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Do Top-Performing Companies Use Business Analytics Differently And Why?

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DO TOP-PERFORMING COMPANIES USE BUSINESS ANALYTICS DIFFERENTLY AND WHY?

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ABSTRACT

It is suggested that companies that use business analytics perform better than those that do not in making strategic decisions and creating business value. However, little academic research based on theories exists to examine the extent to which companies differ in using business analytics and why this difference may contribute to company performance difference. To reduce this knowledge gap, this paper investigates the extent to which top and bottom performing companies differ in using business analytics by means of analysis of variance based on 232 responses collected from UK manufacturers, and seeks to explain how this use difference may be linked to performance difference drawing on the information processing view and path dependence theory. The research findings indicate that top-performing companies are three times more likely than bottom-performing companies to use business analytics and develop a data-driven environment simultaneously; and that the company differences regarding the use of business analytics and the resultant performance may be due to path dependence and how relevant organisational factors are designed. The study contributes to business analytics literature by providing empirical evidences and offering a theoretical-based understanding of business analytics, providing a foundation for future research. This study also has important managerial implications by demonstrating how business analytics can be used to improve performance.

Keywords: Business analytics, data-driven environment, information processing view, organisational performance, ANOVA.

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” [1, p.7]. Facing the challenges of big data, increasing competition, and technological advancement, companies are increasingly using BA to gain valuable data-driven insights thereby to improve organisational performance [2][3]. For instance,[21] suggests 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. While BA’s importance has been recognised and BA is emerging as an important research area [18][5][], little is known about the mechanisms through which BA can be used to create business value [3]. Thus, it remains unclear how BA affects organisational performance and how it is affected by other organisational factors [24]. This paper attempted to examine the following research questions that are key to developing a theory-based understanding of BA: To what extent do top and bottom performing companies differ in using BA and why?

In order to fill this knowledge gap, this paper drew on the information processing view of organisational design [9, 10] and path dependence theory [10][23] to conceptualise the association between BA and organisational performance and the extent to which top and bottom performing companies can be differentiated regarding their use of BA. This paper’s conceptualisation was empirically tested using analysis of variance (ANOVA) based on 232 responses collected from UK manufacturing industry. It focused on the UK manufacturing sector since it is currently the 11th largest manufacturing nation in the world and accounts for about 8.5% of the UK workforce, 54% of the exports, and 12% of the country's national output. Whilst this industry is relatively efficient and in relative decline [27], it faces considerable challenge of generating significant productivity improvement. There is also indication that this industry has been slow in incorporating BA [12] and only a small fraction of them are currently using BA in the areas of operations and across their supply chains [28]. Hence, understanding how to use BA to improve organisational performance is of enormous use to practitioners in the manufacturing sector and academics alike.

This paper’s findings indicated that top-performing companies are more likely than bottom-performing companies to use BA and develop a data-driven environment; and that the company differences regarding the use of BA and the resultant performance may be due to path dependence and how relevant organisational factors are designed. The research findings should be useful to researchers who wish to expand knowledge in this research domain and have important managerial implications for manufacturing companies wanting to use BA. The structure of the paper is as follows. The next section presents the conceptualisation and hypotheses. The subsequent section describes the data collection processes and reports on the empirical results. The final section discusses the results and implications.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

BA consists of the processes and techniques of data analysis for the generation of knowledge and intelligence to support organisational decision-making [16], which can be classified into three main categories: descriptive, predictive, and prescriptive [11]. Descriptive analytics is mainly used to describe the context of and trending information on past or current events, answering what has happened and what is happening. Predictive analytics is used to predict the future happenings and the reasoning as to why, answering what could happen. In addition, prescriptive analytics can be used 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 organisations use descriptive analytics to various degrees while much fewer use prediction and prescription analytics [5][22]. Regardless, BA is seen to offer the possibilities for companies to be more effective at making strategic decisions and creating competitive advantages [4]. Four consecutive large scale questionnaire surveys have consistently showed that companies that use BA perform better than those that do not [19][20][21][22]. The findings from the latest survey suggest that 87% of respondents strongly or somewhat agree that it is important for their organisations to step up the use of BA to make better business decisions [4]. However, these surveys are "predominantly practice driven" [14] and rarely based on testable models and relevant theories. As a result, little is known about the mechanisms through which BA can be used to improve organisational performance; in particular, it remains unclear how companies such as those in manufacturing industry are using and affected by BA.

