How Do Top- and Bottom-Performing Companies Differ in Using Business Analytics?

Purpose – Business analytics (BA) has attracted growing attention mainly due to the phenomena of Big Data. While studies suggest that BA positively affects organizational performance, there is a lack of academic research. This paper therefore examines the extent to which top- and bottom-performing companies differ regarding their use and organizational facilitation of BA.

Design/methodology/approach – Hypotheses are developed drawing on the information processing view and contingency theory, and tested using MANOVA to analyze data collected from 117 UK manufacture companies.

Findings – Top- and bottom-performing companies differ significantly in their use of BA, data-driven environment, and level of fit between BA and data-drain environment.

Practical implications – Extensive use of BA and data-driven decisions will lead to superior firm performance. Companies wishing to use BA to improve decision-making and performance need to develop relevant analytical strategy to guide BA activities and design its structure and business processes to embed BA activities.

Originality/value –This study provides useful management insights into the effective use of BA for improving organizational performance.

Keywords: *Business analytics; information processing view; contingency theory; data-driven environment; organizational performance; MANOVA*

1. Introduction

Business analytics (BA) refers to "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport and Harris 2007, p.7). While BA has been widely examined since 1950s (Davenport 2013), it has attracted growing attention recently (Chen et al. 2012; Holsapple et al. 2014; Watson 2014) mainly due to the emergence of Big Data. Arguably, the BA phenomenon needs to be examined in light of the following three key changes. First, BA is intertwined with big data (Davenport 2013), from which organizations use BA to gain data-driven insights. Second, in order to process big data effectively, BA builds upon new IT such as Hadoop, cloud services (Goes 2014), new agile analytical methods, and machine-learning techniques (Davenport 2013). Third, the confluence of big data, advances in IT, and BA has made it possible for organizations to make effective decisions based on data-driven insights that were previously invisible (Barton and Court 2012) and to move towards "territory which has historically been seen as reliant on human judgment" (Gillon *et al.* 2014, p.288). Kiron *et al.* (2014), for example, suggest that companies that use BA perform better than those that do not in creating competitive advantages and it is important for companies to step up the use of BA to make better business decisions thereby to create strategic value. Cao *et al.* (2015), based on a sample of 740 UK businesses, demonstrate that BA positively influences decision-making effectiveness and in order to use BA effectively, organizations need to develop a data-driven environment reflected by an "analytically driven strategy" (Davenport and Harris 2007), relevant business processes (Barton and Court 2012), and organizational structure (Acito and Khatri 2014).

BA's importance has been well recognized. A number of researchers examine factors affecting BA adoption (e.g. Amrita and Ravi 2016); others investigate the benefits and impact of BA on decision making (e.g. Sharma *et al.* 2014; Cao *et al.* 2015), operations and performance (e.g. Trkman *et al.* 2010; Bronzo *et al.* 2013; Schläfke *et al.* 2013; Mihalis and Michalis 2016), innovation (e.g. Kiron *et al.* 2012c), and competitive advantages (e.g. Klatt *et al.* 2011). However, there is still a paucity of academic research to provide either conceptual understanding of or empirical evidence on the use and facilitation of BA. In particular, no research exists to elucidate whether organizational performance difference is related to BA application difference and the extent to which BA can be affected by other organizational factors. The absence of such an understanding inevitably limits the abilities of organizations to fully understand and realize the benefits from their investments in BA. This paper therefore attempted to address the following research question: To what extent do top- and bottom-performing companies differ in using BA, having data-driven environment, and aligning BA and data-driven environment?

In order to answer this question, this paper developed a conceptual understanding of the organizational design choices around the BA phenomenon drawing on the information processing view of organizational design (Galbraith 1974; Tushman and Nadler 1978) and the association between BA and organizational factors based on contingency theory (Nadler and Tushman 1980; Tosi and Slocum 1984; Donaldson 2001). Although these two theories have been used by prior IT studies to understand the impact of IT on organizations, little research has been conducted to date to examine the BA phenomenon based on these two theories. Thus, this research seeks to contribute to the literature by developing an in-depth understanding of the relationship between company performance difference and the difference in the use and facilitation of BA. To test the proposed research hypotheses empirically, this paper uses multivariate analysis of variance (MANOVA) to analyze data collected from 117 UK manufacturing companies.

This paper's findings indicated that top-performing companies are more likely than bottom-performing companies to use various types of BA extensively, have better data-driven environment to facilitate BA applications, and have higher degree of fit between BA and organizational strategy, structure and process to better achieve organizational objectives. Therefore, this research adds to the growing body of empirical research that supports the information processing view and contingency theory. This research also contributes to managers' knowledge and understanding of BA and the facilitation of BA through appropriate organizational design choices thereby to improve organizational performance.

The structure of the paper is as follows. The next section presents the conceptualization and hypotheses. The subsequent section describes the data collection processes and reports on the empirical results. The final section discusses the results and implications.

2. Literature Review and Hypothesis Development

2.1 Business Analytics (BA) and BA taxonomies

BA consists of the processes and techniques of data analysis for the generation of knowledge and intelligence to support organizational decision-making (Davenport 2013). Since the concept of BA has a long history, it has been classified differently over time based on its key functionality, application domain, or evolution process to reflect technological evolution and emerging applications (Chen *et al.* 2012; Davenport 2013). For example, BA can be classified as descriptive, predictive, or prescriptive (Delen and Demirkan 2013) based on its key functionality or as web analytics, marketing analytics, customer analytics, and the like based on its application domain. From a technology evolution perspective, BA can be classified as Analytics 1.0 that refers to the era of "business intelligence", Analytics 2.0 that is the era of big data , and Analytics 3.0 that is the era of data-enriched offerings (Davenport 2013). Similarly, Chen *et al.* (2012) argue that BA, for which they use the term Business Intelligence & Analytics

(BI&A), has evolved from BI&A 1.0 (data base management system-based structured content), to BI&A 2.0 (web-based unstructured content) and BI&A 3.0 (mobile and sensor based content).

This paper understands BA in terms of descriptive, predictive, and prescriptive analytics (Delen and Demirkan 2013), which is intertwined with big data (Davenport 2013) and builds upon sophisticated IT (Davenport 2006) such as the scale-out architecture (Watson 2014), Hadoop, cloud services (Goes 2014), new “agile” analytical methods, and machine-learning techniques (Davenport 2013). Descriptive analytics uses, for example, business reporting and web analytics, to describe the context of and trending information on past or current events, answering what has happened and what is happening. Predictive analytics use, for example, forecasting and predictive modeling, to predict the future happenings and the reasoning as to why, answering what could happen. In addition, prescriptive analytics uses, for example, optimization, model management, and interactive data visualization, to prescribe one or more courses of action and shows the likely outcome of each decision, providing answers to what should we do. There is general indication that most organizations use descriptive analytics to various degrees while much fewer use prediction and prescription analytics (Davenport and Harris 2009; Davenport *et al.* 2011; Lavalle *et al.* 2011).

