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Improving Strategic Decision-Making through the Use of Business Analytics: A Resource-Based View

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Abstract
While business analytics is suggested to improve organizational decision-making, more empirical research is needed to substantiate this proposition. This study draws on the resource-based view to understand how an organization can use business analytics to improve its strategic decision making (SDM). The analysis of 218 survey responses from UK firms shows that the use of business analytics is related to rational SDM positively and intuitive SDM negatively, while environmental scanning mediates the relationship between the use of business analytics and rational SDM. The findings suggest that an organization can improve its SDM by enhancing its analytics and environmental scanning capabilities.

Keywords: Business analytics; Resource-based view; Analytics capability; Environmental

1. Introduction

While existing theory (e.g. Kahneman 2011) suggests that the use of business analytics can be lined organizational decision-making, it is unclear how this might be achieved (e.g. Grover *et al.* 2018; Krishnamoorthi and Mathew 2018) as there is a dearth of empirical research to substantiate this proposition and practical guidance for managers seeking to use business analytics.

This study seeks to answer two research questions. First, what are the mechanisms of using business analytics to improve strategic decision making (SDM)? While a considerable amount of research on strategic management (e.g. Dean Jr and Sharfman 1996; Lau et al. 2012) has been conducted to investigate how to improve SDM, little research exists to empirically investigate how the use of business analytics may affect SDM (Sharma et al. 2014; Grover et al. 2018). Second, whether and to what extent does the use of business analytics affect rational SDM and intuitive SDM? Rational SDM involves a series of sequential, systematic, and analytical processes (Calabretta et al. 2017), while intuitive SDM depends on holistic hunch and automated expertise (Miller and Ireland 2005). According to Kahneman (2011), the former can be termed “System 2” and the latter “System 1”. System 1 is characterized by retrieving stored experience quickly and accurately to make complex judgments in familiar environments, while System 2 is characterized as a process that is rule-based, analytical and reflective. Literature on strategic management indicates the many company executives use more intuition (or System 1) than formal analysis (or System 2) in SDM (Miller and Ireland 2005; Woiceshyn 2009); however, little empirical research on intuition exists (Khatri and Ng 2000; Elbanna *et al.* 2013). Besides, while a few analytics studies indicated that the use of business analytics or big data analytics is likely to lead to more evidence-based decision making (Seddon *et al.* 2017), little empirical research exists to investigate how the use of business analytics may affect rational SDM and intuitive SDM or the relationship between the latter two.

In an attempt to make contributions to the literature, this study draws on the resource-based view (RBV) (Wernerfelt 1984; Barney 1991) to develop an understanding of the mechanisms through which business analytics can be used to improve SDM. This study argues, firstly, that an organization can improve its SDM by developing its analytics capability to capture, integrate and analyze data and information, and use the insights gained from data and information in the context of organizational decision-making (Tan *et al.* 2016). Secondly, drawing on research suggesting that IT capability and other organizational capabilities/resources might be related and bundling them together could be advantageous (e.g. Tan et al. 2016; Krishnamoorthi and Mathew 2018), this study posits that analytics capability as manifested in the use of business analytics could enhance environmental scanning capability to scan and sense new opportunities (Helfat and Raubitschek 2018). Essentially, an organization's analytics capability allows the organization to generate useful insights for organizational decision-making in general, which enhances the organization's environmental scanning capability to gain competitive intelligence in particular for improving its SDM.

2. Theoretical considerations

2.1. The use of business analytics, rational SDM and intuitive SDM

Business analytics refers to the processes and techniques of data collection, management, and analysis for the generation of knowledge and intelligence (Davenport and Harris 2007). Its processes include a series of steps taken in order to capture, aggregate, and analyze data/information, and disseminate information and insights. There are three key types of business analytics (Delen and Demirkan 2013). Descriptive analytics can be used to describe what has happened and what is happening thereby to provide the context of and trending information on past or current events. Predictive analytics can be used to predict what could happen through providing an accurate projection of future happenings and the reasoning as to why. Prescriptive analytics can be used to prescribe what should be done thus to recommend one or more courses of action and show the likely outcome of each decision.

