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Understanding the Impact of Business Analytics on Innovation

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AN ANALYSIS OF THE IMPACT OF BUSINESS ANALYTICS ON INNOVATION

Complete Research

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Abstract

The advances in Big Data and Business Analytics (BA) have provided unprecedented opportunities for organizations to innovate. With new and unique insights gained from BA, companies are able to develop new or improve existing products/services. However, few studies have investigated the mechanism through which BA contributes to a firm's innovation success. This research aims to address this gap. From an information processing and use perspective, a research model is proposed and empirically validated with data collected from a survey with UK businesses. The evidence from the survey of 296 respondents supports the research model that provides a focused and validated view on BA's contribution to innovation. The key findings suggest that BA directly improves environmental scanning which in turn helps to enhance a company's innovation in terms of new product novelty and meaningfulness. However, the effect of BA's contribution would be increased through the mediation role of data-driven culture in the organization. Data-driven culture directly impacts on new product novelty, but indirectly on product meaningfulness through environmental scanning. The findings also confirm that environmental scanning directly contributes to new product novelty and meaningfulness which in turn enhance competitive advantage. The model testing results also reveal that innovation success can be influenced by many other factors which should be addressed alongside the BA applications.

Key words: Innovation, Big Data, Business Analytics, Data-Driven Culture.

1. Introduction

Organizations are facing increasing competition and turbulence in their marketplaces due to the speed of technological advancement and globalization. This has increased the pressure placed on companies to meet increased market demands for more novel and increasingly individualized solutions (Nilsson and Ritzen 2014). While innovation has become the key characteristic of the competitive landscape in most industries (Nambisan *et al.*, 2014) and successful innovation is critical for firm survival (Van Riel *et al.*, 2004), information technology (IT) has come to bear a critical role in all aspects of innovation (Nambisan et al., 2014). Over the last few years, the field of "Big Data" has emerged as the new frontier in the wide spectrum of IT-enabled innovations and opportunities allowed by the information revolution (Goes, 2014).

Advances in emerging digital technologies have enabled businesses to develop innovative ways to intelligently collect data from both internal and external sources (Davenport, 2013). However, this leads to the explosion of data and unprecedented challenges in making effective use of available data for innovation and competitive advantage. In order to turn big data into big business value, companies are increasing their investment in Business Analytics (BA) and eager to understand how BA can impact on their business performance including innovation.

The term BA has been widely used in various contexts, but there seems no commonly accepted definition on what BA is. Davenport and Harris (2007) defines BA as "*the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions*" (p. 7). A similar definition is also used by Kiron and Shockley (2011) and Kiron *et al.* (2012). Based on Davenport and Harris (2007) and Goes (2014), we define BA as the processes and techniques of data analysis for the generation of knowledge and intelligence to gain competitive advantage.

As the concept of BA has been in existence for many decades (Davenport 2013), there is a need to distinguish between the traditional and emerging BA because of the challenges and opportunities with Big Data. Based on the BA evolution, Davenport (2013) suggests that BA has evolved from Analytics 1.0 which was the era of "business intelligence", to Analytics 2.0 which is the era of big data, and moving towards Analytics 3.0, the era of data-enriched offerings, "*as the emphasis turns to build analytical power into customer products and services*" (p. 67). If we follow Davenport's evolution terms, this study focuses on the applications and impact of Analytics 2.0 and 3.0.

Although BA is increasingly being used in organizations, no empirical research has been conducted to understand how BA impacts on innovation. In particular, little is known about the mechanisms through which BA can contribute to innovation. Despite a strong claim about how BA can enhance innovation through products/service differentiation using Big Data (e.g. Stubbs, 2014), there is no conceptual understanding and empirical evidence to link BA and innovation. The absence of such an understanding inevitably limits the abilities of organizations to fully realise the benefits from their investments in BA. Not surprisingly, many businesses are still struggling to figure out how, where and when to use business analytics to achieve a worthwhile return (Barton and Court, 2012, Kiron *et al.*, 2012, Marchand and Peppard, 2013). Until the mechanisms underlying BA and their contributions to business performance are better understood, realising the desired outcomes, such as innovation, remains uncertain. Therefore, it is imperative to investigate and confirm if, how and to what extent BA contributes to innovation. This paper seeks to fill this research gap by proposing and validating a model to explain the relationships between BA, data-driven culture, environmental scanning, new product/service novelty and meaningfulness, and competitive advantage. From the information processing and use perspective, this study proposes a number of hypotheses which are integrated into a research model to explain how BA, working with data-driven culture and environmental scanning, contributes to new product innovation, and subsequently, competitive advantage. The research model is empirically tested using the Structural Equation Modelling (SEM) technique with data collected from 296 responses working in commercial organizations in the UK. The following sections discuss the theoretical framework, hypotheses, and model testing. The final section discusses the results and implications.

2. Theoretical Background

This research aims to examine BA's contributions to innovation from the information processing and use perspective. Therefore, we draw on the relevant theories and studies in these areas.

