVTN6	4.94	1.25	4.93	1.21	5.40	1.09	4.44	1.26
	Strategic	BVST1	5.11	1.15	4.95	1.03	5.65	0.92	4.66	1.25
		BVST2	5.12	1.11	4.92	1.08	5.62	0.84	4.77	1.21
		BVST3	4.85	1.18	4.92	1.08	5.24	1.01	4.33	1.27
		BVST4	5.03	1.16	4.95	1.07	5.45	1.01	4.63	1.23
		BVST5	5.03	1.21	4.87	1.08	5.66	1.04	4.50	1.22
		BVST6	5.08	1.18	4.94	1.10	5.70	0.94	4.51	1.18
	Transformational	BVTR1	4.83	1.13	5.03	1.18	5.11	1.06	4.31	0.98
		BVTR2	4.96	1.04	5.01	1.07	5.34	0.78	4.48	1.08
		BVTR3	5.01	1.12	4.92	1.18	5.47	0.90	4.58	1.11
		BVTR4	5.03	1.11	4.96	1.12	5.44	0.93	4.64	1.14
		BVTR5	4.91	1.20	4.93	1.25	5.28	1.01	4.48	1.20
na	Satisfaction	SABA1	4.97	1.16	5.20	1.09	4.83	1.33	4.88	0.97
		SABA2	4.77	1.20	5.12	1.14	4.62	1.26	4.59	1.12
		SABA3	4.92	1.11	5.18	1.13	4.85	1.17	4.73	0.97
		SABA4	4.93	1.02	5.12	1.13	4.90	0.98	4.76	0.90
	Firm performance	FPBA1	4.78	1.22	5.03	1.01	5.35	1.11	3.89	1.02
		FPBA2	4.87	1.25	5.03	1.07	5.49	1.09	4.00	1.08
		FPBA3	4.95	1.19	5.06	1.04	5.54	0.92	4.18	1.17
		FPBA4	4.89	1.22	5.08	1.06	5.38	1.00	4.15	1.24

Table X. Item means and standard deviations

model level), we opted for using the traditional inference (i.e. t-test and p-value) to validate the significance of the model's structural coefficients (Table IX). We also computed bootstrapped confidence intervals using $n = 200$ resamples (Table XVI). The results obtained are consistent with the significant coefficients obtained after correction for common method bias (Table XVIII). Each of the inner relationships is discussed below.

Impact on business value. Table IX shows that IQUL has a significant positive effect on BVAL for the global model and for all the three detected local models (G1, G2 and G3), thus supporting *H1* for global model, G1, G2 and G3. According to Cohen (1988), and considering the f^2 values reported in Table XVII, IQUL has a large effect on BVAL at both the global and local levels. In addition, the impact of IQUL on BVAL is significantly higher for respondents in G1, as compared to the global model and the other local models, G2 and G3 (see Table XIV).

Impact on satisfaction. In the proposed model, we assumed that USAT would be explained by IQUL and BVAL. At the global model level, both IQUL and BVAL have

Table XI.
Item means comparison among REBUS Groups

2nd-order LVs	1st-order LVs	Items	G1 vs G2	G1 vs G3	G2 vs G3
IQUL	Completeness	INFQ1	0.069ns	*0.562***	*0.493**
		INFQ2	0.146ns	*0.519***	0.374ns
		INFQ3	*0.394**	*0.905****	*0.512**
	Currency	INFQ4	0.219ns	0.072ns	0.147ns
		INFQ5	0.094ns	0.250ns	0.155ns
		INFQ6	0.166ns	0.083ns	0.249ns
	Format	INFQ7	0.216ns	0.114ns	0.102ns
		INFQ8	0.283ns	0.186ns	0.096ns
		INFQ9	0.181ns	0.041ns	0.140ns
	Accuracy	INFQ10	0.345ns	0.239ns	0.106ns
		INFQ11	0.234ns	0.114ns	0.120ns
		INFQ12	0.222ns	0.050ns	0.172ns
BVAL	Transactional	BVTN1	0.275ns	*0.712****	*0.987****
		BVTN2	0.295ns	*0.687****	*0.983****
		BVTN3	0.062ns	*0.533***	*0.595****
		BVTN4	0.106ns	*0.586***	*0.692****
		BVTN5	*0.497***	*0.481***	*0.978****
		BVTN6	*0.470**	*0.491***	*0.961****
	Strategic	BVST1	*0.699****	0.293ns	*0.992****
		BVST2	*0.702****	0.148ns	*0.850****
		BVST3	0.322ns	*0.585****	*0.907****
		BVST4	*0.505***	0.324ns	*0.829****
		BVST5	*0.790****	0.367ns	*1.157****
		BVST6	*0.765****	*0.428***	*1.193****
	Transformational	BVTR1	0.080ns	*0.718****	*0.799****
		BVTR2	*0.332**	*0.531****	*0.863****
		BVTR3	*0.554****	0.335ns	*0.889****
		BVTR4	*0.485***	0.324ns	*0.809****
		BVTR5	0.349ns	*0.449***	*0.799****
	Satisfaction	SABA1	0.371ns	0.329ns	0.042ns
		SABA2	0.502**	*0.529***	0.027ns
		SABA3	0.332ns	*0.455**	0.123ns
		SABA4	0.224ns	*0.362**	0.138ns
	Firm Performance	FPBA1	*0.321**	*1.145****	*1.466****
		FPBA2	*0.460***	*1.031****	*1.491****
		FPBA3	*0.471***	*0.884****	*1.360****
		FPBA4	0.298ns	*0.936****	*1.234****

