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IMPACT OF BUSINESS ANALYTICS ON INNOVATION

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ABSTRACT

The development of Big Data and Business Analytics (BA) has provided unprecedented opportunities for organizations to innovate. With new and unique information gained from BA, companies are able to develop innovations or improve existing products / services. However, few studies have investigated how BA contributed to the success of the company's re-designation. This study aims to address this gap. From the point of view of data processing and use, a research model is proposed and strongly validated by data collected from a UK business survey. Evidence from a 296 respondent survey supports a research model that provides a focused and validated view of BA's contribution to innovation. Significant findings suggest that BA directly promotes environmental scaling which also helps to improve the company's innovation in terms of new product innovation and purpose. However, the impact of the BA contribution will be enhanced by the role of data mediation driven by data in the organization. Data-driven culture directly affects the innovation of a new product, but indirectly on product understanding through environmental scanning. The findings also confirm that environmental scans have a direct impact on the innovation and innovation of products that also enhance competitive advantage. Model test results also reveal that the success of innovation can be influenced by many other factors that need to be considered close to BA applications.

KEYWORDS: ***Composition, Big Data, Business Statistics, Tradition Driven by Data.***

INTRODUCTION

Organizations face increasing competition and turmoil in their markets due to the rapid development of technology and global trade. This has increased the pressure on companies to meet the growing market demand for additional novels and solutions on their own (Nilsson and Ritzen 2014). Although renaming has become an important element of global competitiveness in many industries (Nambisan et al., 2014) and effective renaming is essential for survival (Van Riel et al., 2004), information technology (IT) has evolved. an important role in all aspects of renaming. Over the past few years, the "Big Data" field has emerged as a new frontier in the broader IT spectrum with new capabilities and opportunities allowed for information transformation.

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

The word BA is widely used in various contexts, but there seems to be no general definition of what BA is. Davenport and Harris (2007) describe BA as “the largest use of data, statistical and quantitative analysis, descriptive models and forecasts, and factual-based management for decision-making and action”. The same 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 data analysis methods and techniques for generating knowledge and intelligence to achieve competition.

As the concept of BA has been around for many years (Davenport 2013), there is a need to differentiate between regular and emerging BA due to the challenges and opportunities with Big Data. Based on the evolution of BA, Davenport (2013) suggests that BA has evolved from Analytics 1.0 which was a period of "business intelligence", went to Analytics 2.0 which is the era of big data, and moves on to Analytics 3.0, the era of data- contributions. “As emphasis is placed on the building analytical capacity into customer products and services”. Following Davenport's evolutionary principles, this study focuses on the application and impact of Analytics 2.0 and 3.0.

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Although BA is increasingly being used in organizations, no knowledge-based research has been conducted to understand how BA contributes to innovation. In particular, little is known about the processes by which BA can contribute to innovation. Despite strong claims about how BA can promote innovation through product / service separation using Big Data, there is no conceptual understanding and strong evidence to link BA with innovation. Such a lack of understanding inevitably limits the ability of organizations to fully reap the benefits from their investment in BA. It is not surprising that many businesses are still struggling to figure out how, where and when to use business statistics to achieve fair returns. Until the basic principles of BA and its role in business performance are better understood, recognizing desirable outcomes, such as innovation, remains uncertain. Therefore, it is important to investigate and verify how BA contributes, how and in what innovation. This paper seeks to fill this research gap by promoting and validating a model to define the relationship between BA, data-driven culture, environmental scaling, new product / service innovation and purpose, and competitive opportunity. From the point of view of processing and application of information, this study proposes a number of ideas compiled into a research model to explain how BA, data-driven culture and environmental scans, contribute to new product design, and later, to competitive advantage. The research model is rigorously tested using the Structural Equation Modeling (SEM) method with data collected from 296 responses applicable to commercial organizations in the UK. The following sections discuss the theoretical framework, theories, and model testing. The last section discusses the effects and implications.