The information processing view (Galbraith, 1974, Tushman and Nadler, 1978) which is underpinned by contingency theory argues that the key task for organizations is to manage uncertainty such as task complexity and the rate of environmental change through deploying mechanisms of information processing. The information processing view emphasises the importance of matching information processing requirements with information processing capabilities: the greater the task uncertainty the greater the amount of information that has to be processed (Galbraith, 1974). Therefore organizations should be designed to facilitate information processing to enable decision makers to process a greater amount of information to improve competitive advantage.

In relation to information processing view, scholars argue that information provided by information systems is an important asset helping organizations gain competitive advantage (Porter and Millar, 1985) and develop innovation (e.g. Ottum and Moore 1997). This view is echoed by a recent report of DHL (2013), "*information has become the fourth production factor and essential to competitive*

differentiation." (p. 29). Many studies have emphasized the role of information, information use and management in organizations (Kettinger et al 2014). For example, from a marketing perspective, Glazer (1991) argues that organizations need to see beyond the technology and focus on how to manage their information to gain competitive advantage. Bendoly et al. (2009) empirically explore how firms' use of different types of enterprise information influences their strategic performance in terms of operational excellence, customer intimacy, and product leadership. Examining high-tech service innovation success from a decision making perspective, van Riel et al (2004) point out that information plays an important role in the reduction of managerial uncertainty in high-tech service innovation success. They argue that information processing perspective proves to be a productive framework. They find that acquisition, diffusion, and use of information all contribute positively to the likelihood of service innovation success. Miller and Friesen (1982) in their study on innovation in conservative and entrepreneurial firms argue that firm's information processing capability affect innovation.

In the context of innovation, the information processing and use view helps us to focus our attention on the key information factors, such as: BA applications that demonstrate an organization's information processing capabilities, data driven culture and environmental scanning which are related to the information use in the organization. The essence of BA is to turn the vast amount of raw data into meaningful information, therefore, studying the relationship between BA and innovation from the information processing and use perceptive deems to be a plausible direction, but it appears that no such attempt has been reported in the literature.

3. Hypothesis Development

3.1 Innovation performance

Innovation success is a multi-dimensional measure and no single innovation measurement is able to capture the complex nature of the concept. A number of studies attempt to measure the overall innovation performance through perceived performance against competitions; others used objective measures such as the number of patterns developed, etc. In the context of this research, the centre theme of our interest is how companies can gain enhanced insights and intelligence from data using BA and be able to use them to develop new products/services or improving the existing ones. Cooper (1979) states that a product's success originated in two processes: information acquisition and proficiency of the new products development process. Information acquisition is captured in environmental scanning in their study and proficiency of the new products development process is captured in innovativeness by Droge (2008).

Kim et al (2013) review the relevant literature and adopt Amabile's (1983) two dimensional perspective on product creativity that is composed of novelty and meaningfulness in their study on impact of knowledge types and strategic orientation on new product creativity and advantage. They define the new product novelty as the degree of the originality and unique differences of the new product, and meaningfulness as the degree to which a new product provides appropriate and useful aspects to target customers (Kim *et al.*, 2013).

Stock and Zacharias (2013) conduct an extensive literature review regarding the dimensions of new product innovation. They find both product innovativeness and meaningfulness have been widely used. We follow the example of van Riel (2004) and Stock and Zacharias (2013) in their innovation study and adopt new product/service novelty and meaningfulness in the present study. Detailed measurement items for novelty and meaningfulness are explained in the following section. The term "new products" in the paper covers both the new products and services.

3.2 BA and Innovation

In a recent report "Innovating with Analytics" published in MIT Sloan Management Review, Kiron et al (2014) claim that "data-savvy organizations are using analytics to innovate and increasingly to gain competitive advantage". In the era of digitalisation and Big Data, BA appears to have been hailed as

an effective solution for businesses to gain greater insights and intelligence from a variety of data types to uncover hidden patterns, unknown correlations and other useful information. Such information can provide competitive advantages over rival organizations and result in business benefits, such as new products and service innovation.

BA is based on statistics, prediction, data mining, and modeling techniques, and focuses on developing new insights and understanding of business performance based on data. Software developers and IT companies are promoting BA applications and claiming that Big Data and Analytics can deliver numerous business benefits, such as: making information transparent, more precisely tailored products or services, developing the next generation of products and services, etc. (McGuire *et al.*, 2012). For example, Stubbs (2014) claims that Big Data enables big innovation by enabling competitive differentiation through BA. Innovation is continually becoming an integral part to organizational success.

In most organizations, information technology has been the catalyst in the innovation process, and a critical tool for the 21st century. BA can turn vast amount of raw data into valuable information, and companies should turn extensive information into business (DHL, 2013). One way to achieve this is products/services innovation with new insights and knowledge. Drawing on prior research on innovation success from information processing and use perspective, we postulate that BA will enhance the company's innovation via a number of organizational factors as discussed in the following sections.

3.3 BA, Data-Driven Culture and New product Novelty and Meaningfulness

Dahlander and Gann (2010) reiterate that innovation is not an isolated activity; it involves engagement and interaction with others both internal and external to the firm to acquire the necessary ideas and resources for the development of innovation.

