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Big Data, Analytic Culture and Analytic-Based Decision Making – Evidence from Australia

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Abstract

This study investigates how managerial decision making is influenced by Big Data, analytics and analytic culture. The results of a cross-sectional survey (n = 163) of senior IT managers reveal that Big Data Analytics creates an incentive for managers to base more of their decisions on the analytic insights. However, we also find that the main driver of analytic-based decision making is analytic culture. Considering that culture – in contrast to Big Data Analytics tools and skills – is a resource which cannot be change easily or quickly, we conclude that firms with a highly analytic culture can use this resource as a competitive weapon. Finally, our analysis reveals that managers in smaller organizations are significantly more likely to base their decisions on analytic outcomes than managers in large organizations, which suggests the former use analytics to remain competitive against their larger counterparts.

Keywords: Big Data Analytics, Decision Making, Analytic Culture, Organizational Culture, Data Science

1. Introduction

During the past few years, the terms ‘Big Data’ (BD) and ‘Big Data Analytics’ (BDA) have become increasingly important for both academics and business professionals in IT-related fields and other disciplines. Furthermore, executives increasingly acknowledge the potential benefits associated with BD[1] and global private and public investment in BD has reached billions of dollars per annum[2,3]. BD has become a popular term which essentially represents the fact that data generated and available today is ‘big’ in terms of volume, variety, and velocity[4,5].

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But being 'big' does not per se make data useful. It is rather the *insights* gained from analyzing the data which provide benefits[7], which in turn requires organizations to develop or acquire analytic capabilities[4]. The claimed power of BD does not replace the need for human insight[8]. Equipped with BDA experts, who can provide such insights from data, managers are expected to make better (informed) decisions[4,9,10].

High-performing organizations believe that BDA is a critical differentiator and a key to growth[1,11,12], but executives still struggle to understand and implement BD strategies effectively[13], and it is unclear to what extent managers actually use the available BDA output to support their decisions. Some even argue that the biggest challenge in BDA is that managers do not comprehend how to gain benefits from analytics[11], and managers themselves are concerned about their ability to uncover and take advantage of meaningful insights[12]. Accordingly, the first research question in this paper is: *Are managers in organizations with sophisticated BDA more likely to base their decisions on analytics (facts, evidence) than managers in organizations low on BDA?*

The second research question addresses the role of culture in the context of BDA and decision making. Organizational culture refers to an aggregation of values, beliefs, knowledge, attitudes, tasks, habits, morals, customs, and norms which are shared and strongly held by members of an organization, so as to provide a frame of reference that indicates organizational practices, behavior, and goals[14-16]. One aspect of organizational culture is analytic culture, i.e. the attitude towards the usefulness, use and benefits of analytics[17]. Since the emergence of knowledge based systems such as expert systems, researchers have attempted to understand the relationship between (analytic) culture and the use of information generated by those systems[18]. There is some evidence that the perceived value of data analytics influences how the decision-making process is configured[17], and in organizations that believe in the reliability and accuracy of their organizations' information, managers tend to use more of that information to support their decisions[19]. In addition, it is suggested that organizations high on analytic culture invest more into data analytic capabilities in terms of tools, methods, and people[17,20]. This leads to our second research question: *Does the level of organizational analytic culture influence (a) how much analytic information managers use in decision making, and (b) the level of sophistication of an organization's BDA?*

The reminder of the paper is organized as follows: Section 2 elaborates on the constructs of interest and makes predictions about their relationships (hypotheses); section 3 explains the research methods, including construct measurement, and section 4 presents the results. Finally, the results, their implications and the limitations of our research are discussed in section 5.

