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Turning information quality into firm performance in the big data economy

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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.

Disciplines

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Turning Information Quality into Firm Performance in Big Data Economy

Purpose

Big data analytics (BDA) increasingly provide value to firms for robust decision making and solving business problems. This paper explores information quality dynamics in big data environment linking business value, user satisfaction and firm performance.

Design/Methodology/Approach

Drawing on appraisal-emotional response-coping framework, we 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 US.

Findings

Our 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

The paper shows how to operationalize information quality, business value, satisfaction and firm performance in BDA using PLS-SEM. In addition, the paper offers 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 big data analytics project, that offers a decision support to managers to enhance user satisfaction and firm performance.

Originality/value

The paper extends big data literature by offering the appraisal-emotional response-coping framework for modelling information quality on firm performance. The methodological novelty lies in embracing REBUS-PLS to handle unobserved heterogeneity in the sample.

Keywords

Big data analytics, business value, user satisfaction, firm performance, REBUS PLS

INTRODUCTION

Big data has emerged as a new frontier for business in either establishing competitive advantages or exploiting the untapped opportunities (Goes, 2014). In every part of the world, every industry collects more data than ever before, yet is also seeking smarter business strategies to harness this big data revolution. The extant literature identifies 'big data' as "the next management revolution" (A. McAfee & E. Brynjolfsson, 2012); "the new raw material for business" (Economist, 2010); or "the new science that holds the answers" (Gelsinger, 2012). This increased attention both in the academic and practitioner literature is rooted in the fact that big data analytics enable better understanding of business, markets and consumers; higher productivity linked with profitability; and improved performance measurement mechanisms (Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; A. McAfee & E. Brynjolfsson, 2012; Verbraken, Lessmann, & Baesens B., 2012), which are constantly reflected in Google, Amazon, Harrah's, Capital One, and Netflix's business models. With the objective of leapfrogging competition, companies are increasingly interested in big data analytics (hereinafter called BDA) to transform their business models by customizing what consumers want, when they want it, how many they want, and what incentives will make them want more in their lifetime (Thomas H Davenport, 2006). However, despite the widespread buzz around BDA, leveraging BDA-driven information to generate business value continues to be a challenge for many organizations. To cope with these challenges, 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" (T. H. Davenport, P. Barth, & R. Bean, 2012). However, there are growing concerns and confusion regarding analytics-driven

information quality (IQUL), business value (BVAL), user satisfaction (USAT), and firm performance (FPER) (T. H. Davenport et al., 2012; Goes, 2014). Clearly, owing to a 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” (Stacie Petter, DeLone, & McLean, 2013,p.30).

Our objective in this article is twofold. First, we investigate ways to leverage IQUL in BDA to achieve enhanced FPER by proposing and testing a theory from the perspective of managers/users. This perspective is put in this context because FPER ultimately depends on managers who are the most critical stakeholder in terms of their interest in knowing more about their businesses by translating big data into better information and improved decisions (A. McAfee & E. 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 (Thomas H. Davenport, 2012; Lavalley et al., 2011). We also examine the managers’ perspective because they want to understand “how to fish out answers to important business questions from today’s tsunami of unstructured information” (Thomas H Davenport & 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. To fill this knowledge gap, we propose a conceptual model which is rooted in the traditional appraisal processes (IQUL, BVAL)-emotional reactions (USAT)-coping responses (FPER) framework (Bagozzi, 1992; Lazarus, 1991). In developing our theoretical model, we

propose that analytics-driven information quality and business value appraisal processes lead to emotional responses (managers' satisfaction), which, in turn, induce coping activities in terms of increasing the target outcomes, that is, firm performance. To empirically test the proposed relationships, we analysed data from 302 managers who rely on BDA for their day-to-day operations and strategic directions across various industries in the USA and France. The study findings suggest that analytics-driven IQUL has a positive impact on BVAL and USAT which again influences FPER.

Second, we attempt to provide insights on unobserved heterogeneity in our sample whilst investigating their perceptions of IQUL-BVAL-USAT and FPER. Because, it is unrealistic to assume that empirical studies are based on homogeneous sample representing a single population in the social and behavioral sciences, such as e-commerce (Becker, Rai, Ringle, & Völckner, 2013). Indeed, unobserved groups might represent significant heterogeneity in data, thus leading to bias parameter estimates and invalid statistical conclusions (Jedidi, Jagpal, & DeSarbo, 1997). Working with unobserved heterogeneity means finding groups of units or clusters having similar behaviours. We used the REBUS-PLS algorithm (Esposito Vinzi, Trinchera, Squillacciotti, & Tenenhaus, 2008) to investigate the presence of unobserved heterogeneity in our sample. REBUS-PLS algorithm has been designed to detect homogenous groups of units with increased predictive power. The differences between model parameter estimates are analysed for significance testing by means of multi-group comparison (Wynne W Chin & Dibbern, 2010).

In putting forward the theory of manager-side BDA strategy, this study extends this research stream in multiple ways. Our study contributes to the big data literature by exploring the impact of BDA on business strategy with regard to IQUL-BVAL-USAT-FPER (Goes, 2014; Sharma, Mithas, & Kankanhalli, 2014). The extant research has largely focused on anecdotal evidence in proposing BDA strategy (D. Barton & D. Court, 2012; A. McAfee & E.

Brynjolfsson, 2012; Shanks, Bekmamedov, & Sharma, 2011; Shanks & Bekmamedova, 2012). We contribute to this research by examining the practical relationships between BDA-driven IQUL and BVAL (Thomas H. Davenport, 2010; Forrester, 2012; Kiron & Shockley, 2011; Lavallo et al., 2011). Furthermore, this study seeks to build on the extant research by investigating IQUL as it relates to BDA and influences USAT and FPER. Methodologically, the application of REBUS-PLS in exploring unobserved heterogeneity provides critical insights on differences among segments in the sample and facilitates theory development by adding additional descriptions on different groups of managers' perceptions regarding IQUL-BVAL-USAT-FPER dynamics (Becker et al., 2013). The research questions of the study are:

How do IQUL perceptions of BDA determine critical business outcomes?