Prior studies have emphasised that in order to leverage BA to gain competitive advantage, a company needs to develop a data-driven culture where managerial decisions rely more on data-based insights (Davenport *et al.*, 2001, Kiron *et al.*, 2012, Kiron and Shockley, 2011, Lavalle *et al.*, 2011). According to Kiron *et al.* (2012), a data-driven culture refers to "a pattern of behaviours and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization" (p. 12). This means essentially that explicit organizational strategies, policies and rules are to be developed to guide BA activities, and well-defined organizational structure and business processes are in place to enable BA activities to be well coordinated (Kiron *et al.*, 2012, Kiron and Shockley, 2011, Lavalle *et al.*, 2011).

Therefore, we propose:

> *H1 – Business Analytics has a positive effect on Data-Driven Culture.*

Organizational culture is the pattern of shared values, norms, and practices that distinguish one organization from another (Higgins and McAllaster, 2002). These values and norms define "what is important around here" and "how we do things around here" (Higgins and McAllaster, 2002, p. 74). The relationship of organization culture and innovation has been subject to extensive research over the last decades (Büschgens *et al.*, 2013) and its role in innovation has been well investigated and discussed by researchers (e.g. Denham and Kaberon, 2012, Kenny and Reedy, 2006, Wyld and Maurin, 2009). Lau and Ngo (2004) argue that a certain type of culture is needed to effect changes in organizations so that innovative and entrepreneurial behaviours could be encouraged.

In the context of Big Data and BA, we focus on one particular aspect of organizational culture from the information processing and use perspective, which is data driven culture as discussed above. Therefore, it is anticipated that

> *H2a –Data-Driven Culture has a positive effect on New Products Novelty.*

> *H2b – Data-Driven Culture has a positive effect on New Products Meaningfulness.*

3.4 BA, Environmental Scanning and New Products Novelty and Meaningfulness

Environmental scanning is a basic process of any organization to acquire data from the external environment to be used in problem definition and decision making (Thayer, 1968). The primary purpose of environmental scanning is to provide a comprehensive view or understanding of the current and future condition of the different environmental constituents and use this view as a foundation for guiding product/service development (Maier *et al.*, 1997). Environmental scanning refers to a firms' activities to gather information about its environment (Miller and Friesen, 1982). Therefore, information processing and use help to generate insights into a firm's changing environment, especially the needs for innovation, perhaps due to changing customers' desires, buying patterns or new development of competitors. Therefore, we propose:

> *H3 - BA has a positive and direct effect on enviornmental scanning.*

With regards to how BA is to be aligned with a data-driven culture to impact on environmental scanning, we use a mediation approach and develop our hypotheses based on the proposition that information technology can be an important determinant of organizational strategy, culture, processes, and/or structure (Hsiao and Ormerod, 1998, Jelinek, 1977, Lee and Grover, 1999, Perrow, 1967, Woodward, 1958 , Woodward, 1965, Yetton *et al.*, 1994). By investigating whether a data-driven culture has a mediating role in affecting the relationship between BA and environmental scanning, we expect to develop a deeper understanding of the mechanism through which BA might impact on innovation. Thus, we have developed the following hypothesis:

> *H4 - BA has a positive and indirect effect on enviornmental scanning through the mediation of data-driven culture.*

Keller and Holland (1975) and Tushman (1977) argue that a primary limitation on a firm's innovativeness is its ability to recognize the needs and demands of its external environment through environmental scanning. For example, Baker et al (1967) found that perceived market needs accounted for 75 per cent of the ideas for innovation. Miller and Friesen (1982) considered environmental scanning as one of the important variables in their innovation study in conservative and entrepreneurial firms. Previous innovation studies (e.g. Miller and Friesen, 1982) has confirmed the contributions of environmental scanning to new product innovation and competitive advantages, therefore, we propose the following relationships:

> *H5a - enviornmental scanning has a positive effect on New Products Novelty.*

> *H5b – enviornmental scanning has a positive effect on New Products Meaningfulness.*

> *H6a – New Product Novelty is positively related to Competitive Advantage.*

> *H6b - New Product Meaningfulness is positively related to Competitive Advantage.*

