The role of Big Data Analytics Maturity on Firm performance: Evidence from the UK manufacturing sector

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Abstract

Scholars have recognised the importance of Big Data Analytics (BDA) capabilities for improving decision making. However, the impact of BDA maturity on operational and innovation performance has not been systematically investigated. Drawing on dynamic capabilities view; this paper discusses how BDA capabilities are instrumental in improving operational and innovation performance. The role of absorptive capacity and data quality on the relationship between BDA maturity and operational and innovation performance is examined in this paper. Analysis of survey data from 221 manufacturing companies shows that BDA significantly improve performance. Finally, implications and suggestions for future research are also discussed.

Keywords: Big Data Analytics, absorptive capacity, operational and innovation performance.

Introduction

Big Data Analytics (BDA) is perceived as one of the prodigious technologies of the 21th century (Kache and Seuring 2017). BDA is emerging into a valuable asset for decision making, as business leaders intent to make decisions based on data-driven insights rather than intuitions(Davenport 2006). Leveraging BDA to drive competitive advantage is becoming a top priority for firms operating in dynamic environment. Yet, it is argued that practitioners face substantial difficulties in understanding the BDA capabilities that have the potential to transform data into value(Arunachalam et al. 2017). The core feature of BDA is its ability to capture, store and analyse a large volume of complex data in real time (Yesudas et al. 2014). Few studies such as (Wamba et al. 2016) have demonstrated the positive outcome of developing BDA capabilities. However, studies articulating the underlying mechanism through which BDA influences performances are limited, especially from maturity and organisational learning perspective. Moreover, BDA is argued to advance innovation (Tan et al. 2015), but the influence of BDA on innovation performance is yet to be confirmed empirically. Therefore, the main purpose of this study is to address these gaps and contribute to the literature by empirically investigating the business value of BDA capabilities.

Drawing from the dynamic capabilities perspective, this study conceptualises BDA as a dynamic capability and examines the impact of BDA capabilities maturity on innovation and operational performance, mediated through Absorptive capacity and Data quality. Through the systematic review of BDA and supply chain literature, the key dimensions of BDA capabilities are identified as data generation, and data integration and management capabilities, advanced analytics capabilities, data visualisation capabilities, data-driven culture and big data skills (Arunachalam et al. 2017). Consequently, a conceptual model depicting the relationship between the BDA capabilities, its technical and behavioural consequences such as data quality and absorptive capacity and its effect on innovation and operational performance is developed. More specifically, the current study extends this stream of research, by analysing data collected from 221 manufacturing companies with Structural Equation Modelling (SEM) technique to test several hypotheses.

The study has obtained some key findings. First, high level of BDA maturity improves ACAP and data quality, which is positively associated with operational performance. Second, the use of BDA capabilities positively influences operational and innovation performance, but its impact on operational performance is indirect and transmitted through ACAP. Third, data quality exhibits indirect effect only on the relationship between BDA maturity and operational performance, but not with the innovation performance. This study makes significant contribution to both theory and practice. Findings imply that, in order for manufacturing firms to gain competitive advantage through the use of BDA, firms should consider ACAP as an integral part of BDA practice.

2. Conceptual framework and hypotheses development

Dynamic capabilities perspective has emerged in strategic management discipline and commonly applied in Information Systems (IS) and operations research. According to Teece et al. (1997), dynamic capabilities are “the firm’s ability to integrate, build, and re-configure internal and external competences to address rapidly changing environments”. In a dynamic and complex environment like supply chain, assets (e.g. BDA technology assets) alone is not sufficient to bring competitive advantage, but organisations need additional dynamic capabilities to gain competence under a changing market environment

(Opresnik and Taisch, 2015). Dynamic Capabilities (DC) are essential to constantly renew, recreate and reconfigure resources and capabilities to address the changing environmental needs and to attain lasting organisational performance (Teece et al., 1997; Opresnik and Taisch, 2015). In this research, BDA capabilities are considered as DC as it indicates the ability of organisations to leverage and reconfigure BDA resources. Organisations who possess bundle of Big Data resources such as advanced databases, analytical tools and skilled employs could reconfigure it in an exceptional way to create BDA capabilities. So, from the DC view, it can be argued that the use of BDA can develop organisations' information processing capabilities, facilitate resource reconfiguration, reduce uncertainties, and predict future resource requirements (Chen et al., 2015a). Consequently, a conceptual model (Figure 1) was developed through the lenses DC and the development of hypotheses is discussed in the following sections.