2. Theory/Hypotheses Development

2.1. Background

Big Data (BD) refers to a set of techniques and technologies that require new forms of integration in order to uncover hidden value from large datasets that are diverse, complex, and of a very large scale. The *volume* of BD is massive, so conventional hardware and software are incapable of handling it within a suitable time-frame[21]. Data volume has increased dramatically and the unit of measuring data will change from zettabytes (10^{21} bytes) in 2012[4] to yottabytes (10^{24} bytes) in 2030[22]. The *variety* of data used for analytics also increased dramatically, because it includes not only traditional relational data, but also raw, semi-structured, and unstructured data from various sources. Unstructured data, such as emails, text-based documents, images, videos, call-center recordings, and sensor-generated data cannot be stored easily within a standard relational database[13] and require new analysis techniques. *Velocity* refers to the speed of both data generation and data processing. Data generation is rapidly increasing as a result of widely-used mobile technologies and 'The Internet of Things'. Real-time or near real-time information enables organizations to be more agile than their competitors[8]. Data today is generated, changed, and removed more frequently than in the past and consequently organizations need new platforms and tools for analyzing them.

"Analytics is the science of analysis"[23]. Data analytics uses data for quantitative and/or qualitative analysis to help an organization better understand its business and markets (knowledge discovery) and to make timely business decisions[5,20,24]. Data analytics in a BD environment is different from conventional data analytics for the reasons mentioned above[8]. With the emergence of BD, the analytic algorithms have changed so as to react more quickly to the high volume, variety, and velocity of data.

2.2. Hypotheses

Big Data Analytics (BDA) applies scientific methods to solve problems previously thought impossible to solve, because either the data or the analytic tools did not exist[25]. BD solutions help organizations create actionable strategies by providing constructive, predictive and real-time analytics, and to gain deeper insights in how to address their business requirements and plans[26]. With new technologies and analytic approaches, BDA can provide managers with information for real-time planning and continuous forecasting[8,21,26]. BDA techniques are capable of analyzing larger amounts of different types of data. With increasingly advanced algorithms, BDA can help improve decision efficiency and effectiveness[27]. In summary, BDA can have a significant impact on decision-making processes, *provided* managers perceive that analytic output as useful and use analytic output to support their decisions.[28-30]

However, research findings are still inconsistent in terms of what managers base their decisions on. Even when managers use a rational approach in their decision-making process, they may still also use heuristics (including intuition), to cope with bounded rationality at some stages in this process[31]. However, when data contradicts intuition, senior managers are said to set aside their intuition and rely on data[8]. We therefore predict as follows:

H1: Big Data Analytics sophistication leads to more analytic-based decision-making.

Organizational analytic culture (OAC) refers to the extent organizations perceive data analytics as useful. OAC is shown by how organizations recognize the value of analytics and whether or not fact-based decisions are encouraged. OAC has been previously recognized as an enhancer of organizational financial performance and a source of competitive advantage[16,32,33]. High-level managers' positive attitude towards analytics is a primary driver for organizations to use analytics as competitive force[34]. OAC is reflected not only in the way people in organizations interact with analytics, but also how their managers support investment and operations related to analytics. Organizational culture bonds intelligence of an individual and organization's core values in establishing a culture of excellence[35]. Organizations with a strong analytic culture tend to support larger investment in analytic assets such as BD, more sophisticated analytic tools, methods, and skills. When an organization has a culture that realizes the importance of BDA, it also reflects on how an organization designs analytic processes[24]. As a result, the sophistication level of BDA tends to be higher in organizations which have a culture that supports data-sharing and advanced analytics.

H2: Organizational analytic culture has a positive effect on Big Data Analytics.

OAC also influences the managerial decision process. One aspect of culture that should be emphasized is managerial attitude toward the benefits and use of analytics[17]. Managers in evidence-based cultures may perceive information as more useful[36]. Analytic culture is reflected in organizations in such a way that senior managers perceive analytics as useful and beneficial, and they therefore seek advice from analysts before making decisions.

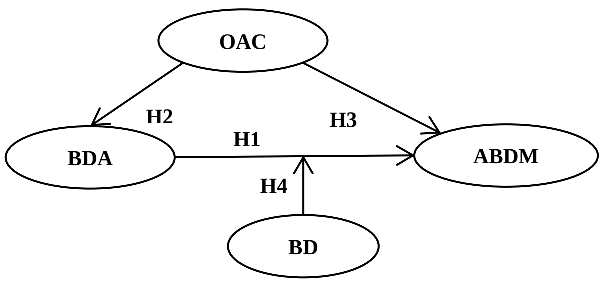

Figure1– Research Model

Across different organizational cultures, managers tend to behave and perceive benefits of analytics differently. If managers think that information is of high quality and can improve their work performance, they will perceive it as being more useful[37]. It is therefore hypothesized that there is a positive effect of OAC on the extent of *analytic-based* decision-making.