Understanding BA from the Information Processing View

In order to understand to what extent and how a company might use various types of BA to improve its performance, the information processing view of organisational design [13][][10] provides a useful theoretical underpinning. This view advocates that an organisation needs to design for example its structure [10] and business processes [26] so that it can match its information processing capabilities with its information processing requirements to inform its decision-making, manage uncertainty, and ultimately improve its performance. The information processing view has been used by a few empirical studies in the context of supply chain management to understand the interactive effect of information processing needs and information processing capabilities on performance [26][2][25]; however, few BA studies underpinned by this view apart from [3].

Nevertheless, a number of practice-oriented BA studies have suggested ideas that are seen to be consistent with the information processing view. For instance, [15] suggests that while BA and big data provide significant opportunities to reshape businesses, the adoption of BA has been slow since processing big data using BA requires not only developing new and innovative forms of information processing capabilities but also considering issues such as centralisation versus decentralisation. Likewise, it is suggested companies need to develop an "analytically driven strategy" [4], relevant business processes [2] and organisational structure [1].

Drawing on the information processing view and existing BA studies, a company can be thus expected to be more likely to use BA to gain data-driven insights to improve its decision-making and performance when it has developed a data-driven environment reflected by developing explicit strategy and policy to guide analytic activities and designing its structure and processes to enable analytics activities [3]. If this assumption is reasonable, then companies that use BA supported by a data-driven environment should be expected 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" [2, p. 122]; consequently, companies that have not developed a data-driven environment are more than likely to be the bottom-performing companies. Thus, it is conceivable to conjecture that a company will be able to significantly improve its performance using BA when it has created a data-driven environment by embedding BA into relevant organisational strategy, structure and processes.

Hypothesis 1. Top-performing companies are more likely to have developed a data-driven environment.
Hypothesis 1a. Top-performing companies are more likely to depend on data-based insights to support decision making
Hypothesis 1b. Top-performing companies are more likely to develop a data-driven strategy to guide BA activities.
Hypothesis 1c. Top-performing companies are more likely to develop relevant organisational structure to enable BA.
Hypothesis 1d. Top-performing companies are more likely to develop relevant organisational process to embed BA.

While the above hypotheses clearly recognise the association between BA and a data-driven environment, the cause-effect relationship between them is beyond the scope of this research.

Understanding BA from Path Dependence

Further, we also posit that top-performing companies' using BA could be path dependent, referring to a stochastic process whose distribution of outcomes evolves as a function of its own history [10]. In other words, a company's current use of BA can be shaped by the path it has travelled: its previous investments in analytics and its relevant history matter and will constrain its future behaviour. Path dependence may help us to understand how a series of early events can initiate a self-reinforcing process such as complementarity and learning effect [29], thereby influence strategic choices made by companies [16].

For instance, [23] demonstrates that firms has been actively developing IT capabilities are more likely to repeat this than firms lacking such experience. This follows because organisational learning in a firm tends to be local and often draw on its previous activities [30]. As a result, the self-reinforcing nature of path dependence is expected to bring about a preferred action pattern, which then gets deeply embedded in organisational practice and replicated [31]. Furthermore, an organization's core technology tends to be path dependent as changing it requires simultaneous adjustments in other organisational features [17]. However, path dependence can also be understood as "a rigidified, potentially inefficient action pattern built up by the unintended consequences of former decisions and positive feedback processes" [31, p. 696]. Thus, it is important to understand that the dynamics of self-reinforcing mechanisms may eventually lead to an irreversible state of total inflexibility [9] and being strategically inefficient [31], thus constrain subsequent choices [17] rather than a virtuous circle.