THEORETICAL BACKGROUND

This study aims to explore the contribution of BA in innovation through information processing and the application of theory. Therefore, we take the relevant theories and lessons in these areas.

The theory of data analysis (Galbraith, 1974, Tushman and Nadler, 1978), supported by emergency theory, states that an important function of organizations is to control uncertainties such as the complexity of tasks and the rate of environmental change through information processing methods. Viewing information processing emphasizes the importance of balancing knowledge processing needs with information processing capabilities: the greater the uncertainty of work the greater the amount of information to be considered (Galbraith, 1974). Organizations should therefore be formed to facilitate information processing so that decision makers can process a large amount of information in order to maximize competitive advantage.

In terms of information processing, scholars argue that the information provided by information systems is an important asset that helps organizations gain competitive advantage (Porter and Millar, 1985) and develop innovation (e.g. Ottum and Moore 1997). This view is echoed in a recent DHL report (2013), "knowledge has become the fourth productive factor and is critical in separating competition". Many studies have emphasized the role of knowledge, information use and management in organizations (Kettinger et al 2014). For example, from a marketing perspective, Glazer (1991) states that organizations need to look beyond technology and focus on how to manage their knowledge in order to gain competitive advantage. Evaluate how companies' use of different types of business information affects their strategic performance in terms of efficiency, customer proximity, and product leadership. To assess the effectiveness of the establishment of a high-tech service from a decision-making perspective, van Riel et al (2004) points out that knowledge plays a key role in reducing management uncertainty in the success of a high-tech service delivery. They argue that the concept of information processing proves a productive framework. They found that the acquisition, dissemination, and use of information all had a significant impact on the success of the service establishment. Miller and Friesen (1982) in their research on innovation in savings and business firms argue that the company's ability to process information affects innovation.

In the context of innovation, information processing and application help us to focus our attention on key information sources, such as: BA applications that demonstrate the organization’s information processing capabilities, data-driven culture and data-related environmental scans. In the organization. The essence of BA is to convert large amounts of raw data into useful information, therefore, studying the relationship between BA and new inventions from data processing and application of perception is considered a sound guide, but it seems that no such effort has been reported.

HYPOTHESIS DEVELOPMENT

3.1 New functionality

The success of the invention is a multi-faceted measure and no single invention can capture the complex nature of the mind. Many studies attempt to measure new global performance through perceived performance against competition; others use policy measurements such as the number of patterns developed, etc. In the context of this study, the central theme we are interested in is how companies can gain advanced knowledge and intelligence in data using BA and be able to use it to develop new products. / services or development of existing ones. Cooper (1979) argues that product success stems from two processes: the acquisition of information and the ability of the process to develop new products. The acquisition of information is captured on environmental photography in their research and the expertise in the process of developing new products is captured by Droge (2008).

Kim et al (2013) reviewed relevant literature and adopted Amabile's (1983) two-dimensional view of creating a product that is youthful and meaningful in their research on the impact of genres and strategic direction on new product development and profitability. They describe the innovation of a new product as the level of departure and the unique difference of a new product, and the purpose as a new product that provides relevant and useful features to guide customers (Kim et al., 2013).

Stock and Zacharias (2013) conducted a comprehensive review of the literature on the scale of new product innovation. They find both product innovation and purpose have been widely used. We follow the example of van Riel (2004) and Stock and Zacharias (2013) in their innovative research and embrace product innovation and purpose in current research. The detailed measurements of the new and sensible material are described in the next section. The term "new products" in the paper includes both new products and services.

3.2 BA and Establishment

In a recent report on "Mathematical Innovation" published in the MIT Sloan Management Review, Kiron et al (2014) stated that "data-informed organizations are using statistics to innovate and are increasingly gaining competitive advantage". In the era of digitalization and Big Data, BA seems to be regarded as an effective solution for businesses to gain greater insight and intelligence from a variety of data sources to reveal hidden patterns, anonymous connections and other useful information. Such information can provide competitive advantages over competing organizations and result in business benefits, such as new products and service innovations.