Based on the RBV, this research suggests that an organization's use of business analytics enables the organization to create or enhance its analytics capability, that is the ability to capture, integrate and analyze data and information, and use the insights gained from data and information in the context of organizational decision-making. Such capabilities, manifested by information processing capability , business analytics capability (Tan et al. 2016), big data analytics capability (Akter et al. 2016; Gupta and George 2016), are shown to be valuable, rare and inimitable, thus can be a source of sustainable competitive advantage. This is believable as existing literature points to the argument that analytics capability is rooted in processes and business routines (Tan et al. 2016), explicit organizational strategy, structure, and processes , data-driven culture, tangible, human and intangible resources (Gupta and George 2016), or a bundle of management, technology, and talent capabilities (Akter et al. 2016).

As a result, analytics capability is seen to have brought organizational decision making to a completely new level that is ever so data-driven, allowing managers to see what was previously invisible and enabling decision making move toward "territory that has historically been seen as reliant on human judgment" (Gillon et al. 2014, p. 288-289). Thus, it is perceivable that the use of business analytics could allow an organization to improve its rational SDM and reduce the need for intuitive SDM. The literature on SDM (e.g. Simon 1987; Khatri and Ng 2000) suggests that rational decision processes are preferred when data is available and reliable, while intuitive decision processes offer a valuable alternative for decision situations where problems are ill-structured and complete, accurate, and timely information is not available. While it is a fallacy to say that rational and intuitive processes are mutually exclusive (Sadler-Smith 2004), it seems reasonable to believe that rational rather than intuitive decision processes are likely to be used when an organization has both the analytics capability and data availability to generate reliable data-driven insights.

While no academic research exists to examine the relationship between rational SDM and intuitive SDM in the context of business analytics, a few prior studies provided some insight into such relationship (Sadler-Smith 2004; Elbanna et al. 2013). Sadler-Smith (2004) assumed rationality and intuition as opposing modes of a manager's information processing and found that the correlation between rationality and intuition is statistically significant and negative. Similarly, this finding was confirmed by Elbanna et al. (2013). However, Simon (1987) argued that it is doubtful that decision-makers depend only on either intuition or rationality; they may need to combine both and could be simultaneously rational and intuitive (Elbanna 2006; Hodgkinson *et al.* 2009), though little is known about how to manage intuition and rationality simultaneously (Calabretta et al. 2017). Since few organizations could have the advantage of having (1) the analytics capabilities that allow them to generate data-driven insights from (2) complete, accurate and timely information to allow fully rational SDM, it is reasonable to assume that the more an organization has both the analytics capability and data availability, the more likely it is to employ rational SDM and reduce the need for intuitive SDM.

Thus, this study expects that an organization is able to significantly improve its rational SDM when it has effectively used business analytics to develop its analytics capability thereby to improve the accuracy, sophistication, and completeness of rational analysis (Molloy and Schwenk 1995). Using data-driven insights obtained from the use of business analytics, organizations can use rational decision processes to systematically identify strategic business problems and opportunities, define strategic objectives and criteria for success, develop and evaluate strategic alternatives, and select the best alternative. For example, business organizations could use business analytics to identify consumer, market, competitor, and new product insights in real-time, which has the potential to lead to real-time decision making (Xu et al. 2016). Thus, this study argues that the use of business analytics allows an organization to develop its analytics capability. As a result, the organization is likely to better identify problems and opportunities, define strategic objectives and criteria for success, develop and evaluate alternatives, and prioritize and select one or more alternatives (Simon 1947). Thus the organization is expected to improve its rational SDM and reduce its needs for intuitive SDM. Therefore, this study posits that:

H1: The use of business analytics is positively associated with rational SDM.
H2: The use of business analytics is negatively associated with intuitive SDM.
H3: Rational SDM is negatively associated with intuitive SDM.

2.2. The mediating role of environmental scanning

According to Aguilar (1967), environmental scanning is the acquisition and use of information about events, trends, and connections in an organization's external environment; its process consists of the identification of scanning needs, information gathering, information analysis, results communication, and informed decision making (Lau *et al.*

2012). Thus, strategic decision-makers use environmental scanning to "gather and interpret pertinent environmental information and introduce the results of analyses into an organization's decision processes" (Lenz and Engledow 1986, p.69) to support top management's strategic planning and decision making. Through environmental scanning to identify competitive intelligence, organizations can make effective strategic decisions to adapt to external changes and incorporate new information into the formulation of strategies to align its strategy with its environment (Calof and Wright 2008). However, prior research on environmental scanning is largely descriptive (Choudhury and Sampler 1997) and little research exists to investigate the relationship among the use of business analytics, environmental scanning and SDM.