2.1. Big Data Analytics capabilities maturity

Prior studies have identified that BDA can improve firm performance(Wamba et al. 2017). BDA can help optimise supply chain activities by obtaining internal and external data from customers, suppliers and competitors. BDA capabilities could facilitate firms to process the operational and manufacturing data(Davenport and Harris 2007). The external information or knowledge provided by BDA would enhance efficiency and effectiveness of firms and could reduce cost, improve product quality, delivery performance and innovate new products and services. BDA is found to increase the accuracy of demand forecasting(Blackburn et al. 2015), predict arrival time of trucks (van der Spoel et al. 2015), innovate new products (Tan et al. 2015), identify contamination in food product (Zhang et al., 2013), and also enhances after sales services (Boone et al. 2016). Based on previous studies, seven dimensions of BDA capabilities is identified to represent BDA maturity (Arunachalam et al. 2017). The dimensions of BDA maturity are data generation capability, data Integration and management capability, advanced analytics capability, digital analytics capability, data visualisation capability, data-driven culture and big data skills. Therefore, following hypotheses have been proposed in this research, which suggests that firms that organisations highly matured in terms of BDA capabilities can achieve improve operational and innovation performance.

H1a: BDA maturity is positively related to operational performance.
H1b: BDA maturity is positively related to innovation performance.

2.2 Absorptive capacity

Absorptive capacity (ACAP) is defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities" (Cohen and Levinthal 1990, p.128). The critical information needed to improve operational performance can be found from external sources (Dobrzykowski et al. 2015). However, information is not readily available for decision making, but BDA can provide that information processing ability. Nevertheless, it is the organisational capability to acquire, assimilate, transform, and exploit the information and knowledge provided by BDA determines the firm performance. Moreover, BDA could increase organisations' ability to learn from external information. But in order to convert the information into commercial advantage organisations should possess the ACAP. Drawing upon the dynamic capabilities perspective, this research suggests that BDA capabilities are dynamic capabilities can facilitate firms to build higher-order capabilities such as ACAP. In comparison to lower-order capabilities, resources provided by higher-order capabilities are difficult to imitate (Grant, 1996). In this study, it is hypothesised that while capabilities related to BDA can directly influence firm performance, a robust model would require ACAP as a mediating factor contemplating an indirect effect. While the effect of ACAP was not investigated empirically in the context of BDA, there are several studies that relate ACAP with supply chain and IT, which supports our argument. For instance, in DeGroote and Marx (2013) and Liu et al. (2013b), ACAP is hypothesised as a mediator to explain the impact of IT capabilities on firm performance. Therefore, following hypotheses are proposed in this research.

H2a: Absorptive capacity positively mediate the relationship between BDA maturity and operational performance

H2b: Absorptive capacity positively mediate the relationship between BDA maturity and innovation performance

2.3 Data quality

Data quality is an important issue, as poor data quality can have a disastrous consequences (Woodall et al. 2013). The availability of quality data could directly affect the process management. It can inform employees about changes in the processes immediately so corrective action can be taken in a timely manner(Kaynak 2003). Malhotra et al (2005) argued that the incompleteness of data may negatively influence the decision-making effectiveness. Big data analytics capabilities, especially data integration and management capability, can improve data quality by acquiring and integrating data from various sources to provide single point of truth(Arunachalam et al. 2017). BDA can improve data quality by utilising its raw data processing capabilities. Because, raw data could inherently contain irregularities due to flawed system design and data input errors. Absence of BDA can create deficiency of complete, accurate, and timely data available for decision making. Also, if data is inaccessible it may decrease the effectiveness of data users who rely on it for performing tasks. Moreover, monitoring supplier quality requires maintenance of supplier performance database, which can provide accurate track of supplier quality performance data. Availability of quality data about supplier performance can support employees to solve problems such as poor product quality and issues with delivery that may stem from the supplier side (Krause et al. 1998), and can also enhance innovation. Data accuracy also found to increase planning quality in manufacturing sector(Chae et al. 2014). Therefore, following hypotheses is proposed:

