International Journal of Technology and Human Interaction
Volume 17 • Issue 2 • April-June 2021

The Long Game:
Technological Innovation and the Transformation of Business Performance

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ABSTRACT

This paper brings a new perspective to knowledge by focusing on the application and exploitation of big data in two UK companies providing, respectively, online and branch retail services. The companies innovatively exploited the data that were generated by new internet technologies to improve business performance. The findings from both case study examples show that benefits do not come simply by adopting technology, but when people think creatively to exploit the potential benefits of ITC. The conclusion drawn is that the realisation of the 'universal benefits' of technological innovation does occur, but not necessarily until the hype has subsided. The paper demonstrates that there is opportunity to create sustainable competitive advantage through the application of ITC although the social, technological, and human challenges of managing technology have to be appreciated and managed. These implications need to be appreciated and if true long-term advantage is to be achieved.

KEYWORDS

Big Data, Data Analysis, Decision-Making, Operations Management, Operations Strategy, Performance Improvement

INTRODUCTION

Technology is a major source of inspiration, innovation and change in today's business world. Talking shortly after the emergence of the internet, Kranzberg (1986:545) noted:

"Technology is neither good nor bad; nor is it neutral… technical developments frequently have environmental, social and human consequences that go far beyond the immediate purposes of the technical devices and practices themselves".

Around the same time, Solow (1987) gave his paradox: "You can see the computer age everywhere except in the productivity statistics".

Given these perspectives, this paper revisits the question of the impact that technology has had on business performance and presents evidence suggesting that human interactions with technology and the resulting impact upon productivity are not as straightforward or immediate as it might appear and can be contradictory (Jain & Kanungo, 2005).

DOI: 10.4018/IJTHI.2021040104

Since Kranzberg's and Solow's writing, the growth and development of the internet and mobile technologies has been exponential, transforming ways of working and ways of living. Moreover, its expansion continues, seemingly unabated. Technology companies (typified by companies whose names have become synonymous with particular technologies, such as SAP, Oracle, IBM, Google and Microsoft) promote the need for businesses to exploit large datastreams to boost productivity and thus to create competitive advantage. As the internet matures and becomes ever more embedded in all aspects of our lives the potential of Big Data (BD) appears huge. Commentators such as Bell (2013) and Porter and Heppelmann (2014) encourage such a view. The OECD (2013:4) went so far as to suggest that:

"The exploitation of data promises to create added value in a variety of operations ranging from optimising the value chain and manufacturing production to more efficient use of labour and better customer relationships".

The implication of this statement is clear - organisations that can harness internally or externally generated data will be able to transform their operational capabilities. There is a collective assumption that the internet and the immense amount of data that it simultaneously creates and makes available to us, will benefit organisations, individuals and society (Barton & Court, 2012; Bughin, Livingston, & Marwaha, 2011).

Interacting with large data sets was once perceived as a problem. Now, computer applications capable of analysing huge data-sets are readily available (Fisher, DeLine, Czerwinski, & Drucker, 2012). More recently however the question of whether BD will ultimately deliver what it promises has been raised (Croxall, 2014; Lury, 2013). Opresnik and Taisch (2015) point out that the challenge for organisations is to develop strategies that exploit BD to generate added-value. Gandomi and Haider (2015) observe that there has been little critical discourse, or empirical academic research, into BD and how it is being harnessed. Although Solow's Paradox emerged at a time when the internet was in its infancy, it may be as relevant today as it was when our interaction with technology was nascent. Although it is fifty years after the emergence of the internet we cannot assume that huge technological innovations have led to comparable increases in productivity. Andrew's et al. (2016) indicate that productivity growth rates in the OECD have fallen in the last decade. Echoing Solow, historical work by Gordon (2012) suggests that there is a significant lag between the emergence of new technologies and its full impact upon economic growth. Gordon's research suggests we should not expect to see the potential of BD to be fully realised until well after the hype has died down.

To look beyond the apparent contradictions between promise, hype and reality this research sought to answer primary and secondary research questions, which were:

RQ1 How has technological innovation transformed business performance? and
RQ2 Has technological innovation transformed management practice?

It sought to identify the ways in which new information technologies are actually being used in traditional businesses to enhance performance. In doing so, the paper examines two organisations' application of BD to create competitive advantage and transform their performance. The findings were that both examples arose from curiosity about business challenges and whether existent large datasets could be utilised to address those challenges. The paper adds to a growing body of literature in a variety of disciplines, encompassing economics, technology, banking and operations management, alongside work such as Solow (1987), Solow (2005), Fosso Wamba, Akter, Edwards, Chopin, and Gnanzou (2015), Gordon (2016), Hulten and Nakamura (2017) and Matthias, Fouweather, Gregory, and Vernon (2017). It contributes to knowledge by detailing the challenges of interacting with BD and how it can be exploited. The two examples used reveal how traditional organisations were able to utilise large data sets to improve business performance. The research shows that improving productivity is dependent upon the quality of our interactions with technology. Adoption alone is insufficient. In both cases performance improvement relied upon the appropriate use of relatively simple, well established methods that predated the birth of the internet by almost a century. The sophisticated Big Data Analytics helped the curiosity; they did not create it.