BA is based on statistics, forecasting, data mining, and modeling methods, and focuses on developing new knowledge and understanding of data-based business operations. Software developers and IT companies promote BA applications and claim that Big Data and Analytics can bring many business benefits, such as: transparency, more precisely designed products or services, improving the next generation of products and services, etc. . (McGuire et al., 2012). For example, Stubbs (2014) argues that Big Data enables innovation by allowing competitive classification by BA. Innovation always plays an important part in the success of an organization.

In many organizations, information technology has been a catalyst for innovation, as well as an important 21st-century tool. BA can convert large amounts of raw data into valuable information, and companies must convert broad information into business (DHL, 2013). One way to achieve this is to develop products / services with new information and information. Drawing on previous research on the success of innovation in information processing and information processing, we set out the view that BA will improve corporate renaming through the many organizational elements as discussed in the following sections.

3.3 BA, Data-driven Culture and New Product and Purpose

Dahlander and Gann (2010) reiterate that innovation is not a work in itself; involves collaborating and collaborating with others both internally and externally within the company to obtain the ideas and resources needed for innovation development.

Previous research has emphasized that in order to use BA to gain competitive advantage, a company needs to develop a data-driven culture where management decisions rely heavily on data-based data. According to Kiron et al. (2012), data-driven culture refers to “the behavior and processes of a group of people who share the same belief that the existence, understanding and use of certain types of data and information plays an important role in the success of their organization”. This means that clear organizational strategies, policies and rules need to be developed to guide BA activities, and a well-defined organizational framework and business processes are in place for BA operations to function smoothly (Kiron et al., 2012, Kiron and Shockley, 2011, Lavalle et al., 2011).

Therefore, we suggest:

H1 - Business Analytics has a positive impact on Data-Driven Culture

Organizational culture is a pattern of shared values, norms, and processes that distinguish an organization from one another (Higgins and McAllaster, 2002). These terms and conditions define "what is important here" and "how we do things here" (Higgins and McAllaster, 2002, p. 74). The association

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of organizational culture and renaming has been the subject of extensive research in recent decades (Büschgens et al., 2013) and its role in the establishment was thoroughly investigated and discussed by researchers.

4. RESEARCH MODEL BUILDS STANDARDS

To test the theater model, a number of building materials and associated steps have been identified. As this emerging BA is a new research space and there are a few strength-based measurements, we have developed new BA structures and measurements, drawing BA books.

The concept of analysis, based on the continuous development of decision-making systems, has been used for many years (Holsapple et al., 2014); however, our focus is on the latest BA applications integrated with big data, namely Analytics 2.0 / 3.0. BA or analytics refers to "broad data usage, statistical and quantitative analysis, descriptive and predictable models, and factual-based management for decision-making and action", or "information production and support intelligence. Decision-making and strategic objectives". In industry, BA has been used as an umbrella term for a variety of business applications and analysis methods (Chae et al., 2014). Knowledge and wisdom, we divide the BA into descriptive statistics, predictive statistics and descriptive statistics.

Descriptive analysis uses for example business intelligence and data mining to provide context and trending information of past or current events, responses that have occurred and what is happening. Predictability statistics use mathematical models and predictions to provide accurate predictions of future events and to think about why, in response to what might happen; while the stated analysis uses for example preparation and imitation to recommend one or more course of action and shows the possible outcome of each decision, providing answers for what we should do.

From a data processing and application perspective, information processing capabilities can be demonstrated by BA applications that demonstrate the company's ability to process different types of data to reveal hidden patterns and trends for descriptive, descriptive and predictable purposes. Drawing on MacKenzie et al. (2011), our BA definition of BA means that a constructive organization is an organization represented by its decision-makers; common assets with data analysis techniques and processes; the concept is identified by systematic data analysis to obtain important business information; its dimensions include descriptive analysis, predictive analysis, and descriptive analysis; and is expected to operate normally in different organizations in different industries.