H3: Organizational analytic culture has a positive effect on analytic-based decision-making.

Some organizational resources are *complementary*, i.e. they have to work together with other resources to maximize their impact[15]. It is argued that such a complementary relationship exists between BD intensity and BDA. When more sophisticated analytic tools and methods are used with 'bigger' data, the analytic outputs are expected to be of higher quality and therefore used more for decision making. It is therefore hypothesized that BD intensity has a positive moderating effect on the relationship between BDA and analytic-based decision making (ABDM).

H4: The positive relationship between Big Data Analytics sophistication and analytic-based decision-making is moderated by Big Data intensity.

3. Research method

As this research is exploratory in nature, a cross-sectional survey has been selected as most suitable research method[51]. Survey procedures used follow the suggestions of Dillman et al.[38] As each variable in the hypotheses is latent, constructing proper indicators and scales was essential. This process was guided by academic literature, but where required, practitioner literature was also consulted. During questionnaire design, necessary procedural remedies were applied to control for and minimize the impact from these common method biases[39].

The *face* and *content validity* of the prototype of the questionnaire as well as the appropriateness of Likert scale endpoints were assessed as follows:[39] Five experts in survey research were invited to evaluate the draft questionnaire, and their feedback was used to refine the design and content of the survey. The revised version of the questionnaire was then delivered to a small sample group of experts for pilot testing.

The survey targeted CIOs and senior IT managers of Australia-based medium to large for-profit organizations.

3.1. Measurement

In this research, *BDA sophistication* is operationalized along two dimensions[40]: (a) analytic tools and (b) analytic methods. *Analytic tools* refer to software applications that analytic professionals use in data analytics. They range from basic to advanced quantitative methods embedded in spreadsheets, business intelligence (BI) tools, statistical packages, data mining suites, data visualization tools, and high performance computing tools. *Analytic methods* refer to quantitative methods that analytic professionals use in data analytics. They include statistical methods, machine learning, data mining, artificial intelligence, operations research, optimization models, and path modelling[41]. Respondents were asked to rate their analytics expert/team in terms of various analytic tools and methods (skills) on a seven-point Likert scale in terms of frequency of use of each analytic tool or method, with 1 = never and 7 = very frequently (see Table 2 in the appendix).

To measure BD a three-dimensional scale for ‘BD-intensity’ was developed based on the three Vs (volume, variety, and velocity). Respondents were asked to rate the level of *increase* of each V in terms of data (a) they have *access to* and (b) data they actually *use* in analytics in their organization using a five-point Likert scale (see Table 2 in the appendix).

In an organization, *decisions* can be made at many levels: strategic, tactical, and operational[42]. Strategic decisions include how an organization initiates new products, services, or market channels, which major suppliers it selects, etc. Operational decisions involve day-to-day decisions in various business functions, e.g. marketing, operations, and procurement. (Tactical decisions were excluded from the questionnaire, because they were deemed to be in a too ‘grey area’ between strategic and operational decisions.) Respondents were asked to rate the level of their organizational strategic and operational decisions relying on insights derived from data analysis/analytics on a seven-point Likert scale, in which 1 = strongly disagree and 7 = strongly agree.

Analytic culture is about how people in an organization value analytics. It may present in the way senior managers perceive analytics as a strategic resource[17], in the reward system of an organization, in the way how people exchange data and information, etc.[19] Respondents were asked to rate the level of their organizations’ analytic culture based on seven statements using a seven-point Likert scale, in which 1 = strongly disagree and 7 = strongly agree (see Table 2 in the appendix).