LITERATURE REVIEW

The Creation of Big Data

As the ability to rapidly process data has increased, so has the ability to generate vast streams of data. Two laws have encapsulated this exuberance. Moore's Law stated that the processing power of computers doubled every eighteen months (Moore, 1965). Kryder's Law stated that digital storage is increasing at a similar rate to data processing power (Esener et al., 1999). Whilst both 'laws' have been called into question (Hruska, 2013; Mellor, 2014), greater processing, storage and the connectivity of the internet have created an explosion of data. The proliferation of smart technologies adds to the data mountain, mostly through social media. Whereas traditional business analytics focus on internally-created data, social media's constant stream of data about individuals offers a previously inaccessible real-time window into people's opinions, wants and needs. Both these streams provide usable data sources for organisations. The challenge is to know what it there and how to use it.

The term BD first emerged in the mid-1990s, a time when the use of the World Wide Web was in its infancy (Diebold, 2012) at a similar time as discussions about data, information, action and outcome were evolving. BD's first appearance in academic literature was at the IEEE's 8th conference on Visualization (1997) where Cox and Ellsworth presented a problem for systems engineers who were pondering how large data-sets that exceeded available memory capacity could be managed - the first articulated BD problem. A few years later, Laney (2001) predicted that enterprises would need to manage ever-larger data-sets as e-commerce became more prevalent. He said the challenge would be in terms of three dimensions: Volume, Velocity and Variety. These refer to large volumes of data arriving at and processed at high velocity, variable in quality and content, often complex and requiring advanced technologies and techniques to capture, store, distribute and manage for subsequently useful analysis. These dimensions have become central to understanding BD. Since then additional dimensions have emerged: Variability, Veracity and Value, although it is the original 3Vs that remain core.

The absence of a universally accepted definition of BD created several contenders to emerge, of which the two predominant ones imply that the challenge of BD is scale, or volume, of processing:

… data-sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse. (Manyika et al., 2011)
Data assets that require innovative forms of information processing for enhanced insight and decision-making Gartner (2014)

Technology companies, whether providers of ERP systems, CRM software or Business Analytics have been promoting BD ever since. It has been asserted that BD would:

transform business processes and alter corporate ecosystems (Brown, Chui, & Manyika, 2011)
be 'the next frontier for innovation, competition and productivity' (Manyika et al., 2011)
and a 'revolution in management' (McAfee & Brynjolfsson, 2012).

The combination of the rhetoric of these messages and increased access to the volumes of data led to considerable hype around the term (Gandomi & Haider, 2015; Gartner, 2013, 2015; George, Haas,

& Pentland, 2014). Much of this seems to have shaped the expectations of academic communities, although the majority of publications have focused on BD technologies and access to data, rather than actual management practice or business transformation (Fosso Wamba et al., 2015). Some scholars have highlighted that BD and what it offers may be neither new nor true. Madsen and Stenheim (2013) were among the first to suggest that BD could be the latest in a long line of management fashions and fads that have 'over-promised and under-delivered'. Wieland, Handfield, and Durach (2014), whilst suggesting that within the field of Supply Chain Management academics expect BD to be 'the hot topic' for the next five years, also advised caution.

Research on data analytics and process improvement is not new although the 'hot topic' aspect of BD may make it seem so (P. Bell, 2013; Chae, 2015; Dubey, Gunasekaran, Childe, Fosso Wamba, & Papadopoulos, 2016; Hsinchun, Chiang, & Storey, 2012; Huang & Handfield, 2015; Wieland et al., 2014). Traditionally data analysis has considered discrete data that can be handled using well-established and sophisticated quantitative techniques, such as data feeds from sensors. Processing such data is straightforward, and can easily be automated by existing ICT. FedEx applied *"scientific methods to its operations*" using advanced analytics when it adopted the RFID transmitter (P. C. Bell, 1999:307). The RFID transmitter is referred to in mainstream management even more than in BD research papers (Ilic, Grössbauer, Michahelles, & Fleisch, 2010; Lee & Özer, 2007; Meyer, Buijs, Szirbik, & Wortmann, 2014; Zelbst, Green, Sower, & Reyes, 2012; Zhong, Lan, Xu, Dai, & Huang, 2015). In their recent case study work (2015), Chongwatpol and Chan describe the use of a large dynamic data-set to enhance operational decision-making and increase effectiveness. Their findings show how data analytics can be used to find alternative ways of assessing business issues without the use of the term BD. Piccoli and Pigni's (2013) work illustrates how Digital Data Streams (DDS), can be used within an operational setting to *replace* routine decision-making activities with predetermined (mindless) responses. This proven technology creates far higher levels of automation than previously possible. They stress that DDS is not BD. Rather, it is an example of closed-loop feedback control.