H3a: Data quality positively mediate the relationship between BDA maturity and operational performance

H3b: Data quality positively mediate the relationship between BDA maturity and innovation performance.

Methodology

This research has adopted a quantitative approach utilising survey methodology to collect data and test the proposed hypotheses. From the conceptual model, it is evident that the survey instrument should contain measures related to constructs namely, BDA capabilities maturity, Absorptive capacity(ACAP), and data quality, SCA capability, operational and innovation performance. Except for BDA Maturity, the measures for ACAP, data quality, and operational and innovation performance are completely derived from the existing literature. A five-point Likert scale is used to measure the dimensions of the conceptual model. This study also included two control variables ‘number of employees’ and ‘annual turnover’.

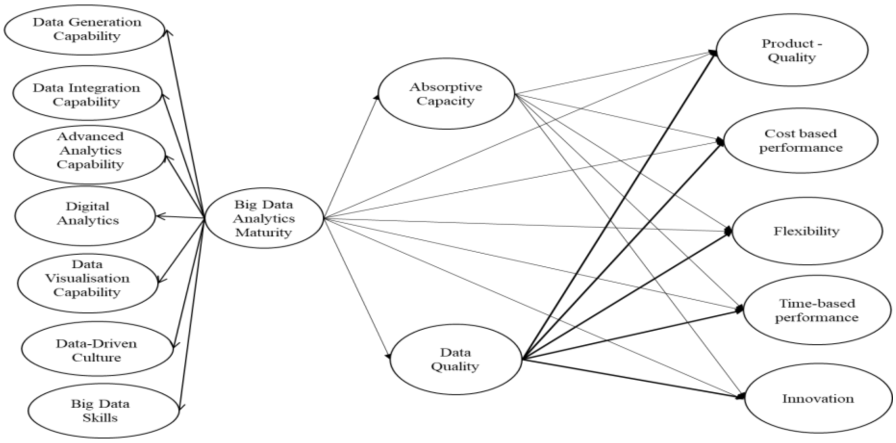

Figure 1 Conceptual model of the study

Through random sampling, 2000 email addresses were selected from the fame database. Survey administration strategies suggested in (Dillman et al. 2014) is adopted in this study. The survey instrument is pilot tested with both supply chain academics and industry experts. Consequently, the questionnaire survey link was distributed online via Qualtrics to the 2000 email addresses. However, 284 email addresses were bounced back, indicating these email addresses are inactive due to several reasons such as employee moved to another organisation or retired. In total, 1716 emails were delivered to the respondents. After a systematic data collection process, a total of 334 submitted responses were received. But, 221 valid responses remained after rigorous pre-processing and considered sufficient to perform Structural Equation Modelling (SEM) (Hair et al. 2010; Tomarken and Waller 2005). The final response rate in this study is calculated to be 13 %, which is within the desirable level of response rate in the domain of operations research (Flynn 1990). The survey participants profile indicate that the top contributors to the survey are CEOs (18.1%), General managers (17.2 %), and middle/senior managers in Information technology or Big data analytics professionals (23%).Moreover, the majority of participant in the survey falls into the manufacturing categories of 'Electrical equipment' (15.4%), 'Metals' (14.0%) and 'Food and dairy products'(10.0%).

Data Analysis and results

Data Screening

The skewness and kurtosis value of all the variables measured in this research. The results indicate that there is no issue of normality in the data set. All the skewness values are within the range of -1 to +1. In case of kurtosis statistics, all the values are less than the 0.978 threshold, which obtained by multiplying the standard error term and the kurtosis value. Moreover, the data set was found to not contain any extreme outliers and no mathematical transformation was required(Leys et al. 2013).