Based on the path dependency theory, it is expected that the use of BA and a data-driven environment in an organisation is closely related and thus path dependent. BA is intertwined with big data [16] and builds on sophisticated information technologies such as the scale-out architecture, Hadoop, cloud services, new "agile" analytical methods, and machine-learning techniques. BA also requires a data-driven environment if it is to be used effectively [1][2][4]. As a result, BA can be seen as a core technology since it is entangled with other key organisational features. Once an organisation has developed a data-driven environment reflected by for instance relevant strategy, structure and process to embed BA activities, this is likely to be path dependent. This practice is also likely to be repeated by self-reinforcing process such as complementarity, coordination, learning and adaptive effects [29]. BAand a data-driven environment are complementary: BA will help provide data-driven insight while a data-driven environment ensures that this insight to be used to support decision-making with maximum effect, which in turn will reinforce the usefulness of BA and a data-driven environment. Enabling BA with a data-driven environment then becomes more attractive and is likely to be repeated in the future, leading to coordination effect. The more an organisation uses BA enabled by a data-driven environment, the more effective it becomes due to accumulated relevant knowledge, experience and skills through using BA, which results in learning effect. When data-driven decision-making is proved to be effective, organisational members will be willing to adopt this practice, thereby leading to adaptive effect. Because of these self-reinforcing processes, BA enabled by a data-driven environment is highly likely to be path dependent.

Therefore, companies with a data-driven environment tend to embark on a virtuous circle. In contrast, companies without a data-driven environment are arguably less likely to use BA or use it as effectively to improve their organisational performance as they lack the self-reinforcing processes. Consequently, it is perceivable that companies with a data-driven environment are more likely to use BA. Again, the above hypotheses focus on the association between data-driven environment and BA rather than the cause-effect relationship between them, which will be addressed in a different research. Thus, we propose:

Hypothesis 2. Companies with a data-driven environment *are more likely to use BA.*
Hypothesis 2a. Companies with a data-driven environment are more likely to use descriptive analytics.
Hypothesis 2b. Companies with a data-driven environment are more likely to use predictive analytics.
Hypothesis 2c. Companies with a data-driven environment are more likely to use prescriptive analytics.

RESEARCH METHODOLOGY

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 250) and large UK manufacturing companies (more than 250 employees) as they are expected to have the "capabilities" and "substantial resources" to employ various types of BA for business improvement [15]. The survey was delivered to the CEO of each company through Qualtrics while the email addresses were identified from the FAME database. 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, it was not known how many e-mails were opened. Of all sent emails, 782 surveys were opened and 232 usable responses were received. The response rate was not calculated as the literature provides no agreed methods for doing this with mass email surveys such as ours.

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 [25].

Based on BA research [3][19][][16][], we measured a company's data-driven environment in terms of its depending on data-based insights to support decision making, having a well-defined organisational structure to enable analytical activities, analytical activities being integrated into business processes and aligned with organisational strategies. Based on [11], we 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 modelling; and prescriptive analytics with reference to the use of optimisation, simulation and scenario development, model management, and interactive data visualisation. Finally, we measured organisational performance with regard to perceived profitability comparing to key competitors. The descriptive statistics of the research variables are presented in Table I.

MAIN FINDINGS

ANOVA was used to test the hypotheses. Participants were divided into three groups according to their 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 medium-performing companies ($n = 115$) with a score of 3 ($M = 3.0$, $SD = 0.000$), and Group 3 including bottom-performing companies ($n = 65$) with a score of 1 or 2 ($M = 1.877$, $SD = 0.328$). A test of homogeneity of variances was conducted. All variables were homogenous except for forecasting, business reporting and spreadsheet. However, these three exceptions' robust tests (Welch and Brown-Forsythe) were significant; thus their homogeneity tests were considered acceptable. A one-way between-group ANOVA was conducted to evaluate the equality of variable means across the groups and thus assess the distinctiveness of each group with reference to data-driven environment, descriptive analytics, predictive analytics and prescriptive analytics. The ANOVA results are summarised in Table II. The F-tests confirmed that, across the three groups, except for all prescriptive variables and two predictive analytics variables, the rest of these means differed statistically significantly. Of these differed, Tukey's HSD tests were conducted to determine which groups in the sample differed. In terms of forecasting, business reporting, spreadsheet, query and analysis, and depending on data-based insights to support decision making, all groups were distinguishable. With regards to statistical analysis, organisational structure developed to enable analytical activities, processes well-developed to embed analytical activities, and organisational strategies developed to guide analytical activities, Group 1 and 3 differed significantly while Group 2 was not.