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 answer to these research questions clearly contributes to the business-technology-analytics alignment of global organizations by framing the impact of IQUL on individual and business outcomes. The organization of this paper is as follows: the next section focuses on the conceptual model and hypotheses development. This is followed by the method and 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

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”(T. H. Davenport et al., 2012). Indeed, BDA enable the coordination of data from a variety of fields to improve information quality and organizational performance. Following the arguments of coordinator theories (e.g.,Malone & Crowston, 1994), this study contends that complex and interdependent BDA platforms produce information in coordination that enhances BVAL, USAT, and FPER.

The extant research assessing the organizational impacts of BDA highlights the importance of IQUL in these environments (Thomas H Davenport, 2006; Schläfke, Silvi, & Möller, 2013). 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; A. McAfee & E. Brynjolfsson, 2012). The extant literature identifies that IQUL influences various outcomes, such as satisfaction (Nelson, Todd, & Wixom, 2005; Xu, Benbasat, & Cenfetelli, 2013); loyalty (Zhou, Lu, & Wang, 2009); trust in the IT artifact (Vance, Elie-Dit-Cosaque, & Straub, 2008); and user and knowledge-sharing behavior (Durcikova & Gray, 2009). We propose that IQUL is a critical component of a firm’s BDA success (DeLone & McLean, 1992; Barbara H Wixom & Todd, 2005). The ultimate managerial challenge in the BDA environment lies in finding patterns in data and translating them 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” (Thomas H Davenport, 2006).

The extant literature identifies four characteristics of information, namely, completeness, accuracy, format, and currency that are often emphasized (see Table 1). These attributes may differ across BDA environments; however, the degree of completeness, accuracy, format, and currency of information significantly contributes to the quality of information perception of managers across organizations. For instance, BDA used in a bank may provide employees with a 360-degree view of more complete information by combining data across multiple platforms, such as online banking, physical visits to the bank, ATMs, and customer complaints (D. Barton & D. Court, 2012). BDA may also vary in terms of accuracy of information as this process requires data from multiple sources to be organized and processed. Information from a variety of sources is often termed “dirty” due to differences in definitions, architectures, and situations. For example, Oakland A’s (Athletics), New England Patriots, the Boston Red Sox, and Italy’s A.C. Milan use a variety of data (e.g., physiological, orthopedic, and psychological) from multiple sources to provide accurate information for player selection and deployment (Thomas H Davenport, 2006).

The IQUL perception also depends on improved information filtering and better visualization of results through presentation in an appealing and well-formatted manner. BDA should “... transform numbers into information and insights that can be readily put to use versus having to rely on further interpretation or leaving them to languish about uncertainty about how to act”(Lavalle et al., 2011,p.23). Organizations with advanced BDA capabilities use maps, colourful dashboard displays, and advanced visualization tools to provide information in a better format to facilitate adoption and productivity (B. H. Wixom, Yen, & Relich, 2013). Similarly, BDA may vary due to the currency of information. For example, BDA may yield low-quality information by not reflecting a bank client’s most recent transaction. BDA should enable currency of information by embracing the continuous flow of information in the big

data environment rather than having it sit idly in a data warehouse. Examples of how real-time information can assist are in identifying fraud or detecting changes in customer sentiments.

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 (B. H. Wixom et al., 2013). BDA with high information quality facilitate intra-organization operational coordination thus enhancing the effectiveness of functional managers and generating different types of business value, as reflected in Table 2. The research model of this study is based on the appraisal-emotional response-coping framework (Bagozzi, 1992; Lazarus, 1991) 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 (1992) as “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”(Stacie 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 (B. H. Wixom et al., 2013). The importance of the relationship between IQUL and BVAL was evidenced by Lavallo et al. (2011)’s 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”(Sunil Mithas, Lee, Earley, Murugesan, & Djavan Shir, 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 (Mirani & Lederer, 1998). As shown by Davenport (2006), an alignment between analytics-driven information quality and operational effectiveness results in identifying profitable customers for Harrah’s, Capital One, and Barclays, and in maximizing yield for Progressive and Marriott. In a similar spirit, Wixom et al. (2013) indicate that GUESS? INC., the 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

Information Quality, Business Value, and Satisfaction

The extant literature in marketing (Brady & Robertson, 2001; Cronin & Taylor, 1992) and IS (Delone, 2003; Mirani & Lederer, 1998; Nelson et al., 2005; Barbara H Wixom & Todd, 2005) identifies information quality as a cognitive construct and as an attitudinal construct. As an ‘affective response’, scholars identify satisfaction from different viewpoints, such as: a summary attribute phenomenon (Oliver, 1993); an overall evaluation (Claes Fornell, 1992); or a fulfillment response (Oliver, 1993). In a recent study, Golder et al. (2012) state that “[p]ositive quality disconfirmation increases satisfaction; negative quality disconfirmation decreases satisfaction”. In this regard, Pitt et al. (1995,p.174) mention that “[t]he principal reason IS departments measure user satisfaction is to improve the quality of service they provide ... Irrespective of whether a user interacts with one or multiple information systems, the quality of service can influence use and user satisfaction”. In a meta-analysis on IS user satisfaction, Zviran and Erlich (2003) identify satisfaction as an important outcome construct to evaluate the performance of a system due to its critical effects on decision making and productivity benefits. In a big data environment, scholars (Thomas H Davenport, 2006; A. McAfee & E. Brynjolfsson, 2012) identify 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. In addition to information quality, business value is an important antecedent of satisfaction. According to Fornell et al. (1996) “[t]he first determinant of overall customer satisfaction is perceived quality. The second determinant of overall customer satisfaction is perceived value”. Although satisfaction has been used in myriad IS contexts, to date there has been no empirical research on users’ satisfaction in BDA. 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 to play a vital role in increasing business and firm performance (B. H. Wixom et al., 2013). The extant literature provides evidence of a relationship between satisfaction and firm performance in, for instance: return on investment (Anderson, Fornell, & Lehmann, 1994; Anderson, Fornell, & Rust, 1997; Zeithaml, 2000); operating margin (Bolton, 1998; Rust, Zahorik, & Keiningham, 1994, 1995); and profitability (C. Fornell, Mithas, & Morgeson, 2009; C. Fornell, Mithas, Morgeson, & Krishnan, 2006; Grover & Ramanlal, 1999; Sunil Mithas et al., 2013; S. Mithas, Tafti, Bardhan, & Goh, 2012). In the context of healthcare, (Srinivasan & 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) show that BDA can improve firm performance by improving productivity both in 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