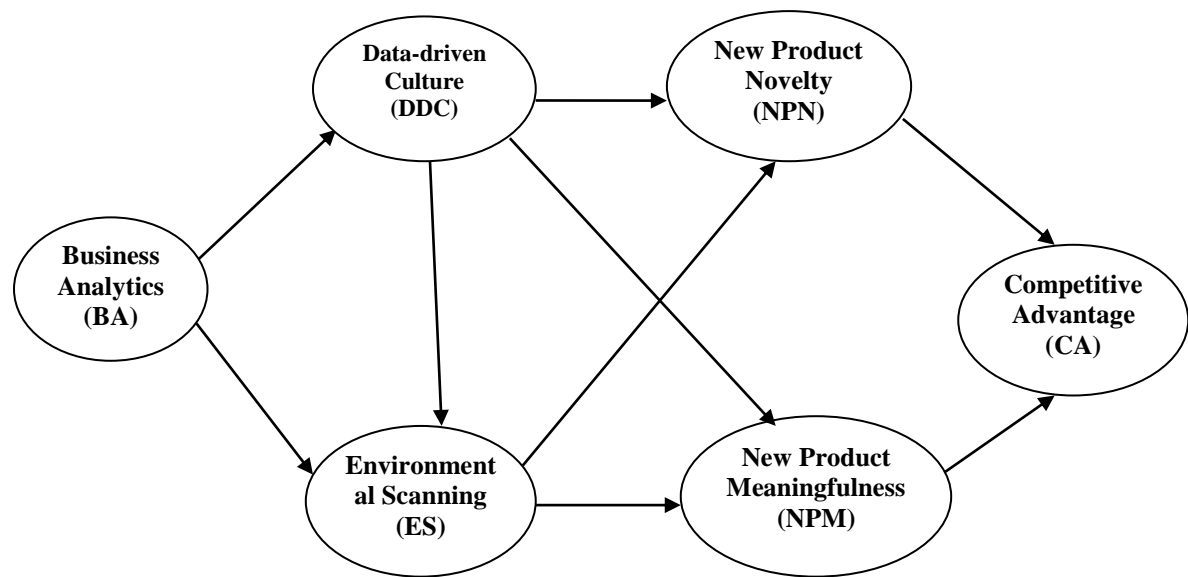As a result, the research model is shown in Figure 1.

Figure 1.   Research Model

4. Research Model Constructs and Measures

In order to test the theoretical model, a number of constructs and their associated measures have been identified. As this emerging BA is a new research area and there are few empirically validated measurement items, we have developed new constructs and measures for BA, drawing on BA literature (Davenport *et al.*, 2001, Delen and Demirkan, 2013, Kiron *et al.*, 2012, Kiron and Shockley, 2011, Lavalle *et al.*, 2011).

The concept of analytics, rooted in the on-going advances of systems to support decision-making, has been used for many years (Holsapple *et al.*, 2014); however, our focus is the recent applications of BA intertwined with big data, i.e. the so called Analytics 2.0/3.0. BA or analytics refers "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and action" (Davenport and Harris, 2007, p. 7), or "the generation of knowledge and intelligence to support decision making and strategic objectives" (Goes, 2014, p. vi). In the industry, BA has been used as an umbrella term referring to various business applications of analytical techniques and methods (Chae *et al.*, 2014). As we define BA as the processes and techniques of data analysis for the generation of knowledge and intelligence, we classify BA into descriptive analytics, predictive analytics and prescriptive analytics.

Descriptive analytics uses for example business intelligence and data mining to provide the context and trending information on past or current events, answering what has happened and what is happening. Predictive analytics uses statistical models and forecasts to provide an accurate projection of the future happenings and the reasoning as to why, answering what could happen; while prescriptive analytics uses for example optimisation and simulation to recommend one or more courses of action and shows the likely outcome of each decision, providing answers to what should we do.

From information processing and use perspective, the information processing capabilities can be demonstrated by BA applications which show a firm's ability to process various types of data to uncover hidden patterns and trends for descriptive, prescriptive and predictive purposes. Drawing on MacKenzie *et al.* (2011), our conceptual definition of BA means that the construct entity is the organization represented by its decision-makers; the general property is techniques and processes of data analysis; the conceptual theme is characterised by systematic data analysis for identifying

valuable business insights; its dimensions include descriptive analytics, predictive analytics, and prescriptive analytics; and it is expected to be generally applicable across different organizations in different industries.

Data-driven culture is another new construct to be defined. Davenport *et al.* (2001) used data-oriented or fact-based culture to refer to "data and information were part of the intrinsic value system" that "values data-based decision making" (p. 127), while Davenport (2006) used the right culture to mean "a companywide respect for measuring, testing and evaluating quantitative evidence" (p. 104). Kiron and Shockley (2011), and Kiron *et al.* (2012), defined data-oriented culture as "a pattern of behaviours and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization" (p. 11), which is also the definition we adopted in this paper. This or similar concept of a data-driven culture have also been accepted by a number of other papers (e.g., Germann *et al.*, 2013, Gillon *et al.*, 2014, Holsapple *et al.*, 2014, Nichols, 2013, Ross *et al.*, 2013, Watson, 2014).

Other constructs such as new product novelty and meaningfulness, and environmental scanning together with their measurements are adapted from innovation literature to the current research context, which had already been empirically validated by prior studies.

We measure competitive advantages in terms of the manager's perception of whether his/her organization has been more profitable, increasing its sales and its market share faster, and had a better return on investment than its key competitors (Im and Workman Jr, 2004, Kiron *et al.*, 2012, Kiron and Shockley, 2011, Lavalle *et al.*, 2011). These perceived measurements have been commonly used by prior studies (e.g., Armstrong and Sambamurthy, 1999, Chan *et al.*, 2006, Kearns and Sabherwal, 2007, Sabherwal and Chan, 2001). The constructs and their indicators are summarised in Table 1.