TABLE I. DESCRIPTIVE STATISTICS (N = 232)

Variables (measured by five-point scales)	Mean	S.D.
Data-driven environment		
Depending on data-based insights to support decision making	2.987	1.186
Organisational structure developed to enable analytical activities	2.879	1.058
Processes well-developed to embed analytical activities	3.000	1.089
Organisational strategies 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 modelling	2.875	1.325
Prescriptive analytics		
Optimisation	2.853	1.204
Simulation and scenario development	2.987	1.236
Model management	2.819	1.381
Interactive data visualisation	2.996	1.416
Perceived profitability comparing to key competitors	2.948	0.851

1-strongly disagree to 5-strongly agree

TABLE II. ANOVA RESULTS

Variables	Group 1 (n=52)		Group 2 (n=115)		Group 3 (n = 65)		F (ANOVA)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Data-driven environment							
Depending on data-based insights to support decision making	3.731	0.992	2.948	1.191	2.462	1.017	19.310***
Organisational structure developed to enable analytical activities	3.250	1.186	2.870	0.996	2.600	0.981	5.682***
Processes well-developed to embed analytical activities	3.423	1.091	3.043	1.021	2.585	1.074	9.377***
Organisational strategies developed to guide analytical activities	3.308	1.058	2.930	1.057	2.569	1.045	7.117***
Descriptive analytics							
Statistical analysis	3.385	1.360	2.922	1.396	2.523	1.288	5.811***
Business reporting	3.962	1.428	2.939	1.754	2.015	1.386	21.734***
Query and analysis	3.673	1.279	2.826	1.372	2.108	1.147	21.216***
Spreadsheet	3.981	1.540	2.791	1.819	1.908	1.497	22.178***
Web analytics	3.077	1.311	2.765	1.327	2.677	1.300	1.469^{ns}
Predictive analytics							
Data and text mining	3.000	1.314	2.852	1.258	3.000	1.436	0.362^{ns}
Forecasting	3.615	1.484	2.877	1.594	2.077	1.373	15.188***
Predictive modelling	2.827	1.339	2.878	1.319	2.908	1.343	0.054^{ns}
Prescriptive analytics							
Optimisation	2.942	1.259	2.896	1.165	2.708	1.234	0.686^{ns}
Simulation and scenario development	3.077	1.384	2.896	1.195	3.077	1.190	0.622^{ns}
Model management	2.673	1.382	2.835	1.420	2.908	1.320	0.430^{ns}
Interactive data visualisation	3.096	1.347	2.861	1.456	3.154	1.395	1.059^{ns}

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

TABLE III. THE ODDS RATIO OF HIGH SCORE IN GROUP 1 TO HIGH SCORES IN GROUP 3

Variables	Group 1 (n=52)		Group 3 (n = 65)		The odds ratio (b/d)
	No of high scores (a)	Odds of high scores (b=a/(52-a))	No of high scores (c)	Odds of high score (d=c/(65-c))	
Data-driven environment					
Depending on data-based insights to support decision making	34	1.889	12	0.226	8.36
Organisational 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
Organisational strategies 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	12.0
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

As Groups 1 and 3 were mostly distinguishable with regards to those variables with a significant F-test, an additional question was to what extent they differed. To answer this question, the odds ratio of high scores (4 and 5) in Group1 to high scores (4 and 5) in Group 3 was calculated in terms of each variable that had a significant F-test. The odds ratios summarised in Table III suggest that top-performing companies are three times more likely than bottom-performing companies to develop a data-driven environment, three to twelve times likely to use descriptive analytics, and almost six times likely to use forecasting.