The extant literature on BDA identifies the relationship between business value and firm performance as one of the key issues for potential investigation (Agarwal & Dhar, 2014; Sunil Mithas et al., 2013; Sharma et al., 2014; B. H. Wixom et al., 2013). 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 &

Kohli, 2000; Hitt & Brynjolfsson, 1996; Kauffman & Kriebel, 1988; Mukhopadhyay, Kekre, & Kalathur, 1995; Xia & Zhang, 2010). This study adopts the “proxy view of IT” in defining the business value of BDA which indicates the individual perceptions of its usefulness or value through firm performance in financial units (Melville, Kraemer, & Gurbaxani, 2004; Orlikowski & Iacono, 2001).

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

MEASUREMENT DEVELOPMENT

In this study, the development of the US survey measurement items followed 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 3). Afterward, eight experienced IS academics went through the survey to ensure the content validity. Next, a pilot testing of the questionnaire was conducted with a total of 52 respondents recruited from various business analytics groups on LinkedIn following the same process as was used for the subsequent main survey (Pavlou & Fygenson, 2006). A 7-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 Venkatesh et al. (2012) 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.

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 prior. 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 fit 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. Moreover, post-hoc analyses were run to characterize the REBUS-PLS-detected groups according to manager demographic characteristics and years of experience as well as firm size.

RESULTS AND DISCUSSION

The REBUS-PLS algorithm is available in XLSTAT-PLS, version 2013.6.04. According to (W. W. Chin, 2010), all item loading values higher than 0.70 are considered to be adequate. Moreover, composite reliability (CR) values higher than 0.70 are considered to be 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 & Zhang, 2008).

Execution of the REBUS-PLS Algorithm and Measurement Validation

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

In addition, composite reliability was verified for all the constructs both in the global model and in the local models (see Table 4) (W. W. Chin, 2010). All items, with the exception of the one associated to BVTR1 in the local model estimated for G2, strongly loaded on the corresponding construct. Since standardized loading associated to 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 and they always exceeded 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 in Table 4, exceeded the inter-construct correlations in all the models (see Table 5 to Table 8) (Barclay, Higgins, & Thompson, 1995; W. W. Chin, 1998; C. Fornell & Larcker, 1981). However, the correlation between IQUL and BVAL exceeded the square root of the AVE associated to BVAL in the local models estimated for both groups 1 and 2 (see Table 6 and Table 7). Multicollinearity among the constructs was tested. Variance inflation factors (VIF) indexes are reported along with the structural model results in Table 9. All the VIF values are smaller than 10 indicating that no serious multicollinearity affected the structural models at either global or local levels (Hair, Tatham, Anderson, & Black, 2006; Neter, Wasserman, & Kutner, 1990; S. Petter, Straub, & Rai, 2007). The only VIF value exceeding the threshold of 5 (Kline, 1998) was the one measuring the multicollinearity between IQUL and BVAL in predicting USAT in G1 (Table 9). 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 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 10, 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 11. According to the results reported in Table 10 and Table 11, 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 associated 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 to FPER. The main construct means are reported in Table 12. The results of pairwise comparisons among the construct means are reported in Table 13. 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 that was more than 1 point (on a 7-point scale) smaller than the other two groups.

The Structural Model

The results of the structural model testing are presented in Figure 2, and Table 9 and Table 14. In Figure 2, we present the estimated structural path models at global model level as well

as at group level. The arrow thickness on the path depends on the significance associated 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 Table 14 and Table 9). In general, G1 shows higher R^2 values than the others, but it is also the group for which the correlations among the latent constructs are higher (see Table 5 to Table 8). Each of the inner relationships is discussed below.

Impact on Business Value

Table 9 shows that IQUL has a significant positive effect on BVAL for the global model and all three detected local models: G1, G2, and G3, thus **support H1 for global model, G1, G2 and G3**. In addition, the impact of IQUL on BVAL is significantly higher for respondents in G1 compared to both the global and the other local models, G2 and G3 (see Table 14).

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 the same significant positive effect on USAT (Table 9), thus **validating H2 and H3 at the global level** (Table 16). Similarly, for respondents in G2, IQUL and BVAL still show significant positive effects on USAT (Table 9), thus **validating H2 and H3 for G2** (Table 16). However, for respondents in G2, the main driver of USAT is BVAL, which contributes about 82% of explained variability, while IQUL only accounts for 8% of explained variability (Table 9). Differences occur when comparing models estimated for respondents in G1 and G3 (Table 14). For respondents in G3, BVAL is the only significant driver of USAT and it alone explains 55% of the variability of USAT ($R^2 = 0.55$) (Table 9), thus **validating only H3 for G3** (Table 16).

On the other hand, for respondents in G1, the only significant driver of USAT is IQUL: that alone accounts for 86% of the variability of USAT ($R^2 = 0.86$) (Table 9), thus **validating H2 for G3** (Table 16). 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 to this structural relationship is smaller than 10 (Table 9), indicating that no serious multicollinearity affects the structural model for G1 (S. Petter et al., 2007).