BA is seen to offer the possibilities for companies to be more effective at making strategic decisions (Cao *et al.* 2015), improving organizational performance (Bronzo *et al.* 2013), and creating competitive advantages (Davenport and Harris 2007). Four consecutive large scale questionnaire surveys have consistently showed that companies that use BA perform better than those that do not (Kiron and Shockley 2011; Lavalle *et al.* 2011; Kiron *et al.* 2012c, 2014). The findings from the latest survey suggest that 87% of respondents strongly or somewhat agree that it is important for their organizations to step up the use of BA to make better business decisions (Kiron *et al.* 2014). Focusing on the manufacturing industry, studies suggest that BA can be used to obtain insights into customer behavior trends and preferences (Dutta and Bose 2015; Opresnik and Taisch 2015), which enables manufacturers to improve product development, demand forecasting, supply chain planning, sales support, and production operations, thereby to achieve “dramatic improvements” or “substantial wave of gains” (Manyika *et al.* 2011).

2.2 Conceptual Foundations

In order to understand the extent to which top- and bottom-performing company differ in their use and facilitation of BA, this paper draws on the information processing view of organizational design (Galbraith 1974; Tushman and Nadler 1978) and contingency theory (Nadler and Tushman 1980; Tosi and Slocum 1984; Donaldson 2001).

Organizational design may include designing organizational structure–the degree and type of horizontal and vertical differentiation, mechanisms of coordination and control, formalization and centralization of power (Greenwood and Hinings 1993) and organizational processes–the routines that transform certain inputs into outputs of value to customers (Hammer 1996). The information processing view advocates that an organization needs to design for example its structure and processes (Galbraith 1974; Tushman and Nadler 1978; Premkumar *et al.* 2005) so that it can match its information processing capabilities to its information processing requirements, thereby to inform its decision-making and ultimately improve its performance. Galbraith (1974) argues that organizations must adopt one or some combination of four organizational designs to improve information processing: creating slack resources to reduce the amount of interdependence between organizational subunits thereby to reduce the requirement of information processing, creating self-contained tasks by changing the authority structure thereby to reduce the amount of information processed, investing in vertical information systems to increase the capacity to acquire and process information, and creating lateral relationships for information processing by employing selectively joint decision processes that cut across lines of authority. Similarly, Daft and Lengel (1986) argue that an organization can design its structure to meet its information processing requirements because organizational structure determines what information will be provided to managers and thus the coordination and control of organizational activities. Focusing on how strategic issues are interpreted, Thomas and McDaniel (1990) demonstrate that structural characteristics could facilitate information processing and use of information. They suggest that low level of formalization and low use of standard procedures facilitate a high level of information processing while high level of formalization and high use of standard procedures restrict information processing. However, top management team without an information processing structure could experience information overload. Therefore, they propose that information processing structure is related to the process of translating data into knowledge and understanding of strategic issues by top management teams in different organizations. Premkumar *et al.* (2005) and Wang *et al.* (2013), on the other hand, focusing on designing business processes in the context of supply chain management, demonstrate that the interactive effect of information processing needs and information processing capabilities has a significant positive effect on organizational performance. While the relationship between organizational designs and performance is generally accepted, certain design choices maybe more or less effective depending on the strategy of the organization (Rockart *et al.* 1996; Fairbank *et al.* 2006). Fairbank *et al.* (2006) demonstrate that for example the association between information processing design choices and organizational performance is moderated by organizational strategy in life and health insurance companies. While the information processing view provides a theoretical foundation to help understand the relationship between organizational design, information processing, decision-making, and performance, there is no research conducted to test this view empirically in the BA context and this paper attempts to fill this research gap.

A number of practice-oriented BA studies have also suggested ideas that are seen to be consistent with the information processing view. For example, it is suggested that in order to use BA effectively, companies need to develop an "analytically driven strategy" (Davenport and Harris 2007), relevant business processes (Barton and Court 2012), or organizational structure (Acito and Khatri 2014; Gillon *et al.* 2014).

Drawing on the information processing view and existing BA studies, a company can be expected to be more likely to use BA effectively when it has developed explicit strategy to guide analytic activities and designed its structure and processes to enable BA applications to form a data-driven environment (Cao *et al.* 2015); consequently, such companies are expected to make data-driven decisions and to be top-performing companies in terms of their financial outcomes. On the contrary, without developing such a data-driven environment, "a company will not know on which data to focus, how to allocate analytic resources, or what it is trying to accomplish in a data-to-knowledge initiative" (Davenport *et al.* 2001, p. 122); accordingly, such companies are less likely to make data-driven decisions and are more likely to be bottom-performing companies. Thus, drawing on the information processing view, it is conceivable to conjecture that a company will be able to perform better when its BA applications are supported by a data-driven environment to embed BA into relevant organizational strategy, structure and processes.

Hypothesis 1. Top-performing companies are more likely than bottom-performing companies to have a better data-driven environment.

Hypothesis 2a. Top-performing companies are more likely than bottom-performing companies to use descriptive analytics more extensively.

Hypothesis 2b. Top-performing companies are more likely than bottom-performing companies to use predictive analytics more extensively.

Hypothesis 2c. Top-performing companies are more likely than bottom-performing companies to use prescriptive analytics more extensively.

Hypothesis 3. Top-performing companies are more likely than bottom-performing companies to make data-driven decisions.

In essence, the information processing view is rooted in contingency theory (Tushman and Nadler 1978; Donaldson 2001; Fairbank *et al.* 2006) to examine the specific fit between an organization's information processing capability and its information processing requirements through organizational design choices (Egelhoff 1982; Huber 1990). While this view can help us understand why organizational design choices may facilitate the use of BA and thus improve organizational performance, however, there are other fit relationships such as the fit between BA and organizational strategy, structure, and process that may significantly affect the use and facilitation of BA. In order to gain insights into these fit relationships, this paper also draws on contingency theory itself and IT studies based on contingency theory, which are seen to be most applicable.

The common proposition of contingency theory is that organizational outcome is the consequence of "fit" or match between two or more factors such as structure, technology, and strategy (Tosi and Slocum 1984; Van de Ven and Drazin 1984) while fit is "the degree to which the needs, demands, goals, objectives, and/or structures of one component are consistent with the needs, demands, goals, objectives, and/or structures of another component" (Nadler and Tushman 1980, pp. 45). IT studies have broadly applied this concept to investigate the performance impact of the fit relationship between IT and various organizational factors (e.g. Weill and Olson 1989; Chan and Reich 2007), which has long been of major concern of senior managers (Zviran 1990). For example, strategic IT alignment (fit) is seen to enable an organization to develop IT applications most critical to achieving its business strategy and the lack of strategic IT alignment often leads to failed IT investments (Lederer and Mendelow 1989; Chan and Reich 2007). IT alignment can positively affect business performance (Gerow *et al.* 2014) and is an important factor in differentiating from competition (Bharadwaj 2000) and achieving competitive advantage (Lederer and Mendelow 1989). Without IT alignment, IT investment might not reflect the overall strategic direction of an organization, resulting in lower returns and erosion of the firm's competitive position (Kearns and Sabherwal 2006).