Exploratory factor analysis

A total of 69 items were used to measure the following constructs; a) data generation capability (3), b) data integration and management capability (7), c) advanced analytics capability (5), d) digital analytics (4), e) data visualisation capability(4), f) data-driven culture (6), g) big data skills (4), h) absorptive capacity (12), i) data quality (5), j) product quality (3), k) cost (4), l) flexibility (3), m) time (6), and n) innovation (3). Since this study has adopted item scales from different studies, Exploratory Factory Analysis (EFA) is carried out to identify scales that are problematic. Moreover, the benefit of EFA is it helps to find hidden factor structure and the inter-relationship between them. While EFA is used to explore the theoretical underpinning of factors, CFA is used to confirm the factor structure (Pallant 2007). Since, the factor structure of BDA maturity is not thoroughly investigated in the previous researches, EFA is used to unravel the dimensions of BDA maturity. Before factor analysis the adequacy of the data sample to perform factor reduction is analysed (Kline 2015). The two estimates that are used in this research to assess the ratio of available cases to variables are Kaiser-Meyer-Olkin measure and Bartlett's test of Sphericity. The results suggest that both the Kaiser-Meyer-Olkin measure (KMO- 0.952, chi-square-17914.017, df-3081) and Bartlett's Test of Sphericity (<0.001) has provided satisfactory results to carry out factor reduction analysis. Consequently, using Maximum likelihood extraction and promax rotation, 14 factors are retained after inspecting the scree-plot (Costello and Osborne 2005), and 'eigen values', which shows that the total variance explained by the 14 factors identified have eigen values above 1. Moreover, the internal consistency reliability is assessed using Cronbach's Alpha for all the constructs (Hair et al. 2014). The Cronbach's Alpha should be greater than 0.7 cut-off level to consider that the constructs are reliable(Kline 2015). All the constructs have attained more than 0.8 Cronbach's Alpha value in reliability test. Moreover, a detailed assessment of construct reliability and validity is performed using Confirmatory Factor Analysis (CFA).

Confirmatory Factor Analysis

To assess the higher-order BDA maturity construct, hierarchical reflective modelling approach is adopted based on suggestions from (Wetzels et al. 2009) and (Wamba et al. 2017). A measurement model is developed with second-order BDA maturity construct (composed of data generation capability, data integration and management capability, advanced analytics capability, digital analytics, data visualisation capability, data-driven culture, big data skills), and ACAP, data quality and operational and innovation performance constructs. The model fit of Second-order measurement Model is assessed using several criteria such as Chi-square (X2) =3805.561, degrees of freedom (df) =2649, chi-square goodness-of-fit (CMIN/DF) =1.437, comparative fit index (CFI) =0.929, parsimony comparative fit index (PCFI) =0.887, Normed fit index (NFI) =0.801, root mean squared error of approximation (RMSEA)=0.045, Tucker-Lewis Index (TLI)=0.926 and PCLOSE =0.998. A satisfactory result is achieved according to the established cut-off criteria (Hu and Bentler 1999; Byrne 2010).