Notes: Differences are expressed in absolute values. Significant differences are in italic. Bonferroni correction for multi-group comparison has been applied. *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001

Table XII.
Construct means and standard deviations

	Overall		G1		G2		G3	
2nd-order constructs	Mean	SD	Mean	SD	Mean	SD	Mean	SD
IQUL	4.99	0.97	4.99	1.04	5.09	0.94	4.87	0.93
BVAL	4.94	0.95	4.93	1.03	5.38	0.71	4.47	0.87
USAT	4.90	1.02	5.16	1.07	4.80	1.07	4.74	0.85
FPER	4.87	1.10	5.05	1.01	5.44	0.88	4.05	0.91

significant and moderate positive effect on USAT (Tables IX and XVII), thus validating *H2* and *H3* at the global level (Table XIX). Similarly, for respondents in G2, IQUL and BVAL still show significant positive effects on USAT (Table IX), thus validating *H2* and *H3* for G2 (Table XIX). However, for respondents in G2, the main driver of USAT is BVAL, which contributes for about 82 percent of the explained variability, while IQUL only accounts for 8 percent of the explained variability (Table IX). Moreover, the effect of BVAL can be considerate as large according to the f^2 value in Table XVII (Cohen, 1988). Differences occur when comparing models estimated for respondents in G1 and G3 (Table XIV). For respondents in G3, BVAL is the only significant driver of USAT and it alone explains 55 percent of the variability of USAT ($R^2 = 0.55$) (Table IX) and shows a large effect on USAT according to the f^2 value in Table XVII, thereby validating only *H3* for G3 (Table XIX). On the other hand, for respondents in G1, the only significant driver of USAT is IQUL: alone, it accounts for 86 percent of the variability of USAT ($R^2 = 0.86$) (Table IX) and shows a large effect on USAT (Table XVII), thus validating *H2* for G3 (Table XIX). The non-significance of the coefficient linking BVAL to USAT in G1 may be due to the high correlation between the two independent variables; therefore, caution must be applied in interpreting this result. However, the VIF value associated with this structural relationship is smaller than 10 (Table IX), indicating that no serious multicollinearity affects the structural model for G1 (Roden *et al.*, 2017).

Impact on firm performance. In the proposed model, we assumed that FPER would be directly dependent on BVAL and USAT. As shown in Table IX, the two exogenous variables have significant positive effects on FPER for all groups, and as a result, *H4* and *H5* are validated for the three groups, G1, G2 and G3, as well as for the global model (Table XIX). However, at the global model level and for respondents in G1, BVAL is the most important driver of FPER explaining 85 percent or more of the explained variability (Table IX). This is confirmed by observing the f^2 values in Table XVII: BVAL has a large effect on FPER, while USAT only shows a small effect on FPER.

This is not true for respondents in G2 and G3, for whom BVAL and USAT have similar impact on FPER. In particular, the effects of both BVAL and USAT are moderated for respondents in G2, while respondents in G3 seem to be more satisfaction-driven than those in G2 (Table XIV), even if BVAL and USAT have small effects on FPER.