BA is intertwined with big data and builds on sophisticated IT (Davenport 2006, 2013; Goes 2014; Watson 2014) and prior BA studies have indicated that in order for a company to benefit from BA, simultaneously the company needs to develop a data-driven environment to support BA applications (Davenport and Harris 2007; Lavalle *et al.* 2011; Barton and Court 2012; Kiron *et al.* 2012c; Acito and Khatri 2014), which is reflected by an analytically driven strategy, relevant business processes and organizational structure (Cao *et al.* 2015). Thus, the association between BA and a data-driven environment could be similarly examined in terms of fit, drawing on IT studies underpinned by contingency theory. It can be expected that when a company has developed a data-driven environment to enable BA activities, a high degree of fit has been achieved: BA will help provide data-driven insight while a data-driven environment ensures that this insight is used to support decision-making with maximum effect. Therefore, it is anticipated that a company with a higher degree of fit between its BA and data-driven environment will outperform those with lower degree of fit; and the better the fit, the better the performance. In line with this view, it is plausible that top-performing companies should have a higher degree of fit between BA and data-driven environment than bottom-performing companies. Thus, it is posited:

Hypothesis 4a. Top-performing companies have a higher degree of fit between BA and organizational strategy than bottom-performing companies.

Hypothesis 4b. Top-performing companies have a higher degree of fit between BA and organizational structure than bottom-performing companies.

Hypothesis 4c. Top-performing companies have a higher degree of fit between BA and organizational process than bottom-performing companies.

As a result, the above hypotheses can be generally summarized in the following research model (Figure 1).

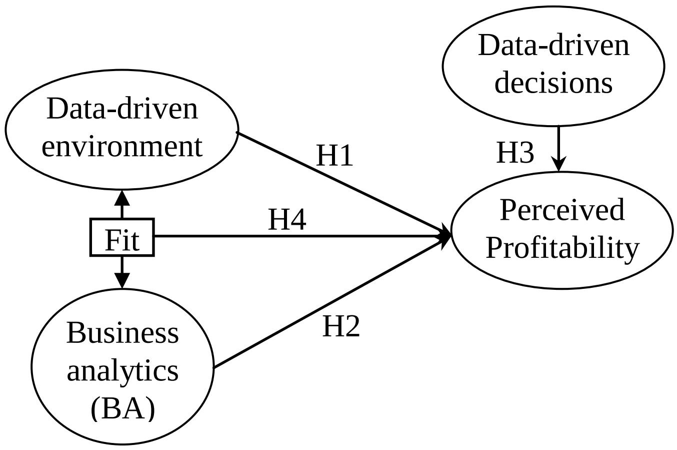

Figure 1. Research model

3. Research Methodology

The hypotheses were empirically tested based on data collected from UK manufacturers. In order to achieve the research objectives, this paper only considered top- and bottom-performing companies selected from all responding companies. Performance was measured by the perceived profitability using the following question: to what extent do you agree that you are more effective than your competitors at generating profit (1 – highly disagree to 5- highly agree). While organizational performance can be measured in terms of a number of different indicators, a firm's profitability relative to its competitors is one major determinant of firm performance (Hansen and Wernerfelt 1989). Consistent with prior research on firm performance (Newbert 2008; Ngo and O'Cass 2013), perceived relative profitability was used to differentiate top- and bottom performing companies in this study. According to the values of the perceived performance scored on the five-point Likert scale, Group 1 included top-performing companies with a score of 4 or 5 and Group 2 included bottom-performing companies with a score of 1 or 2. Companies scored 3 were not included in the analysis.

MANOVA was performed to investigate the differences between top- and bottom-performing companies in using BA, having data-driven environment, and aligning BA and data-driven environment. The independent variable was performance. Three dependent variables were used: BA, data-driven environment, and data-driven decision-making, each was a combination of several variables. BA was a combination of descriptive analytics, predictive analytics, and prescriptive analytics; data-driven environment was a combination of organizational strategy, structure and process; and data-driven decision making was a combination of depending on data-based insights to support decision making and creating new service/product using data-based insights.

The advantages of MANOVA are that it is able to assess group differences across multiple metric dependent variables such as descriptive analytics, predictive analytics, and prescriptive analytics simultaneously (Hair et al. 2010). Additionally, MANOVA is suitable when multiple dependent variables are to be considered as it can take into account the intercorrelation among the multiple dependent variables and reduce the possibility of Type 1 and 2 errors (Haase and Ellis 1987).

Thus, MANOVA was used to test whether the mean differences between top- and bottom-perming companies on the combination of multiple dependent variables were likely to have occurred by chance. If the two groups were statistically different based on post-hoc tests (LSD), an analysis of the odds ratio of high scores was conducted to examine to what extent the two groups differed with respect to each of the dependent variable.

3.1 Data collection

The target population for the survey was the UK manufacturing companies. The UK is currently the 11^{th} largest manufacturing nation in the world and its manufacturing sector accounts for about 8.5% of the UK workforce, 54% of the exports, and 12% of the country's national output. While this industry is relatively efficient and in relative decline (PWC 2009), it faces considerable challenge of generating significant productivity improvement. There is also indication that this industry has been slow in incorporating BA (Dutta and Bose 2015) and only a small fraction of them are currently using BA in the areas of operations and across their supply chains (Sanders and Ganeshan 2015). Hence, understanding how to use BA to improve organizational performance is of enormous use to practitioners in the manufacturing sector and academics alike.

To test the hypotheses empirically, a questionnaire survey using a five-point Likert scale was conducted to collect responses from medium-sized (number of employees between 50 and 249 inclusive) and large UK manufacturing companies (250 or more employees) as they are expected to have the "capabilities" and "substantial resources" to employ various types of BA for business improvement (Gillon et al. 2014). The survey instruments were developed based on the literature review and definitions discussed above and then were scrutinized 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, which resulted in a few minor formatting and presentation modifications. The survey questionnaire was then delivered electronically through Qualtrics to managers, whose email addresses are identified from the FAME (Financial Analysis Made Easy) database that includes companies in the UK and Ireland (FAME 2016). Three rounds, four weeks apart, of emails including a cover letter with a questionnaire were sent. Each intended respondent was offered a summary of the results. While a total of 21,149 emails were sent to managers in these companies (one recipient was identified for each company), Qualtrics software does not provide information about how many e-mails were actually received or read by the recipients. Of all sent emails, 782 surveys were opened and 232 usable responses were received, from which 117 top- and bottom-performing companies were selected based on the respondents' perceived performance assessment (see details in section 4.1). Regarding calculating the response rate, the literature provides no agreed methods for doing this with mass email surveys. Based on the number of emails sent (21,149) and the useable responses (232) received, the response rate is 1%; based on the number of opened surveys (782) and usable responses (232) received, the response rate is 30%. However, none of these rates is considered to be accurate due to the reasons explained.

3.2 Data-screening and MANOVA assumption testing

Data screening was performed using SPSS21. Observations where the missing data exceeded 10% were removed (Hair *et al.* 2010). The remaining data set still had missing values but less than 5% on a single variable, which is of little concern (Amabile 1983). As a result, 252 responses received were reduced to 232 usable responses. However, for the purpose of this research, 117 top- and bottom-performing companies were selected.