Validity and Reliability

Apart from assessing the model fit of measurement models, the validity and reliability of the measurement models were also investigated using statistical tests such as Composite Reliability (CR), Average Variance Extracted (AVE) and Mean Shared Variance (MSV). In the previous section, Cronbach's Alpha is used to measure scale reliability indicating internal consistency of factors. While Composite Reliability also indicates internal consistency, but unlike Cronbach's Alpha, "it does not assume equal indicator loadings" (Hair et al. 2014, p.115). Convergent validity indicates how well the items within the same construct are correlated. On the other hand, discriminant validity indicates how well a construct is different from other constructs in the model(Hair et al. 2014). The Composite reliability of all the constructs are above 0.8 threshold (Byrne 2010; Schumacker and Lomax 2010; Bollen 1989). Moreover, MaxR(H) or Maximum reliability is calculated using AMOS tool (Gaskin, J. & Lim 2017), which is generally considered more robust than CR. Both, CR and MaxR(H) indicate that all the constructs in the model are reliable. Similarly, convergent validity is also assessed. The results indicate that all the constructs in the model have achieved convergent validity and more than 50 % of variance in the constructs are explained by the items used to measure it. To test discriminant validity, Fornell–Larcker criterion is used (Hair et al. 2010), which recommends to compare the square root of AVE and the correlation matrix. Ensuring discriminant validity is highly significant especially when testing for mediation, as the mediators has to be dissimilar from the dependent and independent variables (Zhao et al. 2010). Based on Fornell–Larcker criterion, the square root of the AVE has to be "greater than its highest correlation with any other construct" (Hair et al. 2010). The test results satisfy Fornell–Larcker criterion and each construct measured in the model are highly dissimilar to other constructs, indicating that all the constructs in the model satisfy discriminant validity.

Common Method Bias and Measurement Model Invariance Test

The occurrence of measurement errors due to methodological bias is a common problem in the behavioural research (Podsakoff et al. 2003). Harman's single factor test is conducted, the percentage of variance of first factor identified from the EFA is 43. 65 % which is less than the threshold indicating that there is no bias in the data set(Kwon et al. 2014). The bias is also tested using Common Latent Factor (CLF) method. The standardised regression weights of measurement models with and without the common latent factor is compared. It was found out that only the item AC1 belonging to ACAP construct is affected by bias. But, the bias is slightly above the threshold of 0.2, indicating no significant bias in the dataset. To test metric invariance, the chi-square difference between constrained and unconstrained model is evaluated and the results indicate factor structure is consistent irrespective of different groups in the data set. Furthermore, evaluating the measurement model of different subgroups show that the model fit is adequate for low number of employees vs. high number of employees' subgroups [fit indices: X2 = 204.389; df = 124; X2/df =1.6482; CFI =0.965.; PCFI =0.570; PNFI =0.918; PCLOSE=0.283; RMSEA =0.054; TLI=0.940; GFI =0.903], and also for the low turnover vs. high turnover subgroups [fit indices: X2 = 206.924; df = 124; X2/df =1.669; CFI =0.964;PCFI =0.570; PNFI =0.542; PCLOSE=0.248; RMSEA =0.055; TLI=0.940; GFI =0.898]. The findings suggest that the sample data investigated in this research satisfies the conditions of metric and configural invariance.

Findings

A full structural model is developed incorporating the latent factors proven to be valid from the CFA. The overall fit of the structural model was found to be adequate with the following fit indices; X2 =4185.055, df =2800, X2/df =1.495, CFI= 0.918, SRMR=0.081, RMSEA =0.047and PCLOSE =0.925. As explained, all hypotheses proposed in this research were tested controlling for firm size and annual turnover. Consequently, the direct effect of BDA maturity on operational and innovation performance is assessed. Findings are in support of H1a and H1b, and there is a positive relationship between BDA maturity and operational and innovation performance. Then, to test mediation role of ACAP and data quality, bootstrapping approach is used (Hayes and Preacher 2014).

Mediating role of Absorptive capacity

Hypothesis H2a, H2b states that absorptive capacity as a dynamic capability mediate the positive effect of BDA maturity on operational and innovation performance. Table 1 provides the results of mediation analysis. Findings suggests that, ACAP significantly mediate the positive relationship, supporting H2a and H2b. The effect size of the direct effect between BDA maturity and operation and innovation performance is reduced when adjusted for the mediating variable, but the effect is still significant. Hence, the type of mediation by ACAP on the relationship is complementary in nature(Zhao et al. 2010).