Impact on Firm Performance

In the proposed model, we assumed that FPER would be directly dependent on BVAL and USAT. As shown in Table 9, the two exogenous variables have significant positive effects on FPER for all groups, thus **validating H4 and H5 for the three groups, G1, G2 and G3, as well as for the global model** (Table 16). However, at global model level and for respondents in G1, BVAL is the most important driver of FPER explaining 85% or more of the explained variability (Table 9). This is not true for respondents in G2 and G3, for whom BVAL and USAT have the same impact on FPER. In particular, respondents in G3 seem to be more satisfaction-driven than those in G2 (Table 14).

The groups detected with the REBUS-PLS method can be characterized according to their demographic characteristics. For a given demographic variable, we computed the percentage of respondents showing a specific category (relative frequency per category [%] in Table 15). We tested the difference between the relative frequencies among the groups by applying Chi-square tests for proportion. Manager proportions among the groups were not significantly different with respect to the country of the respondents and the size of the firm where they were employed.

However, G3 is characterized by a more significantly (at a level of significance of 0.05) high percentage of female respondents than all other groups. Moreover, no respondent in this group had a primary qualification. There is a significantly high proportion of young respondents (younger than 33 years old) in G1 and, as a consequence, this group is characterized by managers with less years of experience compared to the other two groups.

there is a paucity of research in this domain leveraging such dynamics in enhancing firm performance. Drawing on IS and BDA literature, the study develops a model on information quality dynamics as a direct response to the research call of manager-side BDA strategies (Agarwal & Dhar, 2014; Goes, 2014; Sharma et al., 2014; B. H. Wixom et al., 2013).

By presenting the theory of information quality driven BDA strategy, this study gives an impetus to research on data quality in big data environment (D Barton & D Court, 2012; Andrew McAfee & Erik Brynjolfsson, 2012). Although data quality are widely known to be important in big data environment, our study extends prior research by showing ways to leverage information quality and business value to enhance firm performance. Further, the encapsulation of quality-value-satisfaction- performance might start a new debate and facilitate new research on the alignment between analytics and business value (Liebowitz, 2013). For example, future research could identify BDA strategies to improve decisions in product and service quality, satisfaction and customer loyalty (T. H. Davenport, 2006), pricing and customer choice preferences (Thomas H Davenport & Harris, 2007), market share analysis (Manyika et al., 2011) and new product adoption rate (Chandrasekaran, Levin, Patel, & Roberts, 2013).

The study also contributes by conceptualizing a manager-side BDA strategy that is focused on information quality. Although information quality, an important aspect in BDA, is evidenced to influence business value and manager satisfaction. Our theory and associated analyses are at the level of overall information quality, which did not take into account individual dimensions of information quality in linking with outcome constructs. Indeed, there might be different impact of four appraisal dimensions of information quality on two emotional responses, namely business value and satisfaction. Future studies might be conducted at a dimension level analysis to extend the literature on information quality in BDA (Stacie Petter et al., 2013; Setia et al., 2013). A dimensional analysis of information quality on business

value and user satisfaction will help analysts assess specific features of information and their role in better decision making in BDA. Future research may also evaluate the quality dynamics for aligning the information systems with BDA and the best practices of IT management (Andrew McAfee & Erik Brynjolfsson, 2012).

Overall, the findings of our study are likely to create new avenues of research to assess appraisal-emotional response-coping of a firm's big data decisions. The findings show that although information quality dimensions have strong direct impact on business value and customer satisfaction, they have strong indirect impact on firm performance. This finding evidences that the quality of information and corresponding business value (appraisal) results in an affective or emotional response (i.e., satisfaction), which again leads toward a coping behaviour (firm performance). This argument indicates that behavioural dynamics play an important role in firm's BDA decision. This conceptualization opens up a new stream of inquiry that reveals the behavioural side of big data strategy (Agarwal & Dhar, 2014; Agarwal & Weill, 2012). Future research might delve into examining customer's perceptions of BDA and firm's ability to meet such expectations on customer value, satisfaction and continuance intentions. Future studies might also explore analytics capability dimensions of a firm, which will definitely facilitate the development of literature in BDA strategy. 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 (Chang, Kauffman, & Kwon, 2014; Saeed, Malhotra, & Grover, 2005).

METHODOLOGICAL CONTRIBUTIONS

This study integrates constructs from Barbara H Wixom and Todd (2005), Gregor et al. (2006), Spreng, MacKenzie, and Olshavsky (1996), and Tippins and Sohi (2003) to study the potential of BDA in enabling 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 business analysts 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 (Jedidi et al., 1997). Consequently, the study uses the REBUS-PLS, which is a response-based method, to capture this unobserved heterogeneity (Esposito Vinzi et al., 2008). In addition, this study is a response to the call by Becker et al. (2013) for more studies that investigate unobserved heterogeneity. The authors found very few articles published in leading IS journals over the last 20 years that had used a structural model and that had “examined unobserved heterogeneity”. In fact, these studies assumed that empirical data are homogeneous and represent a single population, thus leading to possible bias during the assessment of structural model parameters. Furthermore, the application of the REBUS-PLS algorithm allows the identification of three groups of business analytics users (G1, G2, and G3), which are all characterized by different user’s behaviors (e.g., different in values for structural model parameters). These results may facilitate the design of analytics systems that fit each user’s behaviours across each identified group, thus facilitating the adoption and use of the analytics, as well as the extended use of the systems.

IMPLICATIONS FOR PRACTICE

With the advent of analytics driven economy, this study has many practical implications for enhancing organisational performance irrespective of size. Our study suggests that firms need to embrace information quality dynamics to leverage their analytics capability. Because of the importance of IQUL-BVAL-USAT-FPER focus of the BDA organization, such orientation may be a sustained source of long term competitive advantage. Since information quality leads to valuable insights, managers in big data environment need to emphasize on such

priority in order to improve decision making across the organization (Thomas H Davenport et al., 2012).