In order to proceed with the main MANOVA analysis, data were examined to test whether they conformed to the assumptions regarding sample size, normality, outliers, linearity, homogeneity, and multicollinearity (Hair *et al.* 2010). Sample size requirement was met since the smallest individual group size was 52 (Table III) that is greater than the number of dependent variables in this research. This sample size also ensured the MANOVA results to be reasonably robust (Tabachnick and Fidell 2007). The multivariate normality was satisfactory based on the Mahalanobis distance score: only one case was found to be a multivariate outlier. The assumption of linearity was confirmed as the matrix of scatterplots generated showed no obvious evidence of non-linearity. Homogeneity was confirmed by Box's Test of Equality of

Covariance Matrices. Finally, a correlation was run to check for multicollinearity, which indicated that dependent variables were moderately correlated.

3.3 Respondents

The reported positions of the respondents suggested that 26% of the respondents were in a senior managerial position and the rest of them were directors of various departments such as finance or accounting (13%), operations (13%), marketing and sales (11%), and IT (8%). Of all respondents, 49% had been with their firms for more than 10 years, whilst 86% had been in the industry for more than 10 years. Based on their managerial positions and experiences, the respondents were highly likely to participate in decision-making processes related to the topic of the survey (Phillips and Bagozzi 1986).

3.4 Common Method and Non-respondent Bias

In order to control for method bias, which compromises the validity of research conclusions (Podsakoff *et al.* 2003), this research used both procedural and statistical remedies. The procedural remedy used was to improve scale items, especially unfamiliar items, through defining them clearly and keeping the questions simple and specific thereby to eliminate ambiguity. In addition, rather than just labeling the end points, every point on the response scale was labeled, which also helps reduce item ambiguity (Krosnick 1999).

Additionally, Harman's single-factor was conducted as a statistical remedy to assess common method bias that may affect the true correlations between variables and cause biased parameter estimates (Malhotra *et al.* 2007). The test was conducted to assess whether the common method variance associated with the data was high by entering all independent and dependent variables (Podsakoff *et al.* 2003). If a single factor explains most of the variance of all the indicators, then common method bias associated with the data is high. Conversely, if more than one factor emerges to explain most of the variances, then the common method variance is low. The test result indicated that the first factor accounted for 33.90% of the total variance; thus, 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).

3.5 Constructs and Measures

Based on BA research (Kiron and Shockley 2011; Davenport 2013; Cao *et al.* 2015), this paper measured a company's data-driven environment in terms of having a well-defined organizational structure to enable analytical activities, analytical activities being integrated into business processes, and guided by organizational strategy. Based on Delen and Demirkan (2013), this paper measured descriptive analytics in terms of the use of statistical analysis, business reporting, query and analysis, spreadsheet, and web analytics; predictive analytics with regard to the use of data and text mining, forecasting, and predictive modeling; and prescriptive analytics with reference to the use of optimization, simulation and scenario development, model management, and interactive data visualization. Finally, this paper measured organizational performance with regard to perceived profitability comparing to key competitors. The descriptive statistics of the research variables are presented in Table I.

4. Main Findings

The main findings are summarized next, including the perceived profitability differences in data-driven environment and BA applications, and the degree differences of fit between BA and data-driven environment. An analysis of the odds ratio of high scores was also performed to examine to what extent the groups differed when they were statistically distinguishable.

TABLE I. DESCRIPTIVE STATISTICS (N = 117)

Variables (measured by five-point scales: 1-strongly disagree to 5-strongly agree)	Mean	S.D.
Data-driven environment		
Organizational structure developed to enable analytical activities	2.879	1.058
Processes well-developed to embed analytical activities	3.000	1.089
Organizational strategy developed to guide analytical activities	2.914	1.082
Descriptive analytics		
Statistical analysis	2.914	1.387
Business reporting	2.909	1.725
Query and analysis	2.815	1.404
Spreadsheet	2.810	1.821
Web analytics	2.810	1.319
Predictive analytics		
Data and text mining	2.927	1.319
Forecasting	2.823	1.601
Predictive modeling	2.875	1.325
Prescriptive analytics		
Optimization	2.853	1.204
Simulation and scenario development	2.987	1.236
Model management	2.819	1.381
Interactive data visualization	2.996	1.416
Data-driven decision-making		
Depending on data-based insights to support decision making	2.987	1.186
Creating new service/product using data-based insights	3.022	1.179
Perceived profitability comparing to key competitors	2.948	0.851

4.1 Differences in BA Applications and Data-Driven Environment

In order to test Hypotheses 1 to 3, the participating companies were divided into top- and bottom- performing groups according to the respondents' perceived profitability comparing to key competitors scored from 1 to 5 on a five-point Likert scale: Group 1 including top-performing companies (n = 52) with a score of 4 or 5 (M = 4.173, SD = 0.378), Group 2 including bottom-performing companies (n = 65) with a score of 1 or 2 (M = 1.877, SD = 0.328). Companies with a score of 3 (n=115) were considered as medium-performing companies and excluded in our analysis. A one-way MANOVA was performed to investigate perceived profitability differences in data-driven environment, descriptive analytics, predictive analytics, prescriptive analytics, and data-driven decision-making. Preliminary assumption testing was conducted to check for normality, outliers, linearity, homogeneity, and multicollinearity, with no serious violations noted. The multivariate tests with respect to perceived profitability are summarized in Table II.

TABLE II. MULTIVARIATE TESTS (PERCEIVED PROFITABILITY)

Variables	Pillai's Trace	F	*p*-value	partial η^2
Data-driven environment	0.081	3.224	0.004	0.041
Descriptive analytics	0.231	5.893	0.000	0.115
Predictive analytics	0.126	5.110	0.000	0.063
Prescriptive analytics	0.041	1.202	0.296	0.021
Data-driven decision-making	0.151	9.371	0.000	0.076

While all effect sizes (partial η^2) are small (Hair *et al.* 2010), there was a statistically significant difference between the two groups on descriptive analytics, predictive analytics, data-driven decision-making, and data-driven environment that is a combination of organizational strategy, structure and process; however, there was no statistically significant difference between the two groups on prescriptive analytics. The tests of between-subject effects are summarized in Table III.

TABLE III. TESTS OF BETWEEN-SUBJECT EFFECTS (PERCEIVED PROFITABILITY)

Variables	Group 1 (n=52)		Group 2 (n = 65)		F	Partial η^2
	Mean	S.D.	Mean	S.D.		
Data-driven environment						
Organizational structure developed to enable analytical activities	3.250	1.186	2.600	0.981	5.682^{**}	0.047
Processes well-developed to embed analytical activities	3.423	1.091	2.585	1.074	9.377^{***}	0.059
Organizational strategy developed to guide analytical activities	3.308	1.058	2.569	1.045	7.117^{***}	0.076
Descriptive analytics						
Statistical analysis	3.385	1.360	2.523	1.288	5.811^{***}	0.048
Business reporting	3.962	1.428	2.015	1.386	21.734^{***}	0.160
Query and analysis	3.673	1.279	2.108	1.147	21.216^{***}	0.156
Spreadsheet	3.981	1.540	1.908	1.497	22.178^{***}	0.162
Web analytics	3.077	1.311	2.677	1.300	1.469^{ns}	0.013
Predictive analytics						
Data and text mining	3.000	1.314	3.000	1.436	0.362^{ns}	0.003
Forecasting	3.615	1.484	2.077	1.373	15.188^{***}	0.117
Predictive modeling	2.827	1.339	2.908	1.343	0.054^{ns}	0.000
Prescriptive analytics						
Optimization	2.942	1.259	2.708	1.234	0.686^{ns}	0.006
Simulation and scenario development	3.077	1.384	3.077	1.190	0.622^{ns}	0.005
Model management	2.673	1.382	2.908	1.320	0.430^{ns}	0.004
Interactive data visualization	3.096	1.347	3.154	1.395	1.059^{ns}	0.009
Data-driven decision-making						
Depending on data-based insights to support decision making	3.731	0.992	2.462	1.017	19.307^{***}	0.144
Creating new service/product using data-based insights	3.596	1.176	2.738	1.179	9.058^{***}	0.073