Thus, hypothesis 1 is supported, which suggests that top-performing companies are more likely than bottom-performing companies to depend on data-based insights to support decision making, develop a data-driven strategy to guide BA activities, develop relevant organisational structure and process to enable BA and to embed BA.

Similarly, ANOVA and an analysis of the odds ratio of high scores were conducted to test Hypothesis 2. Again, participants were divided into three groups according to the extent to which the responding company depends on data-based insights to support decision making, develops organisational structure to enable analytical activities, develops processes to embed analytical activities, or develops organisational strategies to guide analytical activities. The analysis confirmed that Hypothesis 2 is supported, suggesting that companies with a data-driven environment are more likely to use descriptive analytics, predictive analytics, and prescriptive analytics; and they tend to be top-performing companies.

DISCUSSIONS AND CONCLUSIONS

The results lead us to generally accept the research hypotheses that top-performing companies in the UK manufacturing industry are significantly different from bottom-performing companies with reference to developing a data-driven environment and using BA. Consequently, top-performing companies are more likely than bottom-performers to fully realise the benefits from their investment in BA. However, there are particularities to be further discussed.

The research findings indicate that top-performing manufacturing companies display important characteristics. First, they use BA more coherently by creating a data-driven environment to support and enable the use of BA. Specifically, an analytical strategy is developed to guide the use of BA; relevant organisational structure and process are designed to embed BA, and data-driven insights are used to inform decision-making. Second, top-performing companies are three 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, top-performing companies are more likely to have reliable and accurate information to make successful decisions, to generate viable organisational strategies, and thereby to significantly improve their performance. This provides empirical evidence in support of the ideas that the effective use of BA requires the development of relevant analytical strategy, organisational structure and processes [1][2][4]. Our research findings also contribute to the information processing view by demonstrating that organisational design is essential for organisations to match their information requirements and processing to inform decision-making and improve organisational performance.

Additionally, this research contributes to prior research on path dependence [10][23] by providing empirical support. Our findings imply that the use of BA in a manufacturing company may be path dependent, affected by complementarity, coordination, learning and adaptive effects [29]. Thus one of the key reasons why top-performing manufacturing companies are three times more likely to use BA may perhaps be related to the path they have travelled. While prior research [9][31][] suggests that self-reinforcing process could eventually lead to an irreversible state of total inflexibility and being strategically inefficient, the specific case of the use of BA does not seem to be possible to bring about a deterministic character that render alternative courses of action no longer feasible. In contrast, the use of BAwould help companies to be able to gain data-driven insights, thereby to systematically evaluate alternative courses of action and make better decisions.

However, an awareness of path dependence can certainly impact the choices that bottom-performing companies can make regarding the use of BA. Such an understanding can enable them to reflect practices in terms of path dependence and potentially opens a window for path-breaking [17] or creation [30] activities that allow them to use BA effectively. The findings from this study suggest unless they take steps to create a path to enable them to start to use BA, to develop their learning capabilities and analytical capabilities, they are unlikely to be able to realise the potential benefits offered by BA.

Two key managerial implications can be derived from this study. First, manufacturing companies are likely to be more effective at using BA to inform decision-making and improve their performance by developing a data-driven environment that coherently enables analytics activities. Second, in order for manufacturing companies to realise the benefits from BA, they need to take steps to use, and develop their learning and analytical capabilities to be able to use BA.

Our research is based on survey from UK manufacturing companies and may not be applicable to other sectors and future research can extend this to other industries. Despite this limitation, however, we believe our study offers two other opportunities for future research. First, both predictive and prescriptive analytics could be further investigated to understand how they are used and what their impact on organisations is. Second, the cause-effect relationship between BA and a data-driven environment could also provide an interesting future research area.

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