This study has huge practical implications for various industries using BDA, such as, retail, manufacturing, healthcare and public sector administration. There is a growing focus on information quality dynamics in BDA environment across these industries (Manyika et al., 2011). According to an estimate by BSA Software Alliance (Columbus, 2014) in the US, 10% or more of the growth were related to analytics driven information for 56% of firms in 2014. 81% decision makers see analytics being a major contributor to 10% or more of their companies' growth by 2019. Furthermore, the findings of the study also clearly indicate that analytics driven decision makers will better serve customer needs (79%), increase sales and revenue (76%), create new products and services (70%) and expand into new markets (72%) with the help of quality information and robust insights. Overall, 69% of the US decision makers and 65% of the European decision makers have emphasized analytics driven decision making on quality information (Columbus, 2014), as data have become a torrent flowing into every area of global economy (Cukier, 2010). A recent study shows that BDA can reduce the costs of administrative decision making in EU by \$446 billion and improve global R&D productivity by \$100 billion (Manyika et al., 2011). Companies including Tesco, Amazon, Wal-Mart, Harrah's, Progressive Insurance, Capital One and Smart (Philippines) have already evidenced their early successes by embracing analytics driven information as a competitive weapon. Therefore, the findings of the study recommend a focus on information quality dynamics in big data environment to enhance business value, satisfaction and firm performance. The findings of the study will also help identify distinctive groups of BDA users, which may contribute to facilitating the design of features and interfaces that match user group's desires, thus fostering user acceptance and use of analytics systems. For example, Harrah's Entertainment leverages analytics and quality information to select

customers with the greatest profit potential and customize price and promotions for the targeted segments. In addition to marketing decisions, they also use analytics for people decisions by allocating the right staff to the right touch point for ensuring more satisfaction to its employees as well as guests (Thomas H Davenport, Harris, & Shapiro, 2010). The findings of the study identify distinctive user groups, which may allow project stakeholders in charge of designing training programs and interventions to provide more targeted and personalized training to each group. In a similar spirit, Davenport et al. (2010,p.58) state that, “Future organizational performance is inextricably linked to the capabilities and motivations of a company’s people. Organizations that have used data to gain human-capital insights already have a hard-to replicate competitive advantage”.

LIMITATIONS

The study has several limitations. Firstly, the vast majority of items used for our constructs were measured using a 7-point Likert scale which was anchored ranging from “strongly disagree”(1) to “strongly agree”(7), and thus 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” (W. W. Chin, Johnson, & Schwarz, 2008). Therefore, future studies may consider using the 9-point scale of fast form items with the two-anchor points ranging from -4 to +4 as suggested by Chin et al. (2008). Secondly, 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 (Barbara H Wixom & Todd, 2005), or service quality with information quality (Xu et al., 2013). Thirdly, this study measures the direct impact of a set of determinants of BDA directly on firm performance. Future studies should look at the first-order impact of BDA, which is the impact at the process level (Barua,

Kriebel, & Mukhopadhyay, 1995; Mooney, Gurbaxani, & Kraemer, 1996). Specifically, to offer deeper view of the impacts of BDA, future research may focus on behavioural dynamics in a customer-side BDA strategy. Further, findings on the moderating role of business analytics capability are likely to open new avenues of research.

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 insights for robust decision making and solving business problems. This is a holistic process which deals 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 driven decisions and experienced enormous growth. This study presents a useful starting point for understanding the IQUL dynamics in a big data environment by modelling their impact on BVAL, USAT, and FPER. The study reflects that once BDA-driven IQUL is well understood and challenges are properly addressed, the BDA application will maximize business value, which indeed facilitates pervasive usage and speedy delivery of insights for decision making across organizations.