Common method bias correction. Relations in the structural model may be inflated because of common method bias (Chin *et al.*, 2012). To test for common method bias, we followed the approach proposed by Malhotra *et al.* (2006). We used the smallest observed correlation between the constructs (i.e. 0.328 equals to the correlation between FPER and

Mean comparison	IQUL	BVAL	USAT	FPER
G1 vs G2	0.104ns	0.442***	0.359*	0.386**
G1 vs G3	0.133ns	0.459***	0.416*	0.998***
G2 vs G3	0.216ns	0.902***	0.057ns	1.384***

Notes: Differences are expressed in absolute values. Significant differences are in italic. Bonferroni correction for multi-group comparison has been applied. *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001

Table XIII. Construct means comparison among REBUS Groups

	BVAL	USAT		FPER	
Path coefficient comparison	IQUL→BVAL	IQUL→USAT	BVAL→USAT	BVAL→FPER	USAT→FPER
G1 vs G2	*0.383***	*0.669***	*1.007***	0.179ns	0.173ns
G1 vs G3	*0.272***	*0.779***	*0.562**	*0.455***	0.238ns
G2 vs G3	0.111ns	0.110ns	*0.445**	*0.276***	0.066ns

Notes: Differences are expressed in absolute values. Significant differences are in italic. *p-value < 0.05; **p-value < 0.01; ***p-value < 0.001

Table XIV. Structural model comparison among REBUS Groups

Variable	Categories	Relative frequency per category (%) Global $n = 302$	G1 $n_1 = 98$	G2 $n_2 = 108$	G3 $n_3 = 96$
Country	France	49.67	53.06	53.70	41.67
	USA	50.33	46.94	46.30	58.33
Gender	Female	20.86	15.31	17.59	*30.21*
	Male	79.14	84.69	82.41	69.79
Age	18–25	4.31	*8.16*	3.70	1.04
	26–33	17.22	*23.47*	12.04	16.67
	34–41	28.48	23.47	28.70	33.33
	42–49	24.17	24.49	26.85	20.83
	50 or more	25.83	20.41	28.70	28.13
Education	No formal qualification	0.66	1.02	*0.00*	1.04
	Primary qualification	0.66	1.02	0.93	*0.00*
	Secondary qualification	5.30	4.08	6.48	5.21
	College qualification	12.25	13.27	13.89	9.38
	Undergraduate degree	30.13	25.51	31.48	33.33
	Postgraduate degree	50.99	55.10	47.22	51.04
Years of experience	Less than one year	5.96	8.16	3.70	6.25
	2–5	32.45	35.71	27.78	34.38
	6–10	19.21	21.43	19.44	16.67
	11–15	20.86	17.35	24.07	20.83
	16–20	9.93	11.22	11.11	7.29
	Over 20	11.59	*6.12*	13.89	14.58
Firm size	0–19	1.33	1.02	1.85	1.04
	20–99	3.97	3.06	3.70	5.21
	100–249	5.30	4.08	5.56	6.25
	250–499	6.29	5.10	6.48	7.29
	500–999	6.29	5.10	8.33	5.21
	1,000–2,499	9.27	10.20	9.26	8.33
	2,500–4,999	9.60	9.18	12.04	7.29
	5,000–9,999	9.93	8.16	9.26	12.50
	10,000–24,999	12.58	12.25	11.11	14.58
	25,000–49,999	5.63	3.06	5.56	8.33
	50,000–99,999	11.92	16.33	11.11	8.33
	100,000 or more	17.88	22.45	15.74	15.63