Constructs	Indicators	References
Business Analytics (BA) (Formative)	The extent to which your company uses the following types of Business Analytics • BADESC: Descriptive Analytics provides the context of and trending information on past or current events • BAPRED: Predictive analytics provides an accurate projection of the future happenings and the reasoning as to why • BAPRES: Prescriptive analytics recommends one or more courses of action and show the likely outcome of each decision	(Delen and Demirkan, 2013, Kiron *et al.*, 2012, Kiron and Shockley, 2011)
Data Driven Culture (DDC) (Formative)	The extent to which you agree or disagree with the following statements about you company's culture • DDCBELI: We believe that having, understanding and using data and information plays a critical role • DDCOPEN: We are open to new ideas and approaches that challenge current practices on the basis of new information • DDCDEP: We depend on data-based insights to support decision making • DDCUSE: We use data-based insights for the creation of new services or products • DDCNEED: Individuals have data need for decisions	(Davenport *et al.*, 2001, Kiron *et al.*, 2012, Kiron and Shockley, 2011, Lavalle *et al.*, 2011)
Environmental Scanning (ES) (Formative)	The extent to which the following activities had been undertaken to gather information about its environment in the past five years • ESROU: Routine gathering of opinions from clients • ESSPE: Special market research studies • ESCOM: Explicit tracking of the policies and tactics of competitors • ESFOR: Forecasting sales, customer preferences, technology, etc	Miller & Friesen, 1982
New Product/Service Novelty (NPN) (Formative)	Please consider the following statements with regard to your company's product/service innovation in the past five years on a 7-point scale: NPNRD: 1-There had been a strong emphasis on the marketing of true and tried products/services ---- 7- There had been a strong	(Droge *et al.*, 2008, Miller and Friesen, 1982)

	emphasis on R&D, technological leadership, and innovation NPNDRA: 1 - Changes in products/services had been mostly of a minor nature ---- 7-Changes in products/services had been mostly dramatic NPNMAN: 1 - We had marketed no new lines of products/services ---- 7- We had marketed many new lines of products/services	
New Product/Service Meaningfulness (NPM) (Reflective)	Compared with those of our key competitors in the past five years, the new products or services we offered were • NPMREL: relevant to customers' needs and expectations • NPMSUI: considered suitable for customers' desires • NPMAPP: appropriate for customers' needs and expectations • NPMUSE: useful for customers	(Im and Workman Jr, 2004, Kim *et al.*, 2013)
Competitive Advantage (CA) (Reflective)	The extent to which you agree or disagree with the following statements about your company's performance, on average, in the past five years • CAPRO: We are more profitable than our key competitors • CASAL: Our sales increased faster than our key competitors • CAMAR: Our market share increased faster than our key competitors • CAROI: We had better return on investment than our key competitors	(Im and Workman Jr, 2004)

Table 1.   Constructs and Indicators of the Study.

5. Empirical Analysis

The hypotheses were tested empirically using partial least squares structural equation modeling (PLS-SEM) based on survey data. PLS-SEM is recommended to be well-suited for research situations where theory is less developed (Chung *et al.*, 2003, Gefen *et al.*, 2011, Hair *et al.*, 2013b, Wetzels *et al.*, 2009). In the following section, we outline the instrument development, validation, and dissemination processes.

5.1 Data Collection

To test the hypotheses empirically, we collected data from UK enterprises. We generated a questionnaire survey using a seven-point Likert scale (ranging from 1 - strongly disagree to 7 - strongly agree) to capture the responses to the measurements of all constructs. The survey instruments were developed based on the literature review and definitions discussed above and then were scrutinised by subject experts. After a few revisions, the survey was piloted to ensure that the respondents understood the questions and there were no problems with the wording or measurements. The survey questionnaire was then delivered to managers electronically through Qualtrics, which is a powerful and well-developed online survey tool. The target population was the senior managers in the firm and their email addresses were identified from FAME database. Three rounds, one week apart, of emails including a cover letter with the questionnaire survey were sent. Each respondent was offered a summary of the results and the opportunity to enter into a draw to win one of the five Amazon gift certificates (£100 each). While 131,688 emails were sent with the e-mail subject highlighted as questionnaire survey, the majority of them were never opened. Of all sent emails, 771 surveys were opened; of these surveys started, we received 304 responses and 296 were usable responses, which represent a 38.4% response rate.

5.2 Respondents profile

Table 2 summarises the respondents' characteristics in terms of their organizational positions and years of experience in their current firms and industry.
We used a key informant approach (Bagozzi *et al.*, 1991) to collect data. The reported positions of the respondents suggested that 20% of the respondents were in a senior managerial position and the rest of them were in a middle managerial position. Based on their position within the firm, the respondents

were considered to be able to address the survey questions. They were also reminded to pass the survey to another person if they believe that he/she was not in the best position to answer the survey questions.