Data-driven culture is another new way to be defined. Davenport et al. (2001) used a data-based or fact-based culture to refer to "data and information was part of an internal value system" of "data-based decision-making standards", while Davenport (2006) used customary right to express universal respect for measurement, evaluation and evaluation. Proof of plurality ".Kiron and Shockley (2011), and Kiron et al. (2012), define a data-based culture as "a pattern of behaviors and practices of a group of people who believe that owning, understanding and using certain types of data and information plays an important role in the success of their organization". This or similar concept of data-driven culture has also been adopted by a number of other papers.

Other constructions such as new product innovation and purpose, as well as the scans of the environment and your measurements are exchanged from the founding manuals to the current state of research, which has already been strongly confirmed by previous studies.

We measure the benefits of competition from a manager's perspective on whether his organization is highly profitable, growing its sales and market share faster, and having a better return on investment than its key competitors.

5. CRITICAL ANALYSIS

The hypotheses were rigorously evaluated using partial minimum squares structural equation modeling (PLS-SEM) based on survey data. PLS-SEM is recommended to be well-suited to research situations where theory has not been slightly developed. In the next section, we describe the processes for tool development, validation, and distribution.

5.1 Data collection

In order to test hypotheses more effectively, we have collected data from UK businesses. We conducted a questionnaire survey using a Likert seven-point scale (from 1 - strongly disagree to 7 - strongly agree) in order to capture answers to all your building ratings. The research tools were developed based on a review of the literature and explanations discussed above and were considered by academic experts. After several reviews, the survey was tested to ensure that respondents understood the questions and did not have problems with words or ratings. The survey questionnaire was then presented to management electronically by Qualtrics, a powerful and well-developed online survey tool. The target population was senior executives in the company and their email addresses were identified on the FAME website. Three rounds, one week apart, of emails, including cover letter and questionnaire were sent. Each respondent was given a summary of the results and a chance to enter the competition to win one of five Amazon prize certificates (£ 100 each). While 131,688 emails were sent with an email subject highlighted as a questionnaire survey, most of them never opened. Of all the emails sent, 771 surveys were opened; In these pilot studies, we obtained 304 responses and 296 responsive responses, representing a response rate of 38.4%.

5.2 Respondent profile

Table 2 summarizes the respondents' characteristics in terms of their organizational positions and years of experience in their current firms and industries.

We used an important reporting method to collect data. Reported positions of respondents suggested that 20% of respondents are in senior management positions and the rest are in middle management positions. Based on their position within the firm, respondents were considered able to answer research questions. They were also reminded to hand over the survey to someone if they believed he or she was not in a good position to answer research questions.

5.3 General Method and Non-Respondent Neutrality

The bias of the standard method was assessed by performing an evaluation factor (EFA). Harman single-factor testing was performed by including all independent and dependent species. As the first factor accounted for 35.90% of the total variance, there was no evidence of significant respondent bias in this study.

Non-response bias was then evaluated by comparing the early and late responders in all measures with t. The results of the t test did not find significant differences between the two responding groups, suggesting a lack of unresponsive bias.

5.4 Sample Size and Data Testing

In a building model, the maximum number of arrows pointing to a building is five. To obtain a minimum value of R2 of 0.10 for any construction at a critical level of 1%, the minimum sample size required is 205 (Hair et al., 2013a). With 296 practical answers, a small sample requirement is met.

Data testing was performed using SPSS19. More than 10% non-tracking data has been deleted. The remaining value of non-set data values per indicator was relatively small, less than 1.8%; so the remaining missing amounts are replaced using a median price change.

5.4.1 Evaluation of Visual Measurement Model

Since the model contains both a thoughtful and constructive design due to the nature of the construction, a separate set of analyzes was performed following the recommendations made by Hair et al. (2013a). The luminous rating model was analyzed by considering internal consistency (combination fidelity), subject fidelity, translation validity and discriminatory legitimacy.

Reliable combined scores (CR) summarized in Table 3 indicated that the results based on this design should be equal, as all builders met the recommended value of acceptable reliability, i.e., both CR and Cronbach α should be greater than 0.70.