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Figures

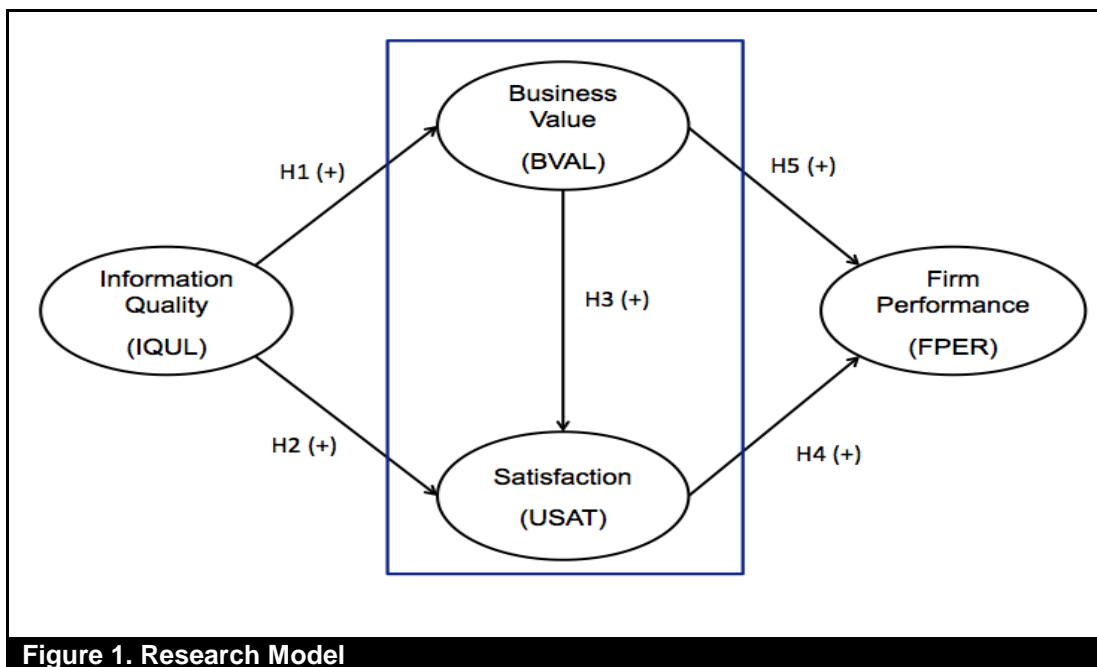
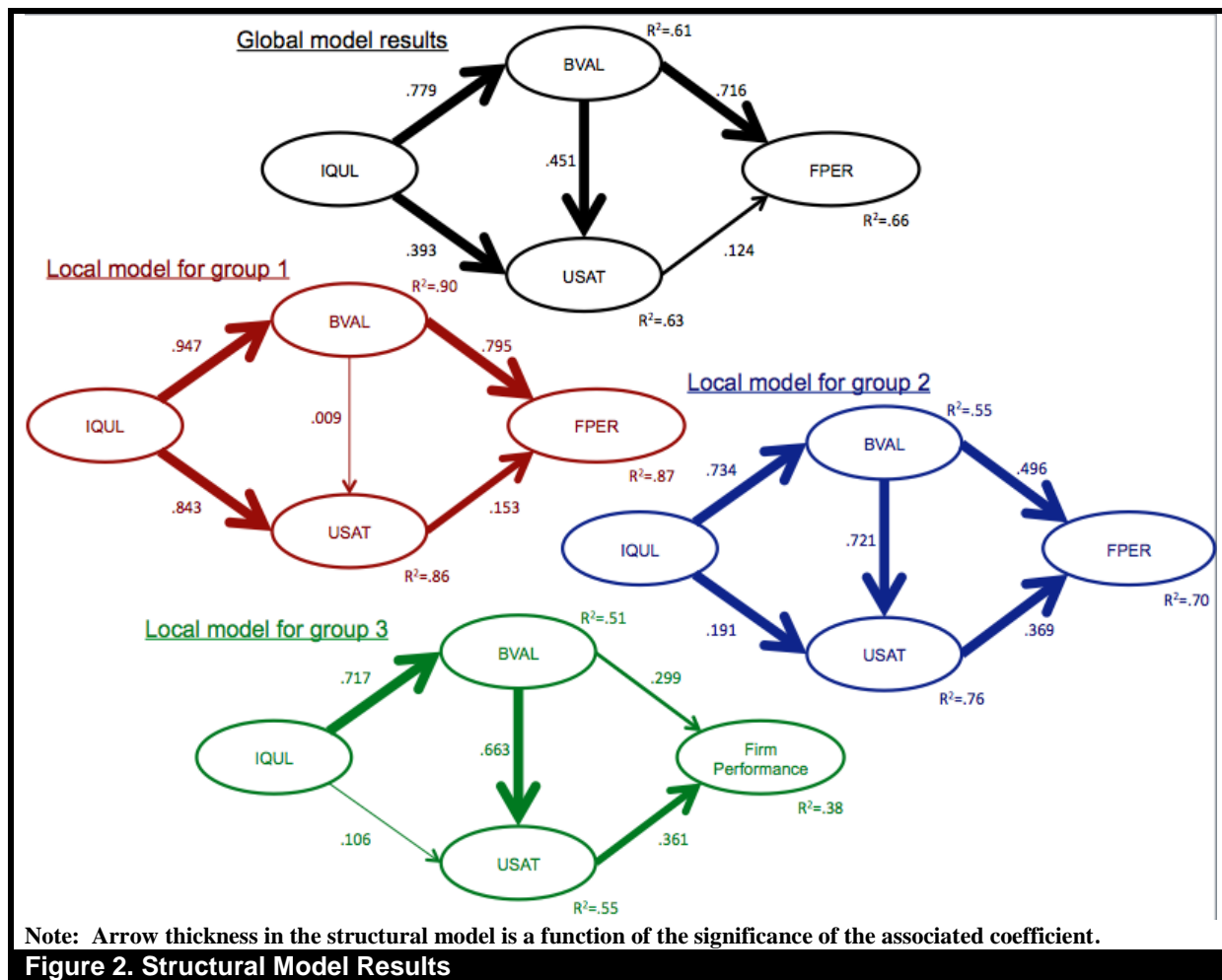


Figure 1. Research Model



Tables

Table 1. Constructs and Definitions	
Construct and Definition	Source
<i>Information quality</i> is defined as the <i>completeness, accuracy, format,</i> and <i>currency</i> 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.	(Barbara H Wixom & Todd, 2005)
<i>Business value</i> is defined as the <i>transactional, strategic,</i> and <i>transformational</i> 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)
<i>Satisfaction</i> refers to users’ feelings about (or affect from) BDA use.	(Sprenge et al., 1996)

<i>Firm performance</i> refers to the firm's ability to gain and retain customers; and to improve sales, profitability, and return on investment (ROI).	(S. Mithas, Ramasubbu, & Sambamurthy, 2011; Tippins & Sohi, 2003)

Table 2. Business Value of Big Data Analytics			
Study	Decision Functions	Business Value	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)

(T. H. Davenport et al., 2012)	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
Davenport et al. (2007)	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. (2012)	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% to 90% of possibly needed information about customers to generate analytics-driven customer insights.	Best Buy

Table 2: Business value of Big Data Analytics (continued)			
Study	Decision Functions	Business Value	Firm(s)
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
	Email marketing	Integrated customer databases with information on some 60 million households to improve response rate of email marketing.	Williams-Sonoma
	Customize service offerings, customer loyalty	Compiled holistic customer profiles in detail, and conduct	Harrah's, Progressive

		experiments and segment their customers systematically and effectively to personalize product offers and increase customer loyalty.	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 advertising 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 3. Measurement of Constructs