Big Data's Role in Business Transformation is Complex

Technology companies are keen to develop more applications that will generate even more data. Customer transactions and electronic feedback is processed to capture demand and levels of satisfaction. Internally myriad smart technologies generate instantaneous feedback on the status and performance of internal resources using a plethora of indicators. The claim is that processes can be controlled more effectively and better decisions to exploit opportunities and solve problems taken because of the information generated by new technology. This gives the impression that the possibilities for data analysis and the opportunities for consequent business transformation are infinite and deflects from a number of significant factors which need to be considered.

Firstly, the assumption that the size of a data-set is seen as a proxy for quality (Bisel, Barge, Dougherty, Lucas, & Tracy, 2014). Yet quantity is not a substitute for quality, as work on The Google Flu Trends Project (GFT) illustrated (Lazer, Kennedy, King, & Vespignani, 2014). They stated: "*foundational issues of measurement and construct validity and reliability and dependencies among data*" cannot be ignored (p1203). Secondly, whilst data mining and analytic techniques may reveal interesting patterns hidden within large datasets, over-reliance on technology can create mindless responses if individuals fail to contextualize information, more likely to reduce performance than improve it (Sætre, Sørnes, Browning, & Stephens, 2003). Searching for patterns is complex, as Lazer et al.'s GFT paper shows. Without an understanding of what the patterns reveal, the information can have little, if any, value or, even worse, lead to incorrect conclusions. This echoes work by Fiol and O'Connor (2003) who drew attention to the perils of simply 'jumping on the bandwagon' when adopting new technologies. To assist in decision-making BD needs to be analysed and utilised with care. Insight and understanding of those involved in the analysis of data (whether big or small), that is central in creating value.

In 2013 almost one billion smartphones were sold (Gartner, 2014), each capable of creating and collecting masses of data. Smart machines are commonplace; new equipment comes with an array of sensors and data trackers that continuously produce and store data (Lucke, Constantinescu, & Westkämper, 2008; Meyer et al., 2014; Zelbst et al., 2012). The social data they create and capture offers new ways to understand the external environment and is thus an essential element of the discourse on BD (Chae, 2015; Dubey et al., 2016). Notwithstanding, data generated through social media presents an enormous challenge. It is unstructured and comes in a range of formats, often with multimedia content and threads of previous textual dialogues embedded within it. Successful analysis of such qualitative textual data with software remains limited (Chen, Chiang, & Storey, 2012), although Bollen et al. (2011) successfully analysed the 'mood' of Twitter feeds to predict movement in the Dow Jones Industrial Average, identifying an accuracy of 86.7%. Tinati et al. (2014) observe that the current forms of analysis of rich unstructured qualitative data is limited to classifying, linking, and revealing distributions of words, reducing it to little more than a word-count survey. Whilst these are essential processes of data reduction which allow analysts to sift through large data-sets quickly, they leave much unexplored. Housley et al. (2014) detail work to enhance capabilities in this area, but sophisticated tools and techniques have yet to be established. Despite all the hype and expectation, it may be some time before ITC provides the solutions we imagine.

An additional dimension to complexity, often overlooked, are the problems of working with OCG (open, complex, giant) systems (Jifa & Lingling, 2014). The internet is an interconnected system, and the data being harnessed is not simply more data about an existing system, it is adding to the system and further complicating itself. It is constantly changing, with positive and negative feedback loops interacting dynamically, which can create stability and chaos. A further complication in utilising social media-generated data which has had little attention is how customers are also transformed. They too have data and information at their fingertips. As such, customer expectations regarding the service they receive, or wish to receive, change. The online searches customers make create individual choices and relationships with businesses, unique up to a point. Customers expect interaction through a channel of their choice at a time of their choice with the same experience regardless of channel or device used. Used properly this new customer-centric knowledge provides organisations with an opportunity to change their processes, create competitive advantage and improve business performance, which is what this research has sought to uncover.

Assessing the veracity of BD can be challenging. Whilst statistical tools can be used to filter out erroneous and missing data, establishing the veracity of a large data-set is not straightforward. Chongwatpol and Chan (2015) illustrate the significant work required to ensure veracity of data and the information generated from large dynamic datasets. Uncritical analysis of poorly understood data-sets does not generate knowledge. Despite the increasing availability of data, using BD to support decision-making is "an enormous challenge" (Li, Song, & Huang, 2016:3). Whatever the size of the data-set, it needs appropriate analysis to create useful information that reveals what is significant within the data. "*Not all information is useful for improving our understanding and judgements*" (Saaty, 2008), and too much information can create uncertainty, hindering decision-making. Insight and understanding of those involved in the analysis of data is central to creating business value.

Moving From Data to Decision-Making

Data has no purpose unless it can be transformed into information that facilitates good decision-making and enhances operational performance (Jifa & Lingling, 2014). Neither definitions of nor promises about BD consider that greater volumes of data, generated at higher rates do not automatically lead to more information and knowledge. However, systems theorists have for decades explored the link between data and information. The insights provided have shaped performance management for many years (Carvajal, 1992). Knowledge is created through the "*application of data and information*" (Ackoff, 1989). Shedroff's (1999) DIKW hierarchy links Data, Information, Knowledge and Wisdom, with the clear statement that knowledge is the ability to use information within a particular context.