Respondent profiles (n=296)						
Industry	%	Positions	%	Years of experience	in the firm %	in the industry %
Manufacturing	28	CEO/MD/Partner	20	≤ 5	13	2
Prof Services	15	Fin/Acc director	12	5 < but ≤ 10	31	10
Retail/Wholesale	9	Operations director	16	10 < but ≤ 15	18	9
Technology	8	Mktg/Sales director	8	15 < but ≤ 20	13	15
Fin Services	6	CIO/IT Manager	7	20 < but ≤ 25	11	13
Other	34	Other directors	37	>25	14	51

Table 2.   Respondent Profiles.

Of all respondents, 46% had been with their firms for more than 10 years, whilst 88% had been in the industry for more than 10 years. The respondents were from a number of different industries; though 28% were from manufacturing sector, 15% from professional services, 9% from retail/wholesale, 8% from technology, and 6% from financial services. Overall, the sample of respondents seemed to be diverse, representing various industries, managerial positions and experiences.

5.3 Common Method and Non-respondent Bias

Common method bias was assessed by conducting an exploratory factor analysis (EFA). Harman's single-factor test was conducted by entering all independent and dependent variables (Podsakoff *et al.*, 2003). As the first factor accounted for 35.90% of the total variance, there is no evidence of a substantial respondent bias in this study.

Non-response bias was then assessed by comparing early and late respondents on all measures through a t-test. The t-test results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias (Armstrong and Overton, 1977).

5.4 Sample Size and Data Screening

In the structural model, the maximum number of arrows pointing at a construct is five. In order to detect a minimum $R2$ value of 0.10 in any of the constructs at a significant level of 1%, the minimum sample size required is 205 (Hair *et al.*, 2013a). Since we have 296 usable responses, the minimum sample size requirement is thus met.

Data screening was performed using SPSS19. Missing data for an observation exceeding 10% had been removed. The remaining number of missing values in the data set per indicator was relatively small, less than 1.8%; thus the remaining missing values were replaced by using the mean value replacement.

5.4.1 Evaluation of the Reflective Measurement Model

Since the model contains both reflective and formative constructs due to the nature of the constructs, a separate set of analysis was conducted following the recommendations made by Hair *et al.* (2013a). The reflective measurement model was evaluated by considering the internal consistency (composite reliability), indictor reliability, convergent validity and discriminant validity.

Composite reliability (CR) scores summarised in Table 3 indicated that results based on these constructs should be consistent, since all constructs met the recommended threshold value for acceptable reliability, that is, both CR and Cronbach's α should be large than 0.70.

Convergent Validity and Internal Consistency Reliability						
Construct	Indicator	Loading	Indicator Reliability	Composite Reliability	Cronbach's Alpha	AVE
NPM	NPMAPP	0.93	0.86	0.95	0.94	0.84
	NPMREL	0.92	0.85			
	NPMSUI	0.91	0.83			
	NPMUSE	0.91	0.83			
CA	CAMAR	0.92	0.85	0.93	0.89	0.76
	CAPRO	0.79	0.62			
	CAROI	0.85	0.72			
	CASAL	0.92	0.85			

Table 3.   Convergent Validity and Internal Consistency Reliability.

Discriminant validity was assessed via on two tests. The first test was to analyse Fornell-Larcker criterion (Hair *et al.*, 2013b) to evaluate if the square root of the AVE value (diagonal elements) for each construct was greater than the correlation of the construct with any other construct (off-diagonal elements), which was true. The second test was to observe if each reflective indicator loaded highest on the construct it was associated with, which was also true, thus demonstrating discriminant validity was satisfactory.

5.4.2 Assessment of Formative Measurement Model

The formative measurement model was evaluated in terms of assessing multicollinearity, the indicator weights, significance of the weights, and the indictor loadings (Hair *et al.*, 2014).

To assess the level of multicollinearity, the values of variance inflation factor (VIF) of all formative constructs were evaluated. The threshold value suggested for VIF is 3.3 (Petter *et al.*, 2007) or 5 (Hair *et al.*, 2014). While all VIF values associated with BA and DDC indicators are below 3.3, thus there are no major collinearity issues.

Based on the Default Report of the bootstrapping process (5,000 samples) of SmartPLS 2.0 M3, all formative indictors' outer loadings, outer weights and the associated significance testing p-values were assessed.

All but four indicators' outer weights are significant, indicating each formative indicator captures a portion of the associated construct's scope. The outer weights of BAPRED, DDCOPEN and ESCOM were not significant; but their outer loadings were above the suggested threshold of 0.5 (Hair *et al.*, 2014) and thus they were retained. DDCNEED's outer weight was not significant and its outer loading was below 0.5; however, this indicator was also kept as it is an indispensable aspect of newly developed DDC while its outer loading was significant and very close to the threshold of 0.5. These outer weights indicated that the associated formative indictors are meaningful and satisfactorily contribute to forming their associated constructs. Therefore, based on the above evaluations, the formative measurement model is valid.