Drawing on research underpinned by the RBV that suggests that analytics capability is likely to be related or need to be bundled together with other organizational capabilities/resources (Akter *et al.* 2016; Tan *et al.* 2016; Krishnamoorthi and Mathew 2018), this study further posits that an organization's analytics capability enhances its environmental scanning capability that is also referred to as an organization's business intelligence capability (Bigley 2018) or dynamic capabilities to scan and sense new opportunities (Helfat and Raubitschek 2018). Furthermore, environmental scanning allows an organization to have competitive intelligence (Lau *et al.* 2012), which in turn enables the organization to evaluate its business practices, to improve internal business efficiencies, and to create new products or services for customers (Davenport 2013). Thus, while the use of business analytics allows an organization to generate useful insights in general, environmental scanning capability will enable the organization to gain competitive intelligence in particular, which can then be used to enable the firm to improve its SDM (Lau *et al.* 2012). Therefore, this study suggests that the use of business analytics will enable an organization to better scan its business environment, which enables the organization to learn about its customers, competitors, and the broader market environment (Ransbotham *et al.* 2016). As a result, competitive intelligence derived from environmental scanning could result in supporting decisions in for example business strategy, business development, market entry decisions, product development, R&D/technology decisions, and M&A decisions (Calof and Wright 2008). Therefore, this study proposes that:

H4: Environmental scanning mediates the relationship between the use of business analytics and rational SDM.

3. Research methodology

3.1. Research model constructs and measures

In order to empirically test the proposed research model, both formative and reflective constructs and their indictors were defined, which are summarized in Table 1. As business analytics is still emerging as an area of study, there are few previously empirically validated measurement items. Thus new construct for the use of business analytics and its indicators have been developed, drawing on the extant literature on business analytics. Other constructs together with their indicators are adapted from SDM studies to the current research context, which have already been empirically validated by prior studies. The use of business analytics is defined formatively as a composite concept measured by using descriptive analytics, predictive analytics and prescriptive analytics, drawing on the four decision rules: the direction of causality between construct and indicators, interchangeability of the indicators, covariation among the indicators, and the nomological net for the indicators (Petter et al. 2007). The rest of the constructs, including rational SDM, intuitive SDM, and environmental scanning together with their measurements, are adapted from SDM studies to the current research context; they have already been empirically validated by prior studies. Additionally,

Construct	Indicator	Reference
The Use of Business analytics (UBA) (Formative)	The extent to which your company uses the following types of Business Analytics (1 - not at all, 7 - very extensively). • UBADESC: Descriptive Analytics provides the context of and trending information on past or current events • UBAPRED: Predictive analytics provides an accurate projection of the future happenings and the reasoning as to why • UBAPRES: Prescriptive analytics recommends one or more courses of action and show the likely outcome of each decision	(Kiron and Shockley 2011; Delen and Demirkan 2013)
Environmental Scanning (ES) (Reflective)	To what extent do you agree or disagree with the following statements about the following activities that had been undertaken to gather information about your company's environment in the past five years (1 – strongly disagree, 7 – strongly agree). • ESROU: Routine gathering of opinions from clients • ESSPE: Special market research studies • ESCOM: Explicit tracking of the policies and tactics of competitors • ESFOR: Forecasting sales, customer preferences, technology, etc.	(Miller 1987)
Rational Strategic Decision Making (RSDM) (Reflective)	Faced with an immediate, important, non-routine threat or opportunity, we usually (1 – strongly disagree, 7 – strongly agree). • SDCCRIT: Consider many different criteria and issues when deciding the course of action to take • SDCMULT: Thoroughly examine multiple explanations for the problem or opportunity • SDCSUGG: Conduct multiple examinations for the suggested course of action • SDCRESP: Search extensively for possible responses • SDCALTE: Develop many alternative responses	(Dean Jr and Sharfman 1996; Goll and Rasheed 1997; Atuahene-Gima and Haiyang 2004)
Intuitive Strategic Decision Making (ISDM) (Reflective)	Faced with an immediate, important, non-routine threat or opportunity, we usually (1 – strongly disagree, 7 – strongly agree): • IDMGUTF: make decisions based on 'gut-feeling' • IDMEXPE: make decisions relying on past experience • IDMJUDG: make decisions relying basically on personal judgment	(Khatri and Ng 2000; Elbanna and Child 2007)
Environmental dynamism (ENV) (Reflective)	• ENV1: Customer preferences change rapidly for this product market • ENV2: There is intense competition for market share in this product market • ENV3: Technological innovations have brought many new product ideas to this product market in the recent past.	(Rai and Tang 2010)