Table 1 Results on the mediating role of absorptive capacity

Hypothesis	Direct effect without mediation (Standardised estimates)	Direct effect with mediation (Mediator =Absorptive capacity)	Indirect effect	Bootstrap (5000 samples) 95% Confident interval		Remarks
				Lower	Upper	

BDA Maturity → ACAP → Product Quality	.595 ***	0.289***	0.269***	0.131	0.427	Complementary Mediation
BDA Maturity → ACAP → Cost	.615 ***	0.336***	0.241**	0.089	0.424	Complementary Mediation
BDA Maturity → ACAP → Flexibility	.554 ***	0.347***	0.187*	0.007	0.365	Complementary Mediation
BDA Maturity → ACAP → Time	.610 ***	0.378***	0.221**	0.042	0.418	Complementary Mediation
BDA Maturity → ACAP → Innovation	.599 ***	0.281***	0.304***	0.125	0.484	Complementary Mediation

Mediating role of Data Quality

The results of the mediation of data quality on the relationship between BDA maturity and firm performance dimensions is given in Table 2. H3a and H3b proposes that data quality as a consequent of BDA maturity mediates its relationships with operational and innovation performance. Here, the intention is to test the importance of resource quality i.e. data quality on value creation. Consequently, the findings have provided adequate evidence to support H2a1 (BDA Maturity → Data Quality → Product Quality), H2a2 (BDA Maturity → Data Quality → cost), and H2a3 (BDA Maturity → Data Quality → time), suggesting complementary mediation. However, the relationship between BDA Maturity → flexibility and BDA Maturity → Innovation are not mediated by data quality, as 95% confidence interval shows a non-significant result. In these cases, it is concluded that the effect is direct-only-non-mediation. It could be argued that data quality is an internal technical capability enhanced by BDA maturity, but innovation is largely depending on behavioural aspect of the organisations.

Table 2 Results on the mediating role of data quality

Hypothesis	Direct effect without mediation (Standardised estimates)	Direct effect with mediation (Mediator =Data Quality)	Indirect effect	Bootstrap (5000 samples)		Remarks
				Lower	Upper	
BDA Maturity → Data Quality → Product Quality	.595 ***	0.439***	0.137*	0.002	0.306	Complementary Mediation
BDA Maturity → Data Quality → Cost	.615 ***	0.408***	0.181*	0.03	0.376	Complementary Mediation
BDA Maturity → Data Quality → Flexibility	.554 ***	0.419***	0.121 (NS)	-0.049	0.295	Direct-only Non-Mediation
BDA Maturity → Data Quality → Time	.610 ***	0.4***	0.212*	0.048	0.423	Complementary Mediation
BDA Maturity → Data Quality → Innovation	.599 ***	0.45***	0.138 (NS)	-0.026	0.321	Direct-only Non-Mediation

6. Discussion and Conclusion

The findings of this study suggest that, there is a significant positive relationship between BDA capabilities maturity and operational and innovation performance. Absorptive capacity (ACAP) is found to partially mediate the relationship between the dimensions of BDA and innovation and operational performance. However, data quality only mediates the influence of BDA on product quality, cost and time dimensions of operational performance but not the flexibility and innovation dimensions. Moreover, BDA maturity is also found to significantly enhance absorptive capacity and data quality of the organisation. A plausible inference for these findings is that, BDA capabilities can be considered as a first-order capability that enhances higher-order dynamic capabilities such as ACAP, and this view is consistent with previous studies   Findings also indicate that absorptive capacity, as a learning capability of an organisation, plays a significant role in extracting value from BDA initiative. It can be argued that BDA can support by processing of huge volume of data and provide information/knowledge, but it is the organisations ability to acquire and assimilate such knowledge and applying it for commercial purpose creates value. The findings of this study provide some implications for practitioners; 1. BDA efforts should be focused on improving ACAP as it will consequently enhance operational and innovation performance, 2. Manufacturing organisations should incorporate all the key capabilities of BDA discussed in this research to realise the full potential of BDA. Hence, this study makes a significant contribution to the literature by explaining the underlying mechanism through which BDA influences performance. This study is the first to determine the relationship between BDA, absorptive capacity and innovation performance. In future, attempts will be made to investigate role of buyer-supplier dyadic relationship on the BDA practice. Further, the dimensions of BDA maturity will be used to explore the adoption trend and disparity between small and large organisations.

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