2nd-order constructs	1st-order constructs	Type	Item labels	Items
Information quality (Barbara H Wixom & Todd, 2005)	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)	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.
	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.	
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	Firm performance (Tippins & Sohi, 2003)	Reflective	FPBA1	Using analytics improved _____ during the last 2 years relative to competitors. _____ Customer retention
		Reflective	FPBA2	_____ Sales growth
		Reflective	FPBA3	_____ Profitability

Table 4. Measurement Model Results, Composite Reliability, and Average Variance Extracted

2nd-order LVs	1st-order LVs	Items	Standardized loadings				Composite reliability and AVE			
			Global	G1	G2	G3	Global	G1	G2	G3
IQUL	Completeness	INFQ1	0.932	0.975	0.901	0.927	CR: .939	CR: .960	CR: .916	CR: .935
		INFQ2	0.942	0.966	0.928	0.933	AVE: .838	AVE: .925	AVE: .784	AVE: .827
		INFQ3	0.871	0.945	0.824	0.866				
	Currency	INFQ4	0.915	0.970	0.889	0.903	CR: .934	CR: .973	CR: .886	CR: .930
		INFQ5	0.870	0.977	0.744	0.873	AVE: .825	AVE: .949	AVE: .723	AVE: .816
		INFQ6	0.940	0.976	0.908	0.932				
	Format	INFQ7	0.953	0.979	0.941	0.947	CR: .969	CR: .977	CR: .965	CR: .962
		INFQ8	0.966	0.979	0.957	0.966	AVE: .913	AVE: .956	AVE: .902	AVE: .894
		INFQ9	0.948	0.975	0.950	0.924				
	Accuracy	INFQ10	0.947	0.980	0.931	0.935	CR: .957	CR: .974	CR: .940	CR: .950
		INFQ11	0.937	0.978	0.904	0.932				

		INFQ12	0.931	0.966	0.917	0.919	AVE: .881	AVE: .950	AVE: .842	AVE: .862
BVAL	Transactional	BVTN1	0.833	0.928	0.712	0.773	CR: .941 AVE: .727	CR: .970 AVE: .870	CR: .902 AVE: .605	CR: .919 AVE: .656
		BVTN2	0.893	0.937	0.826	0.872				
		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: .950 AVE: .760	CR: .975 AVE: .888	CR: .918 AVE: .652	CR: .922 AVE: .665
		BVST2	0.891	0.944	0.821	0.860				
		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: .949 AVE: .788	CR: .979 AVE: .924	CR: .889 AVE: .620	CR: .930 AVE: .728
		BVTR2	0.884	0.953	0.789	0.826				
		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: .950 AVE: .825	CR: .971 AVE: .921	CR: .944 AVE: .807	CR: .913 AVE: .752
SABA2		0.913	0.966	0.908	0.863					
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: .945 AVE: .812	CR: .973 AVE: .924	CR: .914 AVE: .728	CR: .881 AVE: .640	
	FPBA2	0.899	0.953	0.872	0.780					
	FPBA3	0.910	0.963	0.853	0.824					
	FPBA4	0.901	0.972	0.859	0.809					

Note: CR = composite reliability; AVE = average variance extracted

Table 5. Correlation Matrix among Latent Constructs in the Global Model

	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 bold).

Table 6. Correlation Matrix among Latent Constructs in the Local Model for G1

	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 bold).

Table 9. Structural Model Results

Dependent constructs	Structural Paths	Standardized path coefficients				R ² value				Contribution to R ² (%) and R ² value			
		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			
USAT	IQUL --> USAT	0.393***	0.843***	0.191***	0.106 ^{N.S.}	0.63	0.86	0.76	0.55	46.19%	90.64%	18.19%	11.21%
	BVAL --> USAT	0.451***	0.009 ^{N.S.}	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%
	USAT --> FPER	0.124*	0.153**	0.369***	0.361**					12.49%	15.06%	42.12%	55.42%

Note: ***P-value < 0.001; **P-value < 0.01; *P-value < 0.05; ^{N.S.} not significant.

Table 7. Correlation Matrix among Latent Constructs in the Local Model for G2

	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 bold).

Table 8. Correlation Matrix among Latent Constructs in the Local Model for G3

	IQUL	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 bold).

Table 10. Item Means and Standard Deviations

2nd-order LVs	1st-order LVs	Items	Overall		G1		G2		G3	
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
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

	Strategic	BVTN6	4.94	1.25	4.93	1.21	5.40	1.09	4.44	1.26
		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
	Transformational	BVST6	5.08	1.18	4.94	1.10	5.70	0.94	4.51	1.18
		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
N/A	Satisfaction	BVTR5	4.91	1.20	4.93	1.25	5.28	1.01	4.48	1.20
		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
	Firm Performance	SABA4	4.93	1.02	5.12	1.13	4.90	0.98	4.76	0.90
		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

2nd-order LVs	1st-order LVs	Items	G1 vs G2	G1 vs G3	G2 vs G3
IQUL	Completeness	INFQ1	0.069 ^{N.S.}	0.562^{**}	0.493[*]
		INFQ2	0.146 ^{N.S.}	0.519^{**}	0.374 ^{N.S.}
		INFQ3	0.394[*]	0.905^{***}	0.512[*]
	Currency	INFQ4	0.219 ^{N.S.}	0.072 ^{N.S.}	0.147 ^{N.S.}
		INFQ5	0.094 ^{N.S.}	0.250 ^{N.S.}	0.155 ^{N.S.}
		INFQ6	0.166 ^{N.S.}	0.083 ^{N.S.}	0.249 ^{N.S.}
	Format	INFQ7	0.216 ^{N.S.}	0.114 ^{N.S.}	0.102 ^{N.S.}
		INFQ8	0.283 ^{N.S.}	0.186 ^{N.S.}	0.096 ^{N.S.}
		INFQ9	0.181 ^{N.S.}	0.041 ^{N.S.}	0.140 ^{N.S.}
	Accuracy	INFQ10	0.345 ^{N.S.}	0.239 ^{N.S.}	0.106 ^{N.S.}
		INFQ11	0.234 ^{N.S.}	0.114 ^{N.S.}	0.120 ^{N.S.}
		INFQ12	0.222 ^{N.S.}	0.050 ^{N.S.}	0.172 ^{N.S.}
BVAL	Transactional	BVTN1	0.275 ^{N.S.}	0.712^{***}	0.987^{***}
		BVTN2	0.295 ^{N.S.}	0.687^{***}	0.983^{***}
		BVTN3	0.062 ^{N.S.}	0.533^{**}	0.595^{***}
		BVTN4	0.106 ^{N.S.}	0.586^{**}	0.692^{***}
		BVTN5	0.497^{**}	0.481^{**}	0.978^{***}
		BVTN6	0.470[*]	0.491^{**}	0.961^{***}