^{ns}-not significant, **-p<0.01 ***-p<0.001

Regarding data-driven environment, descriptive analytics, predictive analytics, and data-driven decision-making respectively, the results of post-hoc tests (LSD) indicated that Group 1 and Group 2 were statistically distinguishable while all effect sizes (partial η^2) were small (Hair *et al.* 2010). In order to examine to what extent the two groups differed with respect to each of the dependent variables, an analysis of the odds ratio of high scores was performed. The odds ratio of high scores (4 and 5) in Group1 to high scores (4 and 5) in Group 2 was calculated and summarized in Table IV.

TABLE IV. THE ODDS RATIO OF HIGH SCORE IN GROUP 1/GROUP 2 (PERCEIVED PROFITABILITY)

Variables	Group 1 (n=52)		Group 2 (n = 65)		b/d
	No of high scores (a)	b=a/(52-a)	No of high scores (c)	d=c/(65-c)	
Data-driven environment					
Organizational structure developed to enable analytical activities	24	0.857	15	0.300	2.86
Processes well-developed to embed analytical activities	30	1.364	18	0.383	3.56
Organizational strategy developed to guide analytical activities	26	1.000	16	0.327	3.06
Descriptive analytics					
Statistical analysis	27	1.080	15	0.3	3.60
Business reporting	38	2.714	12	0.226	12.00
Query and analysis	31	1.476	11	0.204	7.24
Spreadsheet	31	1.476	12	0.226	6.53
Predictive analytics					
Forecasting	31	1.476	13	0.25	5.90
Data-driven decision-making					
Depending on data-based insights to support decision making	34	1.889	13	0.25	7.56
Creating new service/product using data-based insights	33	1.737	16	0.327	5.31

The odds ratio suggested that compared with bottom-performing companies, top-performing companies were 2.86 times more likely to have developed organizational structure to enable analytical activities, 3.56 times more likely to have developed process to embed analytical activities, 3.06 times more likely to have developed strategy to guide analytical activities, 3.60 times more likely to use statistical analysis, 12.00 times more likely to use business reporting, 7.24 times more likely to use query and analysis, 6.53 times more likely to use spreadsheet, 5.9 times more likely to use forecasting, 7.56 times more likely to make data-driven decisions, and 5.31 times more likely to create new service or product using data-based insights.

4.2 Different Degrees of Fit between BA and Data-driven Environment

In order to test Hypotheses 4a to 4c, MANOVA was performed to examine if different types of BA and organizational strategy, structure, and process were correlated separately within either top- or bottom-performing companies. As each group is already organized in terms of performance, there is no need to explicitly evaluate the impact of fit on performance. If statistical correlation between different types of BA and organizational strategy, structure, and process respectively exists, then there is fit between the two elements.

To test if descriptive analytics was correlated with organizational strategy, structure, and process separately, one-way MANOVAs were performed with Group 1 and Group 2 separately. The results summarized in Table V indicate within top-performing companies, descriptive analytics had a statistically significant correlation with organizational strategy, process, and structure. Within bottom-performing companies, descriptive analytics was correlated with organizational structure and process but not with strategy. As Group 1 had 52 and Group 2 had 65 companies, all effect sizes (partial η^2) were larger than small (Hair *et al.* 2010).

TABLE V. MULTIVARIATE TESTS (GROUP1 N=52/GROUP 2 N=65) (DESCRIPTIVE ANALYTICS)

Variables	Pillai's Trace	F	*p-value*	partial η2
	Group 1 / Group 2	Group 1 / Group 2	Group 1 / Group 2	Group 1 / Group 2
Organizational strategy developed to guide analytical activities	0.397 / 0.222	2.277 / 1.475	*0.020* / 0.157ns*	0.198 / 0.111
Organizational structure developed to enable analytical activities	0.435 / 0.344	2.556 / 2.455	*0.009** / 0.011**	0.217 / 0.172
Organizational processes developed to embed analytical activities	0.514 / 0.302	3.184 / 2.098	*0.002** / 0.030**	0.257 / 0.151

In order to test if forecasting, which is significantly correlated with the perceived performance as shown in table III, was correlated with organizational strategy, structure, and process separately, one-way ANOVAs were performed with Group 1 and Group 2 separately. The results summarized in Table VI indicate forecasting had a statistically significant correlation only with organizational process within either top- or bottom-performing companies.

TABLE VI. MULTIVARIATE TESTS (GROUP1 N=52/GROUP 2 N=65) (FORECASTING)

Variables	F	*p*-value
	Group 1 / Group 2	Group1 / Group 2
Organizational strategy developed to guide analytical activities	2.823 / 0.916	0.069^{ns} / 0.405^{ns}
Organizational structure developed to enable analytical activities	2.387 / 0.954	0.102^{ns} / 0.391^{ns}
Organizational processes developed to embed analytical activities	3.195 / 3.202	0.050^{*} / 0.047^{*}

4.3 Hypothesis Testing

Table VII summarizes the testing results of all hypotheses.

TABLE VII. SUMMARY RESULTS OF HYPOTHESES TESTING

Hypothesis	Empirical evidence
Hypothesis 1. Top-performing companies are more likely than bottom-performing companies to have a data-driven environment.	Yes
Hypothesis 2a. Top-performing companies are more likely than bottom-performing companies to use descriptive analytics more extensively.	Yes
Hypothesis 2b. Top-performing companies are more likely than bottom-performing companies to use predictive analytics more extensively.	Partially
Hypothesis 2c. Top-performing companies are more likely than bottom-performing companies to use prescriptive analytics more extensively.	No
Hypothesis 3. Top-performing companies are more likely than bottom-performing companies to make data-driven decisions.	Yes
Hypothesis 4a. Top-performing companies have a higher degree of fit between BA and organizational strategy than bottom-performing companies.	Partially
Hypothesis 4b. Top-performing companies have a higher degree of fit between BA and organizational structure than bottom-performing companies.	Partially
Hypothesis 4c. Top-performing companies have a higher degree of fit between BA and organizational process than bottom-performing companies.	Partially

Hypothesis 1 suggests that top-performing companies are more likely than bottom-performing companies to have a better data-driven environment, which is supported by the empirical evidence. Table II suggests that data-driven environment and perceive profitability is statistically related. The results of post-hoc tests (LSD) summarized in Table III indicate that top-performing companies (Group 1) and bottom-performing companies (Group 2) are statistically distinguishable with regards to data-driven environment, while the odds ratio (Table IV) suggests that top-performing companies are 2.86 to 3.06 times more likely than bottom-performing companies to have a better data-driven environment.