The DIKW hierarchy provides a theoretical pyramid built on a foundation of data with each successive layer resting on the one beneath. Thus, processing data appropriately makes it "*useful for decisions and or action*" (Liew, 2007). Assuming information is "know what", then knowledge is "know why". Knowledge enables decision-making, allowing the selection of a particular action from a range of possibilities and leads to the "know how" to improve performance and create competitive advantage. In this way the promise of enhanced knowledge and decision-making as a result of bigger (and by implication better) data evolved, but research indicates it may not always be the case (Walker, Stanton, Jenkins, Salmon, & Rafferty, 2010). Recognition that possessing more data without increasing the ability to analyse and understand the data being generated may actually be a hindrance, leads to the central challenge of how our interactions with technology can best be used to unlock the knowledge within the data. It is this challenge of human interactions with technology that the research questions seek to address.

The Power of The Human?

In considering how to create meaning from BD, who should do it and its impact on the business, there is scant mention of the human aspect, despite Kranzberg (1986) identifying the issue some 30 years earlier and Solow (1987) highlighting the paucity of evidence upholding the view of better decision-making leading to greater productivity. In fact, Solow went so far as to say that all the promises only appear to be saying something, rather than actually saying it (ibid). It appears that the transformational idea of BD is not a matter of technology, but one of analysis. It appears that the role of the analyst remains central to the process of interpreting the data. This means an examination of skillsets and possibly the development of new ones.

What new skills are required is something that writers do not necessarily agree upon (Miller, 2014). The OECD (2013:29) acknowledges that an appropriate mix of advanced ICT, statistics and specific sector skills are required. Fawcett and Waller (2014) similarly recognise the need for both data and domain skills, but stress that it is the ability to apply technical skills that is important. Manyika et al. (2011) highlighted that organisations do not have the talent to derive insights from BD. When presented with a complex and ever-changing stream of data and information, the ability to think creatively, grasp the situation and act accordingly may require a diverse range of attributes, such as intelligence, intuition, imagination and creativity, not always recognised or valued in the workplace. Despite advances in AI, technology (as we currently use it) may not replace these increasingly essential skills. Mainstream media (Philipson, 2014) recently reported that the British Intelligence Service (GCHQ) recognised this and employed more than 100 dyslexic and dyspraxic analysts because of their skills in identifying patterns and ability to analyse complex data. Their ability to spot oddities in patterns, which must have been useful survival skills for hunter-gatherers, are now being applied to data-sets rather than animal behaviours, at GCHQ.

Literature Summary

BD describes the large quantity of data generated and stored by modern connected technologies which has forced businesses to consider how they exploit the resultant information flows. The emergence of the internet means that collecting data from multiple channels has never been easier. The hype says that the more data gathered, the better the decision-making. Reality is less straightforward. Usability is critical. Data needs to be converted in a robust and reliable way to be translated into knowledge to be applied. Agility and flexibility in data collection is good, but it is necessary to connect and correlate relationships, hierarchies and multiple data linkages, otherwise the data remains meaningless. Meaningless data is the digital information equivalent of a rubbish heap, as shown by the GFT example.

In an ideal world, big data should help organisations set new levels of performance and new agendas for business. This research shows that advances are being made that make this a possibility but it is a gradual process, and one which requires human interactions with the technology to be the linchpin to any improvement.

METHODOLOGY

This research sought to uncover whether technological innovation transformed business performance and management practice. Its objective was to understand how organisations use BD and if its benefits match its widely-presented potential. Given that this is a relatively new research area and the research largely exploratory, a multiple case study approach was adopted (McCutcheon & Meredith, 1993). Case selection was opportunistic, resulting existing relationships with executives in a regional Business Knowledge Transfer Network in the UK. The researchers approached the Network co-ordinator, who worked at the same University, explaining their interest in finding out if companies dealt with BD challenges and if so, how they did this. Members were contacted by email and asked if they would be willing to share their experiences of BD exploitation for a research project. Of 180 member organisations, 17 responded. The responses varied in the degree of engagement with BD and the researchers spoke with each of the 17 companies to ascertain what was actually going on in the organisations regarding BD.

The 2 chosen cases emerged as being the furthest advanced in terms of actually having carried out internally a project to exploit the data they had. When asked if they would be willing to share the experience for research purposes, each company agreed. Readily-available data and direct access were more important factors than an alternative sampling strategy. Both were traditional organisations in that they did not conform to the stereotypical hi-tech, social media organisation generally associated with BD. They were traditional organisations, both retail, although they had entirely different business operating models. In part, this was another reason for selection. Both had a desire to significantly increase performance and had felt that their available data and technology could be used to help.

Case 1 wished to remain anonymous so in the interests of equitable treatment in the presentation of this paper, Case 2 is anonymous also.