3.2. Survey response

The initial invitation was sent out to 1,595 potential respondents via email, but 263 invitations did not reach the addressees. A total of 174 responses were received during the survey period, but 11 had to be excluded, because they did not meet the required criteria (in terms of minimum tenure etc.). The final response rate of 12.24% may appear low, but is not unusual in Australian business surveys, even more so on a topic which is still only emerging. The spread of the responses reflects Australian industry, as shown by the coefficient of variation (CoV). The CoV of survey responses is 0.844 while that of Australian industry is 0.843. 84% of the responses came from organizations which have more than 100 full-time equivalent employees, and CIOs and other senior IT managers were almost equally represented (52.1% and 47.9%).

3.3. Data characteristics and quality

Test for normality were conducted for both indicator data and latent constructs in order to determine appropriate analysis and testing techniques (parametric vs. non-parametric)[43]. The *Shapiro-Wilk test* and the *Kolmogorov-Smirnov test* both show that none of the indicators is normally distributed ($p < 0.05$), which requires the use of non-parametric data analysis and testing techniques (PLS-SEM, bootstrapping, etc.)[44].

In addition to the procedural remedies applied during the development of the questionnaire, post-hoc statistical remedies were used to test for potential *method bias*[39]. *Harman's single factor test* was run across the set of 32 measurement indicators and the results show that there are 7 factors with eigenvalues greater than 1 indicating that common method variance due to method bias is not present.

Responses were also tested for *non-response bias* by comparing early and late responses. The results of independent samples test (Mann-Whitney U and Levene's Test) confirm that there are no significant differences in the indicator values between the early (n = 83) and late (n = 80) response group.

After the elimination of three low-loading indicators, all remaining indicators have significance levels of $p < .001$, and load primarily on their assigned construct. The measurement model was further assessed for reliability and validity of the construct measures. Reflective measurement models are assessed for: (a) the internal consistency (composite reliability), (b) indicator reliability (composite reliability), (c) convergent validity (average variance extracted and communality), and (d) discriminant validity[62].

Table 3 confirms that the first three of those criteria are fully met. The Fornell-Larcker criterion[45] was applied to assess for *discriminant validity* of latent constructs, and all of them meet the criterion (Table 4). The heterotrait-monotrait (HTMT) ratio between the average of the heterotrait-heteromethod correlations and the average of the monotrait-heteromethod correlations[46] is used to further ensure discriminant validity. A HTMT value of two latent constructs of less than .85 confirms discriminant validity between the pair. Table 5 reveals that there are some measurement 'overlaps' between the '3 Vs' of BD, but considering that they are used to form a second order formative construct, this minor lack of discriminant validity is not considered a concern.

4. Results

Two alternative versions of the structural model were developed. The first structural model was used to test hypotheses 1 to 3. Model 2 was used to determine the moderating effect of BD sophistication on the relationship between BDA and ABDM; to this end, BD and the interaction term BD*ABDM were added to the model. The results of the PLS analysis and bias-corrected bootstrapping are presented in Table 1.

Table 1 – Structural Model Results

	Direct Effect (DE)	Indirect Effect (IE)	Total Effect (TE)	f Square (DE)
Model 1				
BDA → ABDM **(H1)**	**.162****		.162**	**.034**
OAC → BDA **(H2)**	**.489*****		.489***	**.316****
OAC → ABDM **(H3)**	**.530*****	**.079****	**.609*****	**.364****
SIZE → ABDM (Control)	-.143**	.020*	-.122*	.034
SIZE → BDA (Control)	.126*		.126*	.021
R-squares				
ABDM	*.414****			
BDA	*.248****			
Model 2				
BD → ABDM	.170*		.170*	.039
BDA → ABDM	.131*		.131*	.019
BD * ABDM → ABDM **(H4)**	**-.070**		**-.070**	**.007**
OAC → ABDM	.486***	.064*	.550***	.309**
OAC → BDA	.489***		.489***	.316**
SIZE → ABDM (Control)	-.150**	.017	-.134**	.039
SIZE → BDA (Control)	.126*		.126*	.021
R-squares				
ABDM	*.446****			
BDA	*.248****			

1-tailed: p<0.05; p<0.01**; p<0.001****

As predicted in hypothesis 1, BDA sophistication has a significant positive effect on ABDM (H1: $\beta = .16$, $p < .01$), although the effect size (f-square) is rather small (.03). The latter limitation is, however, not surprising, considering there are many other factors contributing to managerial decision making behavior. One of these factors is analytic culture (OAC), which has a very strong direct effect on ABDM (H3: $\beta = .53$, $p < .001$, $f = .36$), partially suppressing the impact of BDA on ABDM (*Spearman correlation* = .40, $p < .001$).