Hypotheses 2a suggests that top-performing companies are more likely than bottom-performing companies to use descriptive analytics more extensively, which is supported by the empirical evidences. Table II suggests that descriptive analytics and perceive profitability is statistically related. The results of post-hoc tests (LSD) summarized in Table III indicate that top-performing companies (Group 1) and bottom-performing companies (Group 2) are statistically distinguishable regarding descriptive analytics, while the odds ratio (Table IV) suggests that top-performing companies are 3.60 to 12.00 times more likely than bottom-performing companies to use various types of descriptive analytics.

Hypotheses 2b proposes that top-performing companies are more likely than bottom-performing companies to use predictive analytics more extensively, which is only partially supported. Table II suggests that predictive analytics and perceive profitability is statistically related. The results of post-hoc tests (LSD) summarized in Table III indicate that top-performing companies (Group 1) and bottom-performing companies (Group 2) are only statistically distinguishable regarding forecasting, while the odds ratio (Table IV) suggests that top-performing companies are 5.90 times more likely than bottom-performing companies to use forecasting.

Hypothesis 2c suggests that top-performing companies are more likely than bottom-performing companies to use prescriptive analytics more extensively, which is rejected. Table II suggests that prescriptive analytics and perceive profitability is not statistically related. Table III indicates that top-performing companies (Group 1) and bottom-performing companies (Group 2) are not statistically distinguishable regarding prescriptive analytics.

Hypothesis 3 proposes that top-performing companies are more likely than bottom-performing companies to make data-driven decisions, which is supported. Table II suggests that data-driven decision is statistically related to perceive profitability. Table III indicates that top-performing companies (Group 1) and bottom-performing companies (Group 2) are statistically distinguishable regarding data-driven decision, while Table IV suggests that top-performing companies are 5.31 to 7.56 times more likely than bottom-performing companies to make data-driven decisions.

Hypothesis 4a suggests that top-performing companies have a higher degree of fit between BA and organizational strategy than bottom-performing companies, which is only partially supported. Table V indicates that top-performing companies have a statistically significant correlation between descriptive analytics and organizational strategy, while bottom-performing companies have no such statistically significant correlation. However, Table VI indicates that both top- and bottom-performing companies have no statistically significant correlation between forecasting and organizational strategy. Prescriptive analytics related fit was not tested as top- and bottom-performing companies were indistinguishable with respect to the use of prescriptive analytics.

Hypothesis 4b suggests that top-performing companies have a higher degree of fit between BA and organizational structure than bottom-performing companies, which is partially supported. Table V indicates that both top- and bottom-performing companies have a statistically significant correlation between descriptive analytics and organizational structure, while top-performing companies have a larger effect size (p=0.009, partial η^2=0.217) than bottom-performing companies (p=0.011, partial η^2=0.172). Table VI indicates that both top- and bottom-performing companies have no statistically significant correlation between forecasting and organizational structure.

Finally, Hypothesis 4c suggests that top-performing companies have a higher degree of fit between BA and organizational process than bottom-performing companies, which is also partially supported. Table V indicates that both top- and bottom-performing companies have a statistically significant correlation between descriptive analytics and organizational process, the effect size of top-performing companies is larger (p=0.002, partial η^2=0.257) than that of bottom-performing companies (p=0.030, partial η^2=0.151). Additionally, Table VI indicates that both top- and bottom-performing companies have statistically significant correlation between forecasting and organizational process.

5. Conclusions

The main objective of this study was to understand the extent to which top- and bottom-performing companies differ regarding their use and organizational facilitation of BA. Almost all hypotheses except hypothesis 2c are supported by the model testing results. The findings suggest that in the UK manufacturing industry top- and bottom-performing companies are significantly different with reference to their BA applications (except prescriptive analytics), data-driven environment, and the fit between BA and data-driven environment. However, there are particularities to be further discussed. More specifically, the following contributions have been made.

5.1 Theoretical contributions

While prior BA studies suggest that companies that use BA perform better than those that do not and in order to use BA effectively companies need to develop a data-driven environment, no research is conducted to examine how top- and bottom- performing companies differ in their use and facilitation of BA. The findings from this research provided an in-depth and focused understanding of these issues.

First, this paper contributes to the information processing view by developing an understanding of the relationship between organizational design choices around BA applications and organizational performance. Compared with bottom-performing companies, top-performing companies use BA more coherently by creating a data-driven environment to support and enable the use of BA. Specifically, an analytical strategy is often developed to guide the use of BA; relevant organizational structure and process are also designed to embed BA. These organizational design choices arguably have facilitated organizational decision-making. The research findings show that top-performing companies are 3.60 to 12.00 times more than bottom-performers to use descriptive analytics to describe what has happened and what is happening and forecasting to predict what could happen. As a result of having reliable and accurate information and business insights, top-performing companies are 5.31 to 7.56 times more likely than bottom-performing companies to make data-driven decisions, which are expected to significantly improve organizational performance. Therefore, this research adds to the growing body of empirical research that supports the information processing view. It demonstrates that organizational design choices associated with BA applications are essential for companies to match their information requirements and processing to inform decision-making thereby to improve organizational performance (Galbraith 1974; Tushman and Nadler 1978). While there are a few studies (e.g. Premkumar *et al.* 2005; Fairbank *et al.* 2006; Wang *et al.* 2013) in other organizational areas to provide empirical support for the information processing view, this paper is among the first to understand the BA phenomenon drawing on, and thus to provide empirical support for, the information processing view.

Second, this paper contributes to contingency theory by demonstrating the importance of achieving appropriate fit between BA and data-driven environment in improving organizational performance. While prior studies have broadly investigated the performance impact of the fit relationship between IT and various organizational factors, limited academic research has examined the performance impact of fit between BA and organizational factors. This research indicates that compared with bottom-performing companies, top-performing companies tend to have a higher degree of fit between BA and organizational strategy, structure, and process. Specifically, top-performing companies tend to have developed relevant analytical strategy to guide BA activities to develop a comprehensive understanding of what has happened and what is happening using various types of descriptive analytics and what could happen using forecasting. This strategic fit arguably allows top-performing companies to identify data-driven insights to make effective decisions thereby to better achieve business strategies, which is consistent with the view of Davenport and Harris (2007). They also tend to have embedded BA activities into relevant structure and core business processes such as operational and decision routines thus the speed and impact of data-driven decisions could be increased thereby to significantly improve organizational performance. This is seen to provide empirical support to the claims made by relevant BA studies (e.g. Barton and Court 2012; Kiron *et al.* 2012a; Davenport 2013). Bottom-performing companies, on the contrary, showed lower degree of fit between BA and organizational strategy, structure and processes, which might be the reason why companies perform poorly since they are unlikely to allocate analytical resources effectively and to design operational and decision processes to embed BA activities (Davenport *et al.* 2001). Hence, this research adds to contingency theory empirically by demonstrating that appropriate fit between BA and organizational factors could have a positive impact on organizational performance.