	Strategic	BVST1	0.699^{***}	0.293 ^{N.S.}	0.992^{***}
		BVST2	0.702^{***}	0.148 ^{N.S.}	0.850^{***}
		BVST3	0.322 ^{N.S.}	0.585^{***}	0.907^{***}
		BVST4	0.505^{**}	0.324 ^{N.S.}	0.829^{***}
		BVST5	0.790^{***}	0.367 ^{N.S.}	1.157^{***}
		BVST6	0.765^{***}	0.428^{**}	1.193^{***}
	Transformational	BVTR1	0.080 ^{N.S.}	0.718^{***}	0.799^{***}
		BVTR2	0.332[*]	0.531^{***}	0.863^{***}
		BVTR3	0.554^{***}	0.335 ^{N.S.}	0.889^{***}
		BVTR4	0.485^{**}	0.324 ^{N.S.}	0.809^{***}
BVTR5		0.349 ^{N.S.}	0.449^{**}	0.799^{***}	
Satisfaction	SABA1	0.371 ^{N.S.}	0.329 ^{N.S.}	0.042 ^{N.S.}	
	SABA2	0.502^{**}	0.529^{**}	0.027 ^{N.S.}	
	SABA3	0.332 ^{N.S.}	0.455[*]	0.123 ^{N.S.}	
	SABA4	0.224 ^{N.S.}	0.362[*]	0.138 ^{N.S.}	
Firm Performance	FPBA1	0.321[*]	1.145^{***}	1.466^{***}	
	FPBA2	0.460^{**}	1.031^{***}	1.491^{***}	
	FPBA3	0.471^{**}	0.884^{***}	1.360^{***}	
	FPBA4	0.298 ^{N.S.}	0.936^{***}	1.234^{***}	

Note: Differences are expressed in absolute values. Significant differences are in bold. ^{***}P-value < 0.001; ^{**}P-value < 0.01; ^{*}P-value < 0.05; ^{N.S.} not significant. Bonferroni correction for multi-group comparison has been applied.

Table 12. Construct Means and Standard Deviations

2nd-order Constructs	Overall		G1		G2		G3	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
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

Table 13. Construct Means Comparison among REBUS Groups

Mean Comparison	IQUL	BVAL	USAT	FPER
G1 vs G2	0.104 ^{N.S.}	0.442^{***}	0.359[*]	0.386^{**}
G1 vs G3	0.133 ^{N.S.}	0.459^{***}	0.416[*]	0.998^{***}
G2 vs G3	0.216 ^{N.S.}	0.902^{***}	0.057 ^{N.S.}	1.384^{***}

Note: Differences are expressed in absolute values. Significant differences are in bold. ^{***}P-value < 0.001; ^{**}P-value < 0.01; ^{*}P-value < 0.05; ^{N.S.} not significant. Bonferroni correction for multi-group comparison has been applied.

Table 14. Structural Model Comparison among REBUS Groups

Path coefficient comparison	BVAL	USAT		FPER	
	IQUL --> BVAL	IQUL --> USAT	BVAL --> USAT	BVAL --> FPER	USAT --> FPER

G1 vs G2	0.383^{**}	0.669^{**}	1.007^{**}	0.179 ^{N.S.}	0.173 ^{N.S.}
G1 vs G3	0.272^{**}	0.779^{**}	0.562[*]	0.455^{**}	0.238 ^{N.S.}
G2 vs G3	0.111 ^{N.S.}	0.110 ^{N.S.}	0.445[*]	0.276^{**}	0.066 ^{N.S.}
<p>Note: Differences are expressed in absolute values. Significant differences are in bold. ^{***}P-value < 0.001; ^{**}P-value < 0.01; [*]P-value < 0.05; ^{N.S.} not significant.</p>					

Table 15. Demographics and Firm Characteristics Distributions

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 to 25	4.31	8.16	3.70	1.04
	26 to 33	17.22	23.47	12.04	16.67
	34 to 41	28.48	23.47	28.70	33.33
	42 to 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 years	32.45	35.71	27.78	34.38
	6-10 years	19.21	21.43	19.44	16.67
	11-15 years	20.86	17.35	24.07	20.83
	16-20 years	9.93	11.22	11.11	7.29
	Over 20 years	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

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

Table 16. Results of Hypotheses				
Hypotheses	Results			
	Global Model	G1	G2	G3
H1: Perceived IQUL has a significant positive impact on perceived BVAL in BDA.	Supported	Supported	Supported	Supported
H2: Perceived IQUL has a significant positive impact on perceived USAT in BDA.	Supported	Supported	Supported	<i>Not Supported</i>
H3: Perceived BVAL has a significant positive impact on perceived USAT in BDA.	Supported	<i>Not supported</i>	Supported	Supported
H4: Perceived USAT has a significant positive impact on perceived FPER in BDA.	Supported	Supported	Supported	Supported
H5: Perceived BVAL has a significant positive impact on perceived FPER in BDA.	Supported	Supported	Supported	Supported