6. DISCUSSION AND CONCLUSION

Our research seeks to understand how BA contributes to the development of innovation through information processing and the application of the concept. We developed and evaluated a research model to assess the impact of BA. Evidence of performance provided strong support for the proposed model. As shown in Figure 2, most of the research ideas are supported, with the exception of the effect of data-driven culture in the understanding of a new product. Significant findings suggest that BA directly promotes environmental scaling which also helps to improve the company’s innovation in terms of innovation and purpose for a new product. However, the impact of the BA contribution will be greatly enhanced by the role of data mediation driven by data in the organization. BA strongly influences the data-driven culture (path coefficient = 0.576 ***), which in turn contributes to the innovation and purpose of the new product. Surprisingly, DDC is compatible with the "new" brand but is NOT compatible with purpose. In other words, data-driven culture has accelerated the development of new products but has not allowed companies to offer products that better fit their customers' needs even though, statistically, DDC has indirect effects on product sensitivity by environmental scans. It is also noted that BA leads to the purpose of a new product (NPM) through an improved environmental scanning method (ES) but not through a data-driven culture (DDC) mediation. The findings confirm that environmental scanning has a direct impact on the development of a new product and that it also improves competition. Model test results also reveal that the success of innovation can be influenced by many other factors that need to be considered close to BA applications.

6.1 Impact of Research

There are many factors that contribute to the success of innovation. Knowledge and knowledge have long been regarded as an important ingredient and the founder of successful inventions. With the widespread availability of data and the increasing use of statistics, companies are now expected to use data and statistics to acquire new information and information to develop new inventions. Therefore, there is a growing need to find out how BA contributes, how and in what innovation and competitive advantage.

Our research makes a number of contributions to the study. First, although many articles and online reports emphasize that BA helps companies innovate, there is no theoretical understanding and strong evidence to substantiate claims. Our research has attempted to close the research gap by linking Business Analytics to innovation. This has been achieved by establishing a methodology that links BA (information processing) directly with data-driven culture and environmental scans (information use) and indirectly with the introduction of new product and competitive advantage. This cheap model only explores how BA contributes to the development of knowledge and the application of the concept, thus providing researchers and clinicians with a more direct and focused understanding of the impact of BA.

Second, our research demonstrates the role of data-driven mediation in advancing the impact of BA on innovation and requires further research on how to create and improve data-driven culture in organizations.

Third, although our model attempts to capture the impact of BA on innovation and innovation, it also points out that there may be many other factors that influence the company's creative success. This is largely based on the low predictability of the proposed model, especially with regard to the purpose of the new product. This suggests that the use of BA alone may not significantly alter the performance of a company establishment. Other factors must also be considered, so an integrated and coherent business strategy and innovation approach must always be considered.

6.2 Management impacts

Our findings have many important management implications. Strong evidence has led to the conclusion that BA can enhance the company's innovation success in terms of new product innovation and purpose, thus leading to better competitive advantage. The impact of BA can be achieved with the company's better information processing skills provided by BA and the effective use of information on business intelligence by scanning the environment. Organizations should take a faster approach to developing and submitting BA applications across the company.

Most importantly, our findings clearly demonstrate the important role of culture, especially the culture driven by data in this context, in helping the impact of BA. With the advent of Big Data and the availability of BA tools and strategies, organizations should create and grow a data-driven culture to increase BA business value. However, installing BA tools alone in the company will not automatically generate new information and information and improve new design. For example, companies should create and nurture a data-driven culture that encourages the company to be open to new ideas and ways that challenge their current practices on the basis of new knowledge, using data-based information to create new products / services. , having data for decision-making needs, using evidence to support decision-making, and believing in the role and value of data and information in an organization. Generating better business intelligence by scanning the environment with a strong data-driven culture will directly contribute to new product innovation and purpose.

Limitations and future research

Current research has a number of limitations. For example, this model focuses only on the impact of BA no innovation success from knowledge processing and the application of the concept, so it does not (and was not intended to) capture all the key factors affecting the success of new inventions.

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