The data collection and analysis methods were chosen and carried out by the respective companies, which facilitated answering the two research questions:

RQ1 How has technological innovation transformed business performance? and
RQ2 Has technological innovation transformed management practice?

The case studies, their drivers, method and outcome, are outlined separately in the findings section. They are compared with the general literature on BD and technology innovation, what it is and what it is supposed to do (Fosso Wamba et al., 2015; Haas, Criscuolo, & George, 2015; Hulten & Nakamura, 2017; Wieland et al., 2014). The aim was to compare the hype with the reality in an operational setting by understanding how organisations interact with and exploit BD, and if this is different to their standard data analysis techniques and 'standard' results.

The operational implications of exploiting BD to improve performance are explored with a critical eye that seeks to re-evaluate the observations of Kranzberg (1986) and Solow (1987) The research complements work undertaken by Dubey et al. (2016).

FINDINGS - THE CASE STUDIES DETAILED

Case Study One – Multi-Channel Retailer

This company had a vision: to create a competitive edge by being the most trusted UK provider in the sector. This retailer has 19 branches nationwide and several brand names linked to it, with 3 divisions: inbound, re-sales and retail. The inbound creates the majority of activity, provides the stock and accounts for 10% of revenue. Re-sales represent 70% of the revenue. Retail reaches the consumer directly and accounts for the remaining 20% of revenue.

Many years' data from multiple outlets tracking all sales operations existed and the company wanted to set up a "scientific platform" to analyse it. An employee suggested that this data could be used to help realise the vision and to this end a project was established to explore the rich and complete dataset. The first problem to arise was variety – inconsistent, incomplete and inaccurate data capture across outlets and delivery channels. Despite being internally generated, data had to be cleaned because of non-standardised data capture processes. There were two product ranges, value and deluxe. Historically the deluxe range had been 'enhanced' by providing a 6 month guarantee. They were surprised to find they lost money on the deluxe and made three times more, per value item, even though it sold more cheaply and it did not have a guarantee. An unexpected pattern in sales was also found: certain models sold for higher prices in certain locations, yet their sales policy was to sell at the location nearest to the previous owner's registered address, regardless of sales value location. Stock days were found to be irrelevant.

These findings meant that the management team reconsidered the positioning of the product range and standardised a number of aspects of their operation hitherto non-standardised.

Data Collection

The organisation generates masses of data in a constant stream across all its business units. Data comes from 'in use', 'off use', retail, wholesale, industry regulators and each individual product item. Wanting to create a competitive edge by becoming the most trusted UK provider in its sector the company set up a project to provide a platform to analyse the data collected from its business operations. The aim was to understand the impact of product variety on workload and profitability. The questions which emerged from management were:

1. Are products with guarantees more profitable?
2. What links are there between wholesale and retail?
3. What is the link between stock days and product profile?

The project manager developed hypotheses to run the data mining (DM) verification paradigm as well as enable descriptive analysis. They were:

H1 – product with guarantees are more profitable than those without
H2 – deluxe products are more profitable than standard

The re-sales division had the largest dataset. An initial exploration revealed enough data-sets to answer the research questions.

Data Preparation

A total of 48 variables were found within the sales data. To enable subsequent analysis the variables were defined into: numeric, categorical (string), Boolean (yes/no) and specific codification attributes. Data cleaning had to be carried out due to 3 main inputting problems – inconsistency (eg BLK and BLACK), character transposition and missing values.

Data Analysis

The company adopted the CRISP-DM (Cross Industry Standard Process for Data Mining) approach as the most viable to mine existing data because it is accepted as the 'gold standard' in the data mining domain (Pechenizkiy, Puuronen, & Tsymbal, 2008; Rennolls & Al-Shawabkeh, 2008).

Using this approach it was found that non-guaranteed products' mean contribution to profitability was higher than those with guarantees, therefore **H1** was rejected. Total revenues from deluxe products was found to be 61.5%, therefore **H2** was also rejected. Further exploration of the deluxe category established there was product differentiation within-category. The DM findings identified the most profitable sales.

Findings

The insight that inherently enhanced products were more profitable than those enhanced by guarantee led the management team to reconsider the market positioning of the product range and the input the company provided pre-sales. The descriptive analysis carried out to answer question 2 highlighted the most searched products nationally, by location, which can help decision-making regarding targeted pricing and promotion decisions. The question 3 analysis ascertained there was no particular link between sales and stock days.

The findings from this analysis illustrate how technology can assist organisational decision-making be it strategic or tactical. In addition, it led to standardisation of data capture to reduce future inconsistency. The company also recognised that having developed an analysis platform there are many other aspects it can explore operationally. Having established an industry overview, further mining of the data could help it enhance its market leader position by further improving organisational performance

Case Study Two – Online White Goods Retailer

Background

This organisation wanted to deliver tailored experiences for new online customers when they visited the company's website. The absence of physical clues about a customer such as gender, clothing and ethnicity that are used in face-to-face encounters meant that the statistically significant real-time sales discrimination based on appearance was not possible (Wise, 1974). An employee was musing one day and wondered if, in the absence of physical clues, the technology the customer used could help the company understand the customer better. The question asked was: "Can historical access data deliver more tailored experiences to new customers when they visit the website?"