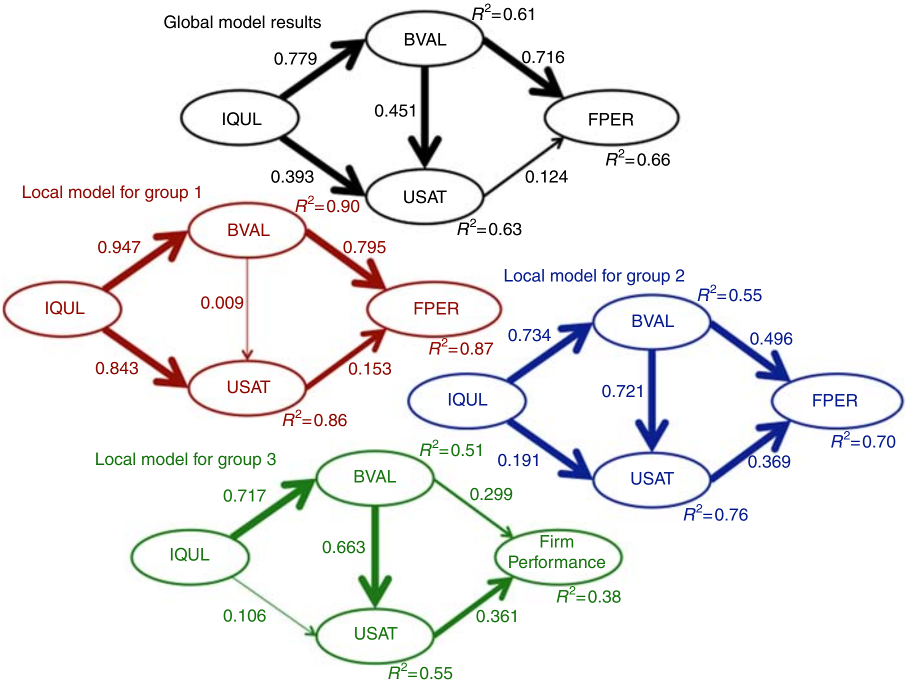
Notes: Value displayed as percentage of total responses. Percentages that are significantly different from the others at level $\alpha = 0.05$ are in italic

Table XV.
Demographics and firm characteristics distributions

completeness) as a proxy of common variance bias. We adjusted the correlations between the LVs for common variance bias and we used the adjusted correlations to estimate adjusted structural model parameters. The coefficients obtained after adjustment for common variance bias remained significantly different from zero (Table XVI), except for the coefficient linking SAT to FPER in the global model. This confirms the absence of common variance bias in our data and the robustness of our results.

Limitations

Prior to discussing the managerial and theoretical implications of this study, a number of limitations need to be recognized. First, the vast majority of items used for our constructs were measured using an anchored seven-point Likert scale ranging from "strongly disagree"(1) to "strongly agree" (7). This may introduce the so-called "acquiescence bias," which is related to the "respondents' tendency to respond to items positively without much regard for its true content" (Chin *et al.*, 2008). Therefore, future studies may consider using the nine-point scale of fast form items with the two-anchor points ranging from −4 to +4 as



Note: Arrow thickness in the structural model is a function of the significance of the associated coefficient

Figure 2. Structural model results

Dependent constructs	Structural paths	Global Lower	Global Upper	G1 Lower	G1 Upper	G2 Lower	G2 Upper	G3 Lower	G3 Upper
		Bootstrap confidence interval obtained with $S = 200$ bootstrap samples							
Business value	IQ→BV	0.645	0.851	0.855	0.998	0.356	0.702	0.510	0.824
Satisfaction	IQ→SAT	0.267	0.605	0.388	1.260	0.068	0.364	−0.120	0.242
	BV→SAT	0.268	0.665	−0.337	0.547	0.847	1.319	0.445	0.893
Overall performance	BV→Perf	0.669	0.982	0.596	0.970	0.294	0.902	−0.001	0.614
	Sat→Perf	0.001	0.265	−0.068	0.322	0.054	0.566	0.032	0.700

Table XVI. The results of the bootstrap procedure

Dependent constructs	Structural paths	Global	G1	G2	G3
		f^2 values			
Business value	IQ→BV	**1.552**	**8.729**	**1.206**	**1.042**
Satisfaction	IQ→SAT	0.164	**0.537**	*0.059*	*0.011*
	BV→SAT	0.217	*0.006*	**1.006**	**0.492**
Overall performance	BV→Perf	**0.652**	**1.017**	0.194	*0.066*
	Sat→Perf	*0.019*	0.038	0.125	*0.093*

Notes: Large effect sizes are in bold, small effect sizes are in italic

Table XVII. The model's explanatory power and predictive validity of the model suggested by Chin *et al.* (2008). Second, the BDA-enabled improved firm performance cannot be fully assessed by a limited set of determinants. Therefore, further research might attempt to integrate more determinants including, for example, information quality with system quality (Wixom and Todd, 2005), or service quality with information quality (Barney, 2001). Third, this study measures the direct impact of a set of determinants of BDA on firm performance. Another area of future research may consist in looking at the first-order impact of BDA, which is the impact at the process level (Forbes, 2013; Mooney *et al.*, 1996).