The effect of BDA on ABDM is further enhanced by the strong indirect effect of OAC on ABDM via BDA ($\beta = .08$, $p < .001$), which results in very strong total effect of OAC on ABDM (H3': $\beta = .61$, $p < .001$). Along this line of prediction in the path model, the strong relationship between OAC and BDA also confirms hypothesis 2 (H2: $\beta = .49$, $p < .001$, $f = .32$).

Model 2 reveals a weak but significant effect of BD on ABDM ($\beta = .17$, $p < .05$, $f = .04$), but the hypothesized interaction effect of BD on the relationship between BDA and ABDM could not be confirmed; or in other words: 'Bigger' data is associated with more analytic-based decision making, but it does not interfere with the relationship between BDA and ABDM.

The structural model results also reveal an interesting – although not hypothesized – side effect: Firm size has the expected positive, but very weak effect on BDA sophistication ($\beta = .13$, $p < .05$, $f = .02$), but interestingly, it has a negative direct ($\beta = -.14$, $p < .01$, $f = .03$) and even total ($\beta = -.12$, $p < .05$) effect on ABDM (despite a small positive indirect effect). So while larger firms are able to provide more sophisticated BDA, managers in those firms tend to base their decisions to a much lesser extent on analytics than managers of smaller firms.

5. Conclusion, implications and limitations

The research presented in this paper attempted to answer the following research questions: (1) Are managers in organizations with sophisticated Big Data Analytics more likely to base their decisions on analytics (facts, evidence) than managers in organizations low on Big Data Analytics? (2) Does the level of organizational analytic culture influence (a) how much analytic information managers use in decision making, and (b) the level of sophistication of an organization's Big Data Analytics?

The results of our analysis suggest that the answer to these questions is uniformly 'yes'. Managers in firms which use sophisticated BDA tools and methods tend to base their decisions more on analytics than managers in low-BDA firms. However, the analytic culture in an organization is a by far stronger predictor of analytic-based decision making than the sophistication of BDA practices.

These findings have important implications for research and practice: First, the findings empirically confirm the often unverified claims that BDA has an impact on managerial decision behavior insofar as more advanced analytics creates an incentive for managers to actually base their decisions on the analytic insights. Second – and most importantly – the findings suggest that the main underlying driver of analytic-based decision making is analytic culture[33], which also manifests in high levels of BDA sophistication. These findings suggest that the impact of BDA investments is predominantly driven by culture and not the BDA investments themselves, or in other words: Organizations which invest in BDA, e.g. by employing advanced data scientists, creating modern BD infrastructures and deploy BDA tools, may create an incentive for managers to 'listen' more to what analytic results suggest, but in the absence of an analytic culture in the organization, such impacts will remain marginal. Despite some apparent shortage of data science skills in the job marked, BDA resources can be sourced from markets in relatively short time. Culture, on the other hand, is generally considered a *valuable*, *rare*, *inimitable*, and *non-substitutable* (VRIN) resource[15], because it cannot be changed easily – let alone quickly. Organizations with a strong analytic culture are therefore in a good position to "compete on analytics"[34], whereas those which are low on analytic culture are well advised to start developing such culture, rather than investing 'blindly' into BDA assets.

Our study also reveals that managers in smaller organizations are significantly more likely to base their decisions on analytic outcomes than managers in large organizations. This finding is in line with some cases reported in the practitioner literature, which suggest that small businesses are in a good position to compete on analytics[13]. Considering that analytic culture plays a very important role in creating BDA impact, these findings suggest that smaller firms owe some of their analytic advantages to the fact that they can change culture more easily and quickly than large firms.