Data Collection

Search advertising is the primary tool directing potential customers to the website and is complemented by display advertising where defined criteria about context and previous browsing behaviour are met. Conversion rate optimisation (CRO) is used to increase the number of website visitors booking a design visit and thereby moving more successfully through the company's sales funnel. CRO positively influences cost-per-lead and permits analysis of the technology in the form of operating system (OS) and browser customers use to access the website. OS and browser data combined was collected for a 12 month period. 1,621,262 website clickstream data was pulled into the company's CRM system at the point of design visit enquiry, and analysed.

Data Analysis

Using Google Analytics to investigate internet traffic data it became apparent that the question could be more precisely defined:

1. Can customer technology use for website navigation predict purchase type and spend?
2. Can this information be used to deliver a more tailored website experience?

Preliminary analysis showed that Microsoft Explorer (IE) and Firefox usage declined by 40% in 12 months while all other browser traffic increased. Devices were identified as the most important influencer because most users stay with the default browser provided (Browser-update.org, 2015). As use of smartphones and tablets increased, so did access to the company website using Safari and

Google Chrome, with corresponding decreases in IE and Firefox OS. The curious employee developed three separate hypotheses to test the correlation between purchasing choice and variables associated with web use that could be captured using Google Analytics.

H1 – Product style preference and device are associated
H2 – Product style preference and operating system are associated
H3 – Product style preference and browser are associated

The clickstream data was segmented into 3 technology categories and number of visits to the top 4 styles of the 2 product categories the company offered. Pearson's Chi-square test of association was selected to test the hypotheses because of its versatility and ability to deal with categorical data (Hair, Money, Samouel, & Page, 2007). Statistical significance was tested to 95%, judged by the organisation to be an appropriate level of confidence to use in the tests.

They found it was possible to accept all three hypotheses.

Because of the interdependency between the operating system and browser, a fourth hypothesis was developed:

H4 – Product style preference and [OS + browser] are associated

A total of 21 different combinations of operating system and browser were identified from the data available. Again using Pearson's Chi square test and the same significance level as before, a p value of 6.1098×10^{-195} indicated this hypothesis could also be accepted. Similarly the critical value of 31.4104 was significantly below the test statistic (χ^2) of 980.3270 .

Findings

The result from H4 definitively answers research question 1 and confirms that assessing customer preference based on technology is viable. Combining OS and browser variables provided a rich set of data segments to use in tailoring the customer experience. Mac OS and Google Chrome suggested a preference for a modern, expensive products whilst IE meant more traditional style and careful spend. Research question 2 was also answered from test 4. The strong association between browser/OS combinations and product style preferences enabled the business to identify three customer categories based on the technologies used for browsing:

- more interested in traditional
- more interested in modern
- no bias

The website was redeveloped to act upon insights produced from the statistical analysis of browsing behaviour data. By collecting information about the OS and browser combination during the initial online contact and applying the knowledge of likely customer preferences, customers could be direct towards specific webpages tailored to meet their likely preferences. Customers benefited by quicker navigation to the products they were likely to be interested in, with a corresponding improvement in the "hits:design visit" ratio.

Considering the case carefully, it is clear that the analysis undertaken was relatively straightforward and might appear rather trivial. It could have been extended and refined considerably but the project was not intended to showcase analytic skills, but rather generate productivity improvements. The project generated growth in both revenue and profit, making the business more sustainable. This would not have been possible without the right question being asked and an association between variables being identified. Additionally it should be recognised that this was achieved with no investment other than the time of those involved.

Table 1. Case Study One. Hypotheses Testing.

H1 – There is association between product preference and the device used to browse	
H_0	Product preference and device are not associated
H_1	Product preference and device are associated
Significance Level	$\alpha = 0.05$
Pearson's Chi Square Test	$(\chi^2) = 509.2441896$
Test Statistics	$P = 2.6244 \times 10^{-111}$ Critical Test = 5.991464547
Evaluation	$(\chi^2) >$ Critical Test $p > \alpha$ From both tests Reject H_0 and accept H_1
H2 There is an association between product preference and the operating system used whilst browsing.	
H_0	Product preference and operating system are not associated
H_1	Product preference and operating system are associated
Significance Level	$\alpha = 0.05$
Pearson's Chi Square Test	$(\chi^2) = 839.9343174$
Test Statistics	$P = 4.4630 \times 10^{-177}$ Critical Test 14.06714045
Evaluation	$(\chi^2) >$ Critical Test $p > \alpha$ From both tests Reject H_0 and accept H_1
H3 There is an association between product preference and the browser used	
H_0	Product preference and browser are not associated
H_1	Product preference and browser are associated
Significance Level	$\alpha = 0.05$
Pearson's Chi Square Test	$(\chi^2) = 685.4852838$
Test Statistics	$P = 6\ 7527 \times 10^{-146}$ Critical Test 11.07049769
Evaluation	$(\chi^2) >$ Critical Test $p > \alpha$ From both tests Reject H_0 and accept H_1

DISCUSSION

In evaluating both Kranzberg's (1986) and Solow's (1987) statements, the two case studies demonstrate that business performance is only indirectly linked to technological innovation. Each case is discussed to show how it compares against key aspects of the literature, and what this could mean for other organisations as well as for the meaningful contribution of BD to business performance in general. Each case demonstrates different aspects of both the problems of dealing with the outcomes of technological innovation and the importance of human interaction for successful business performance. The evidence from both case studies confirms Jain and Kanungo's (2005) research findings - human interaction with technology and the resulting impact upon business performance is not straightforward.