Table 1. Constructs and indicators of the study

based on prior research (e.g. Amason and Mooney 2008; Miller 2008), this study controlled for industries, firm size, respondent's job tile and job tenure, and environmental dynamism. Except for environmental dynamism that was measured based on indicators adopted from

(Rai and Tang 2010), all other control variables were categorical in this research and measured by the use of dummy variables.

3.2. Data collection

Data was collected from both medium and large UK enterprises as they are expected to have the capabilities and substantial resources to employ various types of business analytics for business improvement. The survey instruments were developed based on the literature review and definitions discussed above and then were scrutinized by subject experts. The sample, targeting senior and middle managers of all UK companies, was identified based on managers' email addresses provided by the FAME database; thus a non-probability sampling approach was used. Four rounds, one week apart, of emails with the questionnaire survey were sent using Qualtrics software. 232 responses were received and 218 were usable responses.

A key informant approach (Bagozzi *et al.* 1991) was used to collect data. The reported positions of the respondents suggested that 20% of the respondents were in a senior managerial position and the rest of them were in a middle managerial position. Based on their position within the firm, the respondents were considered to have relevant knowledge and experience to be able to address the survey questions. Of all respondents, 46% had been with their firms for more than 10 years. The respondents included 28% from the manufacturing sector, 15% from professional services, 9% from retail/wholesale, 8% from technology, and 6% from financial services.

3.3. Common method and non-respondent bias

A full collinearity assessment approach suggested by Kock (2015) was performed 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 if the VIFs (variance inflation factors) generated from a full collinearity test for all latent variables in the current research model were equal to or lower than 3.3, which indicates the model is free of common method bias. The test result indicated that all the VIFs were below 2; thus, there is no evidence of a substantial respondent bias in this study.

To evaluate the presence of non-response bias, two tests were conducted. First, the distribution of the company size of the respondents was compared with that of the complete sampling frame, based on the known value for the population approach (Armstrong and Overton 1977). A nonparametric chi-square test found that there are no significant differences between respondents and non-respondents. As a second test for non-response bias, early and late respondents were compared on all measures through a t-test. The results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias.

3.4. Evaluation of the research model an hypotheses testing

The reflective measurement model was evaluated by considering the internal consistency, indictor reliability, convergent validity and discriminant validity. The formative measurement model was evaluated in terms of multicollinearity, the indicator weights, significance of weights, the indictor loadings (Hair *et al.* 2014), and nomological validity (MacKenzie *et al.* 2011). All the tests were satisfactory.

SmartPLS was then used for testing the hypotheses, which is summarized in Figure 1. All the hypotheses are found to be significant. H1 suggests that the use of business analytics (UBA) has a positive effect on rational SDM (RSDM), which is supported as UBA's effect on RSDM is 0.191 (p<0.005). H2 suggests that UBA has a negative effect on intuitive SDM (ISDM), which is supported as UBA's effect on ISDM is -0.265 (p<0.001). H3 proposes that RSDM is negatively associated with ISDM, which is supported as RSDM's effect on ISDM is -0.258 (p<0.004). H4 assumes that environmental scanning (ES) mediates UBA's effect on RSDM, which was analyzed based on bootstrapping (Preacher and Hayes 2004; Hayes 2009; Hair *et al.* 2014). The analysis indicated that UBA's indirect effect on RSDM through ES is 0.213 (p<0.004), suggesting that ES mediates the effect of UBA on RSDM. Thus, H4 is supported.