In addition to developing a conceptual understanding of BA drawing on the information processing view and contingency theory, this paper contributes to the literature on BA by providing empirical evidence in support of the ideas that companies that use BA perform better than those that do not (e.g. Kiron *et al.* 2014) and that the effective use of BA requires the development of relevant analytical strategy, organizational structure and processes (e.g. Davenport and Harris 2007; Barton and Court 2012; Acito and Khatri 2014). In particular, this research supports the idea that manufacturing companies could use BA to obtain data-driven insights into customer behavior trends and preferences (Dutta and Bose 2015; Opresnik and Taisch 2015), thus to improve for example product development, supply chain planning, sales support, and production operations, and ultimately organizational performance (Manyika *et al.* 2011). However, there is no statistical difference between top- and bottom-performing companies with respect to the use of prescriptive analytics and two types of predictive analytics: data and text mining and predictive modeling. This result is seen to be consistent with the notion that not many companies have used prediction and prescription analytics (Davenport and Harris 2009; Davenport *et al.* 2011; Lavalle *et al.* 2011), which is worth further investigation.

5.2 Practical implications

Several practical implications can be derived from this study. First, it is evident that top-performing companies use BA extensively and make data-driven decisions, which suggests that the extensive use of BA and data-driven decisions are associated with superior performance. Second, companies wishing to use BA to improve decision-making and performance need to develop relevant analytical strategy to guide BA activities and design its structure and business processes to embed BA activities. Third, companies need to have a higher degree of fit between BA and organizational strategy so that BA is used to help achieve strategic objectives. Moreover, a higher degree of fit between BA and organizational structure is likely to improve information processing so managers can better coordinate and control organizational activities; and a higher degree of fit between BA and organizational process can increase the speed and impact of data-driven decision-making. Without such a fit, companies are unlikely to use BA effectively and tend to perform poorly.

5.3 Limitations and future research

This research has a number of limitations that provide opportunities for future studies. First, this research is based on a survey from UK manufacturing companies and may not be applicable to other sectors and future research can extend this to other industries. Second, the focus was to examine to what extent top- and bottom-performing companies differ in using BA and developing data-driven environment through statistical analysis, thus it was not possible to offer rich contextual understanding and explanation due to the limitation of the quantitative research.

Despite these limitations, however, this study offers opportunities for future research. First, both predictive and prescriptive analytics could be further investigated to understand how they are used and what their specific impact on organizations is. Second, the fit between BA and organizational strategy, structure and process could also provide an interesting future research area. In particular, it is worth investigating how the fit between BA and different types of organizational design choices may affect organizational performance. Third and finally, this study could serve as a basis for future in-depth qualitative studies to further elucidate the BA phenomenon.

References

Acito, F. and Khatri, V. 2014. "Business analytics: Why now and what next?" *Business Horizons* 57: 565-570.

Amabile, T. M. 1983. "The social psychology of creativity: A componential conceptualization." *Journal of personality and social psychology* 45 (2): 357.

Amrita, G. and Ravi, S. 2016. "Strategies in managing risks in the adoption of business analytics practices: A case study of a telecom service provider." *Journal of Enterprise Information Management* 29 (3): 374-399.

Armstrong, J. S. and Overton, T. S. 1977. "Estimating Nonresponse Bias in Mail Surveys." *Journal of Marketing Research (JMR)* 14 (3): 396-402.

Barton, D. and Court, D. 2012. "Making Advanced Analytics Work For You." *Harvard Business Review* 90 (10): 78-83.

Bharadwaj, A. S. 2000. "A resource-based perspective on information technology capability and firm performance: an empirical investigation." *MIS Quarterly* 24 (1): 169-196.

Bronzo, M., de Resende, P. T. V., de Oliveira, M. P. V., McCormack, K. P., de Sousa, P. R. and Ferreira, R. L. 2013. "Improving performance aligning business analytics with process orientation." *International Journal of Information Management* 33 (2): 300-307.

Cao, G., Duan, Y. and Li, G. 2015. "Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis." *IEEE Transactions on Engineering Management* 62 (3): 384-395.

Chan, Y., E. and Reich, B. H. 2007. "IT alignment: what have we learned?" *Journal of Information Technology* 22 (4): 297-315.

Chen, H., Chiang, R. H. L. and Storey, V. C. 2012. "Business intelligence and analytics: from big data to big impact." *MIS Quarterly* 36 (4): 1165-1188.

Daft, R. L. and Lengel, R. H. 1986. "Organizational information requirements, media richness and structural design." *Management science* 32 (5): 554-571.

Davenport, T. H. 2006. "Competing on analytics." *Harvard Business Review* 84 (1): 98-107.

Davenport, T. H. 2013. "Analytics 3.0." *Harvard Business Review* 91 (12): 64-72.

Davenport, T. H. and Harris, J. G. 2007. *Competing on Analytics: The New Science of Winning*, Harvard Business School Review Press, Boston, MA.

Davenport, T. H. and Harris, J. G. 2009. "What People Want (and How to Predict It)." *MIT Sloan Management Review* 50 (2): 23-31.

Davenport, T. H., Harris, J. G., De Long, D. W. and Jacobson, A. L. 2001. "Data to Knowledge to Results: Building an analytic capability." *California Management Review* 43 (2): 117-138.

Davenport, T. H., Mule, L. D. and Lucker, J. 2011. "Know What Your Customers Want Before They Do." *Harvard Business Review* 89 (12): 84-92.

Delen, D. and Demirkan, H. 2013. "Data, information and analytics as services." *Decision Support Systems* 55: 359-363.

Donaldson, L. 2001. *The Contingency Theory of Organizations*, Sage, London.

Dutta, D. and Bose, I. 2015. "Managing a Big Data project: The case of Ramco Cements Limited." *International Journal of Production Economics* 165: 293-306.

Egelhoff, W. G. 1982. "Strategy and structure in multinational corporations: An information-processing approach." *Administrative Science Quarterly*: 435-458.

Fairbank, J. F., Labianca, G., Steensma, H. K. and Metters, R. 2006. "Information Processing Design Choices, Strategy, and Risk Management Performance." *Journal of Management Information Systems* 23 (1): 293-319.

FAME. 2016. *The definitive source of information on companies in the UK and Ireland* [Online]. Available: http://www.bvdinfo.com/en-gb/our-products/company-information/national-products/fame [Accessed September 2016].

Galbraith, J. R. 1974. "Organization design: an information processing view." *Interfaces* 4 (3): 28-36.

Gerow, J. E., Grover, V., Thatcher, J. and Roth, P. L. 2014. "LOOKING TOWARD THE FUTURE OF IT–BUSINESS STRATEGIC ALIGNMENT THROUGH THE PAST: A META-ANALYSIS1." *MIS Quarterly* 38 (4): 1159-1186.

Gillon, K., Aral, S., Ching-Yung, L., Mithas, S. and Zozulia, M. 2014. "Business analytics: radical shift or incremental change?" *Communications of the Association for Information Systems* 34 (1): 287-296.

Goes, P. B. 2014. "Big Data and IS Research." *MIS Quarterly* 38 (3): iii-viii.

Greenwood, R. and Hinings, C. R. 1993. "Understanding strategic change: The contribution of archetypes." *Academy of Management journal* 36 (5): 1052-1081.