Case Study One

This company had a vision to become the pre-eminent and most trusted UK provider in its sector. They had wanted to fulfil this ambition for a number of years. They held data on all the purchases and sales they had ever made since 1970 in every branch, from every channel. What they did not have was knowledge of what information a ''scientific analysis" of those figures could provide. The trigger for the project which gave them the necessary insight came from one of the managers who had been thinking about ways of gleaning more information from all the data. The questions he had been asking himself became the questions the company asked of the data. The first thing they found was that they were unable to answer those questions because of a classic BD challenge, one of the 3Vs (Laney, 2001). Variety was their big problem, caused by inconsistent, incomplete and inaccurate data. The data, whilst not quite unstructured, lacked a standardised company format and input was open to interpretation. The same products were differently captured on the system by each branch, creating a cleaning project first, then a project to systematically identically capture data throughout the organisation, regardless of product or channel.

The fact that internally-created data needed a project all to itself to cleanse the database highlighted a serious shortcoming with the company's data collection for management information purposes. It also highlighted that decisions had hitherto really only been taken piecemeal rather than organisationally, since the data had not actually supported company-wide decision-making. The difficulties encountered with inconsistent data emphasised to the management team the importance of reliability and robustness. The availability of accurate company-wide data showed how to maximise service levels through decision-making based on complete knowledge of long-term performance of new sales and used sales over a period of years. This echoes P. Bell (2013) and Hsinchun et al. (2012) much more than Brown et al. (2011), Manyika et al. (2011) or McAfee and Brynjolfsson (2012).

Clearly, their large dataset with all its variety problems indicated that the size of a dataset does not equate to its quality (Bisel et al., 2014; Lazer et al., 2014). Because the data was internally-generated, essentially for management and accounting information, this company did not contend with the issues around social media generated data and OCG systems (Jifa & Lingling, 2014). Nevertheless, they had a significant workload to ensure the veracity of the data they had in order to create truly usable information (Chongwatpol & Chan, 2015). In keeping with Chongwatpol and Chan (2015), this company created a clean dynamic data-set and changed internal processes to ensure future data collection would be accurate through standardised capture. This enabled them to find alternative ways to assess business issues and have informed decision-making. At last they were able to process data in a way "*useful for decisions and or action" (*Liew, 2007).

Case Study Two

The driver for this online kitchen retailer was to enhance the customer experience through delivering a tailored service. In this way they foresaw greater profitability through being able to increase clicks:sale conversions. Without the benefit of physical cues as in a traditional retail environment (Wise, 1974), real-time sales discrimination was impossible. An employee musing over the conundrum of finding things out about customers whilst knowing nothing about them eventually thought the data they had on customer access might prove useful. Whilst they knew nothing about the customer from the point of view of gender, clothing or ethnicity for instance, they did know how customers accessed the company website. This led to their two key questions, which were could this information be used to predict purchase type and spend, and if so, could the company bundle webpages in a way to make browsing easier and hit customer 'hot spots' sooner.

The organisation posed these questions into hypotheses and ran a number of tests to ascertain their veracity. Whilst hypothesis testing is a traditional testing method, the configuration of the data being tested in this way belongs very much in the domain of BD since it is about the capture of customer data based on the availability of technologies to customers, and process improvement through data analytics is not new, as many scholars have stated, including Walker et al. (2010) and Meyer et al.

(2014). From an analytics perspective, the chi-square test shows significance rather than the strength of the association, yet this company chose this method as their preferred way of gaining insight. Moreover, they were able to make choices and business decisions based on what the analysis revealed. They found a correlation between customer hardware (device) and operating system (browser). They used this new-found knowledge about their customer to compartmentalise them, 'customise' bundles of webpages and generate revenue and profit growth. Whilst Solow (1987) bemoaned the paucity of evidence that the computer age did not provide evidence of productivity gains, this case study shows that evidence, and performance gains, can be obtained.

This case highlights the importance of understanding what knowledge is required about the customer, combining this with fundamental knowledge about your product range and, most importantly, the value of asking interesting and insightful questions.

Overall Discussion

This research shows how technological innovation can be harnessed to improve business performance. Case 1 highlights the difficulties of inconsistent data and the importance of reliability and robustness. Case 2 highlighted the importance of knowing your customers and your products.