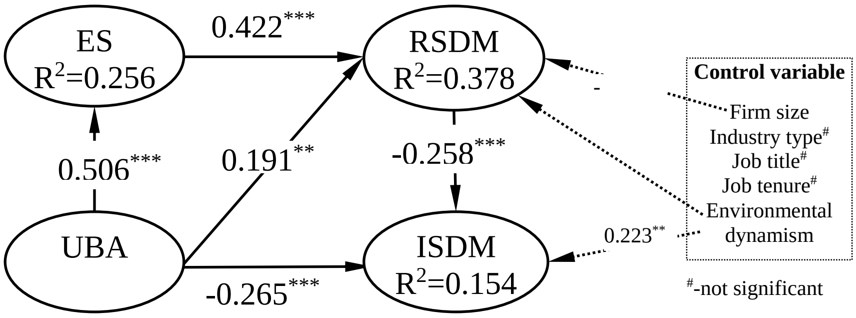

Figure 1. Hypothesis test results

4. Discussion and Conclusions

4.1. Discussions

Understanding how business analytics can be used to improve SDM is important to both organizations and scholarly research since the processes of SDM matter for organizational outcomes (Elbanna 2006). The study's outcomes suggest that the use of business analytics directly affects rational SDM positively and intuitive SDM negatively. The findings, on the one hand, provide empirical evidence in support of the practice-oriented studies of the impact of using business analytics on organizational decision making (e.g. Davenport 2013; Kiron *et al.* 2014). On the other hand and more importantly, the findings explicate that the use of business analytics could enable an organization to develop its analytics capability, thereby to improve its rational SDM and reduce the need for intuitive SDM. Thus, the findings provide conceptual and empirical evidence not only to support the notion suggested by Sharma *et al.* (2014) and Seddon *et al.* (2017) that the use of business analytics influences organizational decision making processes, but also to add new work to the under-researched area of intuitive SDM (Khatri and Ng 2000; Elbanna 2006; Elbanna *et al.* 2013) in the context of business analytics.

Regarding the relationship between rational SDM and intuitive SDM, the findings suggest that rational SDM is negatively associated with intuitive SDM. This study, drawing on the RBV, assumes that the more an organization uses business analytics to develop its analytics capability, the more likely it is to employ rational SDM and reduce the need for intuitive SDM.

With respect to the mediation role of environmental scanning, the findings indicate that the use of business analytics indeed has a significant and positive indirect effect on rational SDM through environmental scanning. This means that an organization could improve its rational SDM not only directly by developing its analytics capability but also indirectly through environmental scanning.

4.2. Theoretical contributions

This study offers several significant contributions that improve the understanding of the mechanisms through which business analytics improves SDM. Firstly, this study integrates the RBV with research on business analytics to advance our understanding of the mechanism for improving SDM from the use of business analytics.

Secondly, this study has based on the RBV and empirically substantiated the relationship between rational SDM and intuitive SDM in the context of business analytics. The findings of this study suggest that an organization is more likely to employ rational SDM when its use of business analytics allows it to generate useful insights.

Thirdly, this study has conceptualized and empirically confirmed that environmental scanning mediates the relationship between the use of business analytics and rational SDM. Thus, the findings of this study indicate that conducting environmental scanning based on the use of business analytics would allow an organization to be more fully appropriate the potentials afforded by the use of business analytics for SDM.

4.3. Practical implications

Furthermore, the findings of this study have significant managerial implications. The first important implication for organizations is that they should have incentives to invest in the use of business analytics because this investment allows them to significantly improve their rational SDM and reduce the need for intuitive SDM. The second major implication to decision makers is that a clear understanding of the need for carefully blending rationality and intuition is a key to improve SDM. The third important implication for organizations is that in order for it to improve SDM significantly, it needs to not only use business analytics but also conduct environmental scanning.

4.4. Limitations and future research

This study has several limitations that also provide areas for future research. Firstly, this research focused on the impact of the use of business analytics on SDM but not on organizational performance. Thus, future work could include additional variables to examine the effect of business analytics. Secondly, this study suggests that intuitive SDM and rational SDM are negatively related; thus further research is required for a better understanding of the roles that business analytics use plays in influencing both rational SDM and intuitive SDM across various decision contexts. Finally, one interesting finding from this study is that environmental scanning plays an important role in mediating the relationship between the use of business analytics and rational SDM. Future research could further test this relationship across different research contexts.

4.5. Conclusions

Underpinned by the RBV, this study developed and tested a research model to understand the mechanisms through which business analytics could be used to improve SDM. Essentially, the current study suggests that an organization can improve its SDM through developing its analytics and environmental scanning capabilities; and that environmental scanning significantly mediates the relationship between business analytics use and SDM.

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