Haase, R. F. and Ellis, M. V. 1987. "Multivariate analysis of variance." *Journal of Counseling Psychology* 34 (4): 404.

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. 2010. *Multivariate Data Analysis*, Prentice Hall Higher Education,

Hammer, M. 1996. *Beyond Reengineering*, Harper Business, London.

Hansen, G. S. and Wernerfelt, B. 1989. "Determinants of firm performance: The relative importance of economic and organizational factors." *Strategic management journal* 10 (5): 399-411.

Holsapple, C., Lee-Post, A. and Pakath, R. 2014. "A unified foundation for business analytics." *Decision Support Systems* 64: 130-141.

Huber, G. P. 1990. "A Theory of the Effects of Advanced Information Technologies on Organizational Design, Intelligence, and Decision Making." *Academy of Management Review* 15 (1): 47-71.

Kearns, G. S. and Sabherwal, R. 2006. "Strategic Alignment Between Business and Information Technology: A Knowledge-Based View of Behaviors, Outcome, and Consequences." *Journal of Management Information Systems* 23 (3): 129-162.

Kiron, D., Ferguson, R. and Prentice, P. 2012a. "From Value to Vision: Reimagining the Possible with Data Analytics." *MIT Sloan Management Review* 54 (1): 47-52.

Kiron, D., Kirk Prentice, P. and Boucher Ferguson, R. 2012b. "Innovating With Analytics. (cover story)." *MIT Sloan Management Review* 54 (1): 47-52.

Kiron, D., Prentice, P. K. and Ferguson, R. B. 2012c. "Innovating with analytics." *MIT Sloan Management Review* 54 (1): 47-52.

Kiron, D., Prentice, P. K. and Ferguson, R. B. 2014. "Raising the Bar With Analytics." *MIT Sloan Management Review* 55 (2): 29-33.

Kiron, D. and Shockley, R. 2011. "Creating Business Value Analytics." *MIT Sloan Management Review* 53 (1): 57-63.

Klatt, T., Schlaefke, M. and Moeller, K. 2011. "Integrating business analytics into strategic planning for better performance." *Journal of Business Strategy* 32 (6): 30-39.

Krosnick, J. A. 1999. "Survey research." *Annual Review of Psychology* 50 (1): 537.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S. and Kruschwitz, N. 2011. "Special Report: Analytics and the New Path to Value." *MIT Sloan Management Review* 52 (2): 22-32.

Lederer, A. L. and Mendelow, A. L. 1989. "Coordination of information systems plans with business plans." *Journal of Management Information Systems* 6 (2): 5-19.

Malhotra, N. K., Patil, A. and Kim, S. S. 2007. "BIAS Breakdown." *Marketing Research* 19 (1): 24-29.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Byers, A. H. 2011. "Big data: The next frontier for innovation, competition, and productivity." Available: http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation [Accessed 11th June 2015].

Mihalis, G. and Michalis, L. 2016. "A multi-agent based system with big data processing for enhanced supply chain agility." *Journal of Enterprise Information Management* 29 (5): 706-727.

Nadler, D. A. and Tushman, M. L. 1980. "A Model for Diagnosing Organizational Behavior." *Organizational Dynamics* 9 (2): 35-51.
Newbert, S. L. 2008. "Value, rareness, competitive advantage, and performance: a conceptual-level empirical investigation of the resource-based view of the firm." *Strategic management journal* 29 (7): 745-768.
Ngo, L. V. and O'Cass, A. 2013. "Innovation and business success: The mediating role of customer participation." *Journal of Business Research* 66 (8): 1134-1142.
Opresnik, D. and Taisch, M. 2015. "The value of Big Data in servitization." *International Journal of Production Economics* 165: 174-184.
Phillips, L. W. and Bagozzi, R. P. 1986. "On measuring organizational properties of distribution channels: methodological issues in the use of key informants." *Research in Marketing* 8: 313-369.
Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y. and Podsakoff, N. P. 2003. "Common method biases in behavioral research: A critical review of the literature and recommended remedies." *Journal of Applied Psychology* 88 (5): 879-903.
Podsakoff, P. M., MacKenzie, S. B. and Podsakoff, N. P. 2012. "Sources of Method Bias in Social Science Research and Recommendations on How to Control It." *Annual Review of Psychology* 63 (1): 539-569.
Premkumar, G., Ramamurthy, K. and Saunders, C. S. 2005. "Information Processing View of Organizations: An Exploratory Examination of Fit in the Context of Interorganizational Relationships." *Journal of Management Information Systems* 22 (1): 257-294.
PWC. 2009. "The future of UK manufacturing: Reports of its death are greatly exaggerated." Available: https://www.pwc.co.uk/assets/pdf/ukmanufacturing-300309.pdf [Accessed 11th June 2015].
Rockart, J. F., Earl, M. J. and Ross, J. W. 1996. "Eight imperatives for the new IT organization." *MIT Sloan Management Review* 38 (1): 43.
Sanders, N. R. and Ganeshan, R. 2015. "Special Issue of Production and Operations Management on 'Big Data in Supply Chain Management'." 24: 852-853.
Schläfke, M., Silvi, R. and Möller, K. 2013. "A framework for business analytics in performance management." *International Journal of Productivity & Performance Management* 62 (1): 110-122.
Sharma, R., Mithas, S. and Kankanhalli, A. 2014. "Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations." *European Journal of Information Systems* 23 (4): 433-441.
Tabachnick, B. G. and Fidell, L. S. 2007. *Using multivariate statistics*, Pearson Education, Boston.
Tambe, P. 2014. "Big data investment, skills, and firm value." *Management Science* 60 (6): 1452-1469.
Thomas, J. A. and McDaniel, J. R. R. 1990. "Interpreting strategic issues: effects of strategy and the information-processing structure of top management teams." *Academy of Management Journal* 33 (2): 286-306.
Tosi, H. L. and Slocum, J. W. 1984. "Contingency Theory: Some Suggested Directions." *Journal of Management* 10 (1): 9-26.
Trkman, P., McCormack, K., de Oliveira, M. P. V. and Ladeira, M. B. 2010. "The impact of business analytics on supply chain performance." *Decision Support Systems* 49 (3): 318-327.
Tushman, M. L. and Nadler, D. A. 1978. "Information Processing as an Integrating Concept in Organizational Design." *Academy of Management Review* 3 (3): 613-624.
Van de Ven, A. H. and Drazin, R. 1984. The Concept of Fit in Contingency Theory. DTIC Document.
Wang, E. T., F. Tai, J. C. and Grover, V. 2013. "Examining the relational benefits of improved interfirm information processing capability in buyer-supplier dyads." *MIS Quarterly* 37 (1): 149-173.
Watson, H. J. 2014. "Tutorial: big data analytics: concepts, technologies, and applications." *Communications of the Association for Information Systems* 34 (1): 1247-1268.
Weill, P. and Olson, M. H. 1989. "An Assessment of the Contingency Theory of Management Information Systems." *Journal of Management Information Systems* 6 (1): 59-85.
Zviran, M. 1990. "Relationships between organizational and information systems objectives: some empirical evidence." *Journal of Management Information Systems* 7 (1): 65-84.