5.5 Evaluation of the Structural Model and Hypothesis Testing

Smart PLS 2.0 M3 was used for testing the hypotheses and assessing the predictive power of the research model. A bootstrapping procedure (5,000 samples) was used to assess the significance of the hypothesised paths and the amount of variance in the dependent variables attributed to the explanatory variables (Hair *et al.*, 2013a). The results of the analysis are presented in Figure 2.
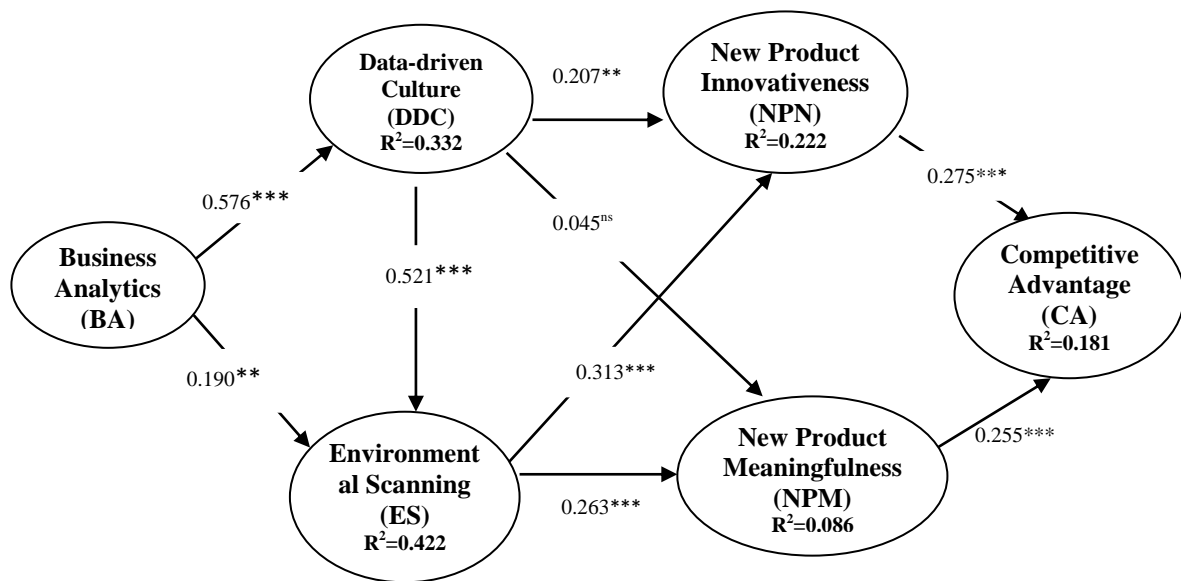
Figure 2.   Hypothesis test results

The predictive power of the model can be assessed by observing the amount of variance attributed to the latent variables (i.e., R2) and the value of the predictive relevance Q2.

All Q2 in Table 4 are above zero, thus providing support for the model's predictive relevance regarding the latent variables. The model's predictive accuracy is reflected by the variables' R2 values, which are also seen to be satisfactory. Based on the paper published in MIS Quarterly (Wetzels *et al.*, 2009), the effect sizes suggested for R2 is small (0.1-0.24), medium (0.25-0.36), and large (>0.36). In line with this suggested threshold, the effect sizes of ES can be classified as large; the effect sizes of DDC is medium; the effect sizes of CA, NPN and NPM are small.

Results of R^2 and Q^2 Values

	CA	DDC	ES	NPN	NPM
R^2 Value	0.18	0.33	0.42	0.22	0.09
Q^2 Value	0.14	0.19	0.25	0.13	0.07

Table 4.   Results of R^2 and Q^2 Values

5.6 Mediation Analysis

To evaluate Hypothesis 4, the mediating role of DDC (data-driven culture) on the relationship between BA and ES was analysed, following the analysis processes recommended by Baron and Kenny (1986); however, our analysis is based on a bootstrapping procedure (5,000 samples) that makes no assumptions about the shape of the variable's distribution (Hair *et al.*, 2013a, Preacher and Hayes, 2008). The results are summarised in Table 5. To begin the analysis, the direct relationship between BA and ES was estimated, which was significant. Then the mediator, DDC, was included to analyse whether the indirect effect of BA via DDC on ES is significant. The evaluation indicated the significance of the relationship between BA and DDC (path coefficient 0.576***), as well as between DDC and ES (path coefficient 0.521***). Thus, the indirect effect of BA via DDC on ES was 0.300 (0.576×0.521), and its significance was confirmed by calculating the p-value of the indirect effect. The relative size of the mediating effect was decided by calculating the variance accounted for (VAF)

based onShrout and Bolger (2002). The VAF value suggested that DDC partially but strongly mediated the effect of BA on ES.

The Mediation of DDC on the Relationship between BA and ES

Hypothesis	Direct effect without mediation	Direct effect with mediation	Indirect effect	VAF	Mediation type observed
Hypothesis 4	0.496***	0.19**	0.300***	0.611	Partial

***p<0.001, **p<0.01, *p<0.05   VAF>0.80 full mediation, 0.20 ≤ VAF ≤ 0.80 partial mediation, VAF < 0.20 no mediation

Table 5.   The Mediation of DDV on the relationship between BA and ES.