Both companies used internal data about committed customers to create competitive advantage. Unlike GFT (Lazer et al., 2014), where individuals other than those suffering flu would make searches about the topic, in this case the stream of data was a complete picture of the companies' customers and their behaviour. The use of BD techniques meant that is was unnecessary to draw samples of behaviour and try to use this to predict individual responses. By using BD techniques both companies were able to optimise management decisions based on a complete picture of the behaviour of their total customer base. It is also a true application of BD, whereas the GFT case, despite collating social media and other externally-generated data was actually using a population sample. Sampling and hypothesis-building is traditional data analysis, not BD, despite the constant stream of largely unstructured data created from multiple sources and in a range of formats which causes the BD analytics challenge (Bisel et al., 2014; Chen et al., 2012; Tinati et al., 2014).

In both cases organisational constraints restricted the scope of the analysis undertaken. Without access to advanced tools, both cases relied upon the initial inspiration of individual employees who were willing to interact with the data using nothing more than a spreadsheet and a passable understanding of statistics. The outcomes described would not have been realised had a member of staff not wondered about a particular problem and been willing to immerse themselves in the data. Modern software enables speedier computations and can facilitate 'pattern spotting' but it cannot decide what to look at, or indeed what questions to ask. So, far from being helpful BD has the potential to create misunderstandings and misdirection, of which numerous examples exist (Duhigg, 2012; Hazen, Boone, Ezell, & Jones-Farmer, 2014; Ilic et al., 2010; Lazer et al., 2014). Whilst technology is important and does create opportunities, it is our interaction with technology and our ability to see (and realise) opportunities which are essential. There is a clear need, for people with a level of curiosity, insight and skills to exploit the information that is now available. Solely relying on algorithms and system tools is unlikely to generate the productivity gains that are expected. The key challenge therefore is to identify the new skills people need in order to be able to maximise the potential BD offers and underlines the relevance of the GCHQ development (Philipson, 2014).

The case-specific points relate to the respective organisations, although they can generally be seen to be in keeping with the OECD (2013) suggestion and confirm the importance of developing the correct strategy to advantageously exploit the data (Opresnik & Taisch, 2015). There are also problems consistent with the core concerns of performance management which scholars have studied over many years (Ackoff, 1989; P. C. Bell, 1999; Kranzberg, 1986; Saaty, 2008). It is this aspect which has led to observations that BD is another step in data-driven improvement, following in the footsteps of SPC and then 6 Sigma (Madsen & Stenheim, 2013). This interpretation suggests that whilst BD and the internet increase the volume of data that can be accessed, many of the challenges related to handling data remain the same. Despite all the hype, the productivity gains emerging from the BD revolution might be less dramatic than we expect. How we interact with data which makes the difference. This research emphasises the importance of inquisitive ness and how people skills required for both interpreting data-sets and developing relevant, impactful insight.

CONCLUSION

This paper has explored the challenges and opportunities that BD offers. Through this exploration, it contributes to the body of empirical performance-based evidence regarding the application of BD (Fosso Wamba et al., 2015). Whilst there are limitations within both case studies, the research illustrates that there is promise in using BD to uncover previously unavailable insights for improved performance as long as it is coupled with curiosity and cognitive skills. The volume and variety of data available to organisations will undoubtedly continue to grow and technology will be increasingly important in handling the data. Limitless data does not guarantee better performance. The challenge remains in harnessing technology and interacting with the data it makes available to improve operational performance. Organisations and individuals need to learn how to use new technologies and develop the cognitive skills necessary to interact with the data it creates to generate the knowledge and wisdom required to manage processes within an increasingly connected, complex and rapidly changing world. These skills are emerging, but there remains a gap between the possibilities of new technology and the ability to generate productivity improvements, just as it did when Solow first pointed to his productivity paradox.

There are limitations to this research. Firstly, the chosen cases had their own data and analysis methods. These differed from each other. However, the authors found that the journey of each organisation illustrated well the struggle to interact meaningfully with technology and data in order to improve performance. Each case did so in their own way, with the skills and technologies available, along with a strong input of inquisitiveness. However, there are general conclusions which can be drawn about the impact of technological innovation on business performance.

Whilst technology can do many things faster and more reliably than people, more ‘real time’ data may mean greater confusion as people struggle to respond what can appear a constantly changing environment. This places greater demands upon us when we interact with data, and increases the need for “inference, imagination, integration and problem solving” to understand what is going on (Weick, 1990: 32). There needs to be a step change in competences for some of the tasks expected to be done as a matter of course in a connected world where data is everywhere. New data science skill-sets are required, because without insightful and curious employees able to interact effectively with a continuously changing dataset, more data cannot create greater productivity (Philipson, 2014). The key challenge is to identify the new skills people need in order to be able to maximise the potential BD offers. Until organisations have sufficient people with these skills continued technological innovation may do nothing to address Solow’s Paradox.

The insights from this research offer a useful starting point for understanding where and how organisations can respond to the opportunities offered by BD. Future organisational success, if not survival, may well be predicated not on the data available but our insightful interactions with the interconnected systems that generate it.

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