Implications for practice

From the managerial perspective, the following implications can be underscored. First, the study offers a set of determinants for business analytics that managers might use to assess the BDA potential within their organization. Second, the ability of the REBUS-PLS algorithm to automatically detect three distinctive groups of business analytics users may contribute to facilitating the design of IT features and interfaces that match each user group's desires, thus fostering user acceptance and the use of IT systems. Third, the developed ability to identify distinctive user behavior groups within a sample may allow project stakeholders in charge of designing training programs and interventions to provide more targeted and personalized training to each group identified by the REBUS-PLS algorithm.

Implications for research

This study integrates constructs from Wixom and Todd (2005), Gregor *et al.* (2006), Spreng *et al.* (1996) and Tippins and Sohi to study the potential of BDA in enabling improved firm performance. However, unlike these earlier studies that investigated the relationship between the independent and dependent variables at the global level, the current study argues that the adoption behavior varies among adopters of any given IT artifact. Therefore, only assessing the importance of the relationship between independent and dependent variables at the global level does not capture these differences or the unobserved heterogeneity that exists in social data (Zhang and Wu, 2017). Consequently, this study uses

		CMB adjusted estimates ($r_M = 0.328$)			
Dependent constructs	Structural paths	Global	G1	G2	G3
Business value	IQ→BV	0.671***	0.921***	0.605***	0.579***
Satisfaction	IQ→SAT	0.348***	0.826***	0.165*	0.035ns
	BV→SAT	0.405***	0.074ns	0.694***	0.592***
Overall performance	BV→Perf	0.668***	0.781***	0.459***	0.195****
	Sat→Perf	0.076ns	0.139****	0.332**	0.258*

Notes: $r_M =$ shared correlation resulting from CMB using the correlation between FPER and completeness as marker variable. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; ****$p < 0.1$

Table XVIII. Path coefficients before and after correcting for CMB

	Results				
Hypotheses	Global model	G1	G2	G3
H1	Supported	Supported	Supported	Supported
H2	Supported	Supported	Supported	Not supported
H3	Supported	Not supported	Supported	Supported
H4	Supported	Supported	Supported	Supported
H5	Supported	Supported	Supported	Supported

Table XIX. Results of hypotheses testing the REBUS-PLS algorithm, which is a response-based method, to capture this unobserved heterogeneity (Esposito Vinzi *et al.*, 2008). In addition, this research work is a response to the call by Becker *et al.* (2013) for more studies to investigate unobserved heterogeneity more thoroughly. These authors actually found that over the last 20 years, the leading IS journals in the world had published very few articles having used a structural model in their research and having "examined unobserved heterogeneity." In such articles, it was assumed that empirical data were homogeneous and represented a single population, and that this could lead to possible bias during the assessment of structural model parameters. Another implication triggered by our study is that, by applying the REBUS-PLS algorithm, it is possible to identify three groups of business analytics users (G1, G2, and G3), which are all characterized by different user's behaviors (e.g. difference in values for structural model parameters). These results may facilitate the design of IT systems that fit each user's behavior across each identified group, thus facilitating the adoption and use of the IT systems, as well as the extended use of the said IT systems.

In addition, this study provides some insights into the nature and role of IS quality, business value and satisfaction in creating improved firm performance through BDA, thus contributing to the emerging literature on BDA. Given the increased importance of business analytics in facilitating firm competitive advantage, future studies may build upon our proposed determinants to explore the potential of business analytics at the process, inter-organizational and societal levels (Chee *et al.*, 2012; Singh and Gaur, 2017).

Conclusion

BDA have emerged as the new frontier of innovation and competition in the wide spectrum of the business landscape due to the challenges and opportunities created by the information revolution. BDA increasingly provide value to firms using the dynamics of information quality that transform data into practical insights for robust informed decision making and business problems solving. This is a holistic process which deals concurrently with data, sources, skills, and systems in order to create a competitive advantage. Leading e-commerce firms like Google, Amazon, and Facebook have already embraced BDA and experienced enormous growth. This study presents a useful starting point for understanding the IQUL dynamics in a big data environment, notably by modeling their impact on BVAL, USAT, and FPER. The study reflects that once BDA-driven IQUL is well understood and the identified challenges properly addressed, the BDA application will maximize business value, which facilitates pervasive usage and speedy delivery of insights across organizations.

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