6. Discussion and Conclusion

Our research attempts to understand the mechanisms through which BA contributes to innovation from an information processing and use perspective. We proposed and tested a research model to evaluate the BA impact. The empirical evidence has provided strong support to the proposed model. As shown in Figure 2, most of the research hypotheses are supported, except for the effect of data-driven culture on new product meaningfulness. The key findings suggest that BA directly improves environmental scanning which in turn helps to enhance the company's innovation in terms of new product novelty and meaningfulness. However, the effect of BA's contribution would be greatly increased through the mediation role of data driven culture in the organization. BA significantly influence the data driven culture (path coefficient =0.576***), through which to impact on new product novelty and meaningfulness. It is surprising that DDC corresponds to new product "novelty" but does NOT correspond to meaningfulness. In other words, the data-driven culture has increased the rapidity of new product creation but has not enabled companies to provide products that better match what their customers need although, statistically, DDC indirectly impacts on product meaningfulness through environmental scanning. It is also noted that BA leads to new product meaningfulness (NPM) through the avenue of improved environmental scanning (ES) but not through the mediation of the data-driven culture (DDC). The findings confirm that environmental scanning directly contribute to new product novelty and meaningfulness which in turn enhance competitive advantage. The model testing results also reveal that innovation success can be influenced by many other factors which should be addressed alongside the BA applications.

6.1 Research implications

Many factors contribute to a firm's innovation success. Knowledge and information have long been regarded as the key ingredient and catalyst for successful innovation. With the widening availability of data and increasing use of analytics, companies are now expected to harness the data with analytics to gain new insights and knowledge to improve innovation. Therefore, there is an emerging need to establish if, how and to what extent BA contributes to innovation and competitive advantage.

Our study makes a number of contributions to research. Firstly, although a number of articles and online report stress that BA helps companies to innovate, there is no theoretical understanding and empirical evidence to substantiate the claims. Our study has attempted to fill a research gap by linking Business Analytics to innovation. This has been achieved by establishing a path model linking BA (information processing) directly with data driven culture and environmental scanning (information use) and indirectly with new product innovation and competitive advantage. This parsimonious model examines only how BA contributes to innovation from an information processing and use perspective, thus providing researchers and practitioners with a specific and focused understanding of BA's impact.

Secondly, our study demonstrates the mediating role of data driven culture in facilitating BA impact on innovation and calls for more research on how to create and nurture a data driven culture in organizations.

Thirdly, although our model attempts to capture BA impact on new product innovation in terms of novelty and meaningfulness, it also reveals that there may be many other factors influencing a firm's innovation success. This is mainly based on the low predictive power of the proposed model, especially in relation to new product meaningfulness. This suggests that the application of BA alone might not significantly transform a firm's innovation performance. Other factors must also be taken into account, so an integrated and coherent business strategy and approach for innovation success should always be considered.

Managerial implications

Our findings have a number of important managerial implications. The empirical evidence led to the conclusion that BA can improve a firm's innovation success in terms of new product novelty and meaningfulness, thus leading to better competitive advantage. BA's impact can be achieved through a firm's better information processing capabilities provided by BA and effective information use for business intelligence through environmental scanning. Organizations should take a proactive approach in developing and deploying company-wide BA applications.

Most importantly, our findings clearly demonstrate the important role of culture, more specifically data driven culture in this context, in facilitating BA impact. With the emergence of Big Data and the availability of BA tools and techniques, organizations should create and nurture a data driven culture in order to maximise the BA's business value. However, installing BA tools alone in the company would not automatically generate new insights and knowledge and improve innovation. For example, companies should create and nurture a data driven culture that encourages the company to be open to new ideas and approaches that challenge their current practices on the basis of new information, to use data-based insights for the creation of new products/services, to have data needs for decisions, to use evidence to support decision making, and to believe the role and value of data and information in the organization. Generating better business intelligence through environmental scanning facilitated with strong data driven culture will directly contribute to new product novelty and meaningfulness.

Limitations and Future research

The present study has a number of limitations. For example, this model only focuses on the BA impact no innovation success from an information processing and use perspective, thus it doesn't (and was not intended to in this case) capture all the key factors affecting innovation success. Therefore, caution must be taken when applying the model to predict a company's innovation success because many other factors such as business strategy, management practices, human resource management, leadership, inter-firm networks, etc. may also influence innovation success. Also, the mediating role of data driven culture is based on our theoretical argument that BA's impact on environmental scanning may be contingent on organizational culture. The possibility of a positive feedback loop from DDC to BA can be considered in the future analysis. Regarding the DDC's impact on product meaningfulness and BA's indirect impact on NPN and NPM through DDC and ES, more investigations should be carried out to understand these mechanisms. In future research, multi-dimensional and more specific measures for BA applications can be employed. A longitudinal study will also help researchers to trace the transformational change and associated impact over a period of time. This may provide a more accurate judgment on BA's impact in the organization.

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