Like any study, our research is not free of limitations. Despite the fact that we deployed several procedural and statistical remedies to avoid biases[39], survey-based research is never completely immune against biases. Second, the survey respondents were exclusively CIOs and other senior IT managers, which inevitably introduces an IT-centric perspective. Future research could attempt to capture a more balanced perception, especially with regards to managerial decision making. Finally, we do not explicitly measure decision making quality or performance, but rather rely on prior research[31,48] which suggests that ABDM is associated with better decision making.

Appendix A.

Table 2 – Descriptive Statistics (First Order Constructs)

	Mean	Std. Dev.
Analytic Tools	**1 - 7**	
Spreadsheets	6.55	0.795
BI Planning/Reporting Suites	4.88	2.056
Data ETL/Management Solutions	4.32	2.246
Statistical Suites – Basic Use	2.73	1.966
Statistical Suites – Advanced Use	2.42	1.866
Specialised Data Mining Suites	2.02	1.593
Data Visualisation Tools	3.53	2.215
BD/High Performance Computing Tools	2.13	1.709
Analytic Methods	**1 - 7**	
Statistical Methods	3.44	2.114
Machine Learning, Data Mining, AI	2.45	1.846
OR, Optimisation Methods	2.53	1.789
Path Modelling	1.76	1.285
Organisational Analytic Culture	**1 - 7**	
Fact-Based Decision Making	5.02	1.434
Easy to Convince of Analytics Value	4.83	1.557
Seeking Advice from Analysts	4.39	1.642
Sharing of Data	4.71	1.485
Analytics as Strategic Resource	4.96	1.606
Support Investment in Analytics	4.55	1.580
Act upon an Explicit BD Strategy	3.17	1.853
Analytic-Based Decision-Making	**1 - 7**	
Decisions about Products/Services/Markets	4.73	1.667
Decisions about Strategic/Key Suppliers	4.46	1.508
Decisions about Outsourcing/BPM	4.32	1.570
Decisions about Sales and Marketing	4.80	1.576
Decisions about Operations	5.02	1.486
Decisions about Procurement	4.52	1.446
Overall, Organisation Acts on Insights	4.78	1.445
Volume	**1 - 5**	
Volume of Data – Access	4.51	0.781
Volume of Data – Use	4.13	0.972
Variety	**1 - 5**	
Diversity of Unstructured Data – Access	4.04	0.974
Diversity of Unstructured Data – Use	3.26	1.159
Velocity	**1 - 5**	
Rate of Change of Data – Access	4.16	0.831
Rate of Change of Data - Use	3.77	1.026

Table 3 – Measures of Validity and Reliability (First Order Constructs)

First Order Construct	Composite Reliability	Cronbach's Alpha	Avg. Variance Extracted (AVE)
Tools	.861***	.807***	.508***
Methods	.911***	.855***	.774***
Volume	.868***	.711***	.768***
Variety	.831***	.595***	.711***
Velocity	.858***	.691***	.752***
ABDM	.936***	.918***	.710***
OAC	.880***	.828***	.597***

1-tailed: p<.05; p<.01**; p<.001****

Table 4 – Fornell-Larcker Criterion for Discriminant Validity (First Order Constructs)

	1	2	3	4	5	6	7
Tools (1)	**.713**						
Methods (2)	.592	**.880**					
Volume (3)	.339	.337	**.876**				
Variety (4)	.284	.248	.381	**.843**			
Velocity (5)	.323	.325	.714	.593	**.867**		
ABDM (6)	.363	.384	.398	.260	.374	**.842**	
OAC (7)	.453	.394	.400	.145	.353	.616	**.772**

Values in the diagonal are the square-roots of the AVE of each of the constructs.

Table 5 – HTMT Values for Discriminant Validity (First Order Constructs)

	Tools	2	3	4	5	6
Methods (2)	.718					
Volume (3)	.432	.418				
Variety (4)	.412	.347	.577			
Velocity (5)	.405	.395	*1.020*	*.920*		
ABDM (6)	.408	.427	.474	.351	.443	
OAC (7)	.556	.474	.488	.